Corporate Runs and Credit Reallocation

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July 24, 2026

We study how corporate clients' behavior on both sides of bank balance sheet shapes bank distress. Exploiting the 2017 regional bank failures in Italy, we show that corporate clients withdraw their deposits and that creditworthy firms switch to healthier banks at the first signs of weakness. This deteriorates loan portfolio quality and erodes capital ratios at distressed banks, amplifying fragility. The inflow of high-quality borrowers from the distressed banks allows the receiving banks to reallocate credit away from their own risky borrowers. Timely recapitalizations and targeted interventions that discourage the premature exit of high-quality borrowers may help mitigate bank fragility.

JEL classification: G21, G28

Keywords: bank runs, bank failures; loan applications; credit spillovers

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1 Introduction

Bank failures generate significant economic and social costs by disrupting credit availability and economic activity (Bernanke, 1983; Peek and Rosengren, 2000; Calomiris and Mason, 2003; Ashcraft, 2005; Huber, 2018). A large body of research examines the fragility of bank liabilities, with particular attention to depositor runs as triggers of bank failures and contagion across banks (e.g., Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005; Iyer and Puri, 2012; Iyer, Puri, and Ryan, 2016; Martin, Puri, and Ufier, 2026). Much less is known, however, about asset-side fragility, especially that arising from borrower behavior in the period leading up to large-scale depositor runs and bank failures.

This paper examines the early-stage dynamics of bank distress, focusing on how banks' corporate clients respond to emerging signs of weakness at their banks. Corporate clients can amplify bank fragility not only because their deposits are typically large and uninsured,[1] but also because they are simultaneously borrowers (Cao, Garcia-Appendini, and Huylebroek, 2024). Concerned about potential liquidity and credit disruptions, firms may act preemptively by drawing down committed credit lines (Ivashina and Scharfstein, 2010) or seeking new lending relationships with healthier banks (Detragiache, Garella, and Guiso, 2000) to secure uninterrupted access to credit. Because creditworthy firms are better positioned to establish new relationships, distressed banks may be left with weaker borrower pools, triggering a process of endogenous asset-side deterioration that undermines recapitalization efforts and leaves distressed banks more susceptible to runs.

We study these mechanisms in the context of the 2017 failures of two regional banking groups in Italy, which offer a clear setting for studying the dynamics of bank distress. Our objective is to trace how corporate clients' behavior on both

[1] See Beck, Ioannidou, Perotti, Sánchez Serrano, Suarez, and Vives (2024) for stylized facts on bank deposits in Europe.

sides of the banks' balance sheets shaped the evolution of distress, from the first public signals of weakness to the banks' eventual collapse. Specifically, leveraging granular data from the Bank of Italy, we track firms' deposit withdrawals, credit line drawdowns, and loan applications to other banks, assessing how the banks' corporate clients simultaneously weakened both sides of the banks' balance sheets and produced significant spillovers to other banks and firms in the region.

Two pivotal events mark the timeline. The first, in early 2015, followed revelations in the financial press that the two banks had inflated their regulatory capital using improper accounting practices, triggering a first wave of deposit outflows. The second, at the end of 2015, came after the ECB's Supervisory Review revealed that the banks failed to meet minimum capital requirements, sparking a second and much more severe wave of depositor runs.

Our analysis focuses on the period between these two events (i.e., the "first phase of distress") to understand how early liability- and asset-side dynamics weakened the banks and set the stage for the second run that precipitated their collapse. We begin by documenting deposit outflows to capture the timing and composition of runs on the liability side. We then turn to the asset side, the main focus of the paper, and study how credit line drawdowns and credit reallocation during the first phase of distress have contributed to the banks' deterioration.

We find that the early actions of corporate clients simultaneously weakened the banks on both sides of the balance sheet. On the liability side, deposit withdrawals reduced funding. On the asset side, credit line drawdowns and the reallocation of new borrowing to other banks lowered loan quality, eroding capital ratios at a critical moment. This made it harder to attract the new capital needed to restore confidence, leaving the banks more fragile and exposed to the second, larger wave of depositor runs. We also find that other banks in the region absorbed the high-quality borrowers from the distressed banks and decreased credit to their own risky clients. Overall, our evidence suggests that, at the onset of distress, when deposit outflows were still moderate, the deterioration in loan portfolios was driven primarily by demand rather than supply forces. In what follows, we discuss our findings in greater detail.

First, on the liability side, we find that their corporate clients began withdrawing deposits as soon as the banks' problems became public. During the first phase of distress (i.e., after the initial press revelations but before the second run), deposits at the distressed banks fell by about 7% relative to other banks. This first wave of outflows, concentrated among firms, drained roughly a quarter of the distressed banks' initial liquidity. The second wave, following the publication of the ECB's SREP report, was broader and far more severe, driven by both firms and households. By the end of this second second wave, deposits declined by 34% relative to other banks, fully exhausting the distressed banks' liquidity.

Second, on the asset side, we find that as soon as the banks' problems became public, the riskiest corporate borrowers increased drawdowns on existing credit lines, while the creditworthy clients began applying for and established new lending relationships with healthier "outside" banks.[2] Several results suggest that the early departure of low-risk borrowers was primarily demand-driven, reflecting precautionary motives rather than a contemporaneous contraction in credit supply. First, loan applications to outside banks were concentrated among low-risk firms with single relationships. Consistent with Detragiache et al. (2000), these firms face greater opportunity costs from credit disruptions due to higher continuation values and thus have stronger incentives to diversify. Second, low-risk firms were among banks' most profitable borrowers on a risk-adjusted basis, making it unlikely that the distressed banks would have chosen to cut credit to these firms. Third, within-firm analysis (Khwaja and Mian, 2008) shows that lending rates to

[2] Starting with Sharpe (1990), the terms "inside" and "outside" banks are used in the literature to distinguish between lenders with and without a prior lending relationship with a borrower.

these borrowers did not increase during the first phase of distress; if anything, they declined, indicating that the distressed banks were initially trying to retain these clients with more favorable terms. Fourth, in line with the departing borrowers being highly desirable, the spillover analysis shows that other banks in the region absorbed these new clients while reducing credit to their own risky borrowers. As a result, low-risk firms transitioned smoothly to healthier banks without significant declines in credit or investment, whereas riskier firms, unable to switch, experienced marked reductions in both.

Taken together, our results suggest the credit reallocation occured during the first phase of distress increased balance-sheet risk and undermined the distressed banks' capital position. During Post1, the total lost loan business to other banks was substantial, amounting to 11% of the distressed banks' loan portfolios, and was driven almost entirely by their most creditworthy and profitable borrowers. Counterfactual back-of-the-envelope calculations highlight the significance of this "adverse" composition effect: had this initial deleveraging come from riskier, rather than their most creditworthy clients, the banks' Common Equity Tier 1 (CET1) ratio would have increased by 62 basis points (bps). This is sizable. By way of comparison, the 2014 Asset Quality Review (AQR), conducted just before the first distress phase, identified an aggregate CET1 shortfall of approximately 40 bps. Similarly, the 2011 EBA Capital Exercise, which mandated capital increases during a crisis and significantly curtailed lending (Gropp, Mosk, Ongena, and Wix, 2019), involved an aggregate CET1 shortfall of 49 bps.

Our paper offers new valuable insights into the dynamics of bank distress, contributing to several strands of the literature. First, it provides novel micro-level evidence on the asset-side dynamics of bank distress, complementing and extending the literature on bank runs and bank failures (e.g., Iyer and Puri, 2012; Iyer et al., 2016; Acharya, Das, Kulkarni, Mishra, and Prabhala, 2023; Correia, Luck, and

Verner, 2025). We show that the liability- and asset-dynamics interact, jointly accelerating balance-sheet deterioration. Concerns about the banks' viability and potential liquidity disruptions prompt early runs by corporate clients, triggering a process of endogenous deterioration on both sides of the balance sheet.

Second, we contribute to the literature on credit-line runs (e.g., Ivashina and Scharfstein, 2010; Ippolito, Peydrò, Polo, and Sette, 2016; Chodorow-Reich, Darmouni, Luck, and Plosser, 2022; Greenwald, Krainer, and Paul, 2025). While existing work highlights widespread drawdowns during systemic crises, we show that, in the case of idiosyncratic bank distress, precautionary drawdowns are far more contained, driven primarily by high-risk firms with no alternative funding sources. These results shed new light on the mechanisms underpinning synergies in banks' joint provision of deposits and credit lines (Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006). Our results point to the existence of a stabilizing force in times of idiosyncratic bank distress, where creditworthy firms can turn to other lenders, complementing a similar mechanism based on interest rate sensitivity identified by Bräuning and Ivashina (2024).

Our findings carry important lessons for bank supervision and crisis management. They show that early-stage distress erodes both sides of the balance sheet well before large-scale depositor runs occur. Therefore, supervisors should monitor abnormal patterns in loan applications by high-quality borrowers, as these may serve as early warning signals of bank distress. In addition, policymakers could design interventions aimed at preventing the premature exit of high-quality borrowers. Such interventions may include targeted liquidity facilities for banks experiencing unusually high outflows of these borrowers. Finally, swift supervisory action to address solvency weaknesses, particularly through early recapitalization, is essential to restore confidence and prevent the loss of the best borrowers.

Our spillover analysis also highlights the importance of bank capital in determining which institutions can retain and attract creditworthy firms, beyond its well understood loss absorption role. The same market forces that destabilize weak banks can strengthen sound ones, supporting the reallocation of credit across the system. The matching of bank-dependent, high-quality borrowers with well-capitalized lenders may also help dampen procyclicality of aggregate credit and mitigate the transmission of bank shocks to the real economy (Schwert, 2018).

2 Timeline of Distress

In this section, we provide an overview of the distressed banks and a chronological account of the events which ultimately led to their collapse.

Comprising of six mutual banks within two banking groups, the distressed banks were prominent regional banks in Northern Italy, in one of Italy's wealthiest and most economically powerful region.[3] During the sample period, the regional GDP growth was 1.7%, nearly twice as large as the 1% national growth rate. The distressed banks were not publicly listed. They were predominantly owned by local households and entrepreneurs, and despite a modest size on a national scale (ranked 10^{th} and 11^{th} by total assets in 2013), they had an active lending relationship with a quarter of the region's firms at the time of distress.

The problems, which led to their eventual downfall, began in 2012. Following the European sovereign debt crisis, many Italian banks needed to raise fresh equity to address growing losses on non-performing loans. Given the high cost of raising equity at the time, some banks, including the distressed banks, resorted to "loan for shares" schemes, requiring that loan applicants use part of their loan proceeds to purchase shares of the lending bank. While not illegal, equity raised through

[3]Following Bank of Italy disclosure rules we cannot disclose the identity of the six banks and of the two banking groups that are included in the "distressed banks" aggregate.

such schemes must be excluded from the computation of regulatory capital.[4]

The first signs of trouble surfaced in November 2014, when the ECB Comprehensive Assessment revealed small capital shortfalls at both institutions. These shortfalls were not markedly different from those of other banks and, at the time, appeared manageable. Consistent with this, Figure 1 shows no uptick in Google searches for the banks' names during this period. In mid-February 2015, however, an article in the Italian financial press (based on interviews with former bank employees) revealed that the banks had been using "loan-for-shares" schemes since 2012 without deducting the associated equity from regulatory capital. This revelation drew widespread attention, as reflected in the sharp spike in Google search activity (the first spike in Figure 1), and marked the onset of heightened public scrutiny and uncertainty regarding their future viability.[5]

Over the next two months, the situation escalated further as negative press coverage continued, with articles pointing to excessive remuneration for directors and favorable financing deals for board members. Shortly after, the (unlisted) stock prices of the distressed banks were devalued by their respective boards by approximately 23%. In late November 2015, the ECB's Supervisory Review and Evaluation Process (SREP) concluded that the "loan-for-shares" practices were more widespread than initially believed, resulting in significant capital shortfalls relative to minimum regulatory requirements. This made it clear that the banks' continued viability depended on a substantial capital increase and Google searches for the banks' names surged again (second spike in Figure 1), marking the start of

[4]The Franco-Belgian bank Dexia, which failed in 2012, used similar schemes to inflate its regulatory capital. More generally, for computing their regulatory capital, banks must deduct various elements from their book equity, which do not enhance the bank's ability to withstand unexpected losses. These capital deductions, also referred to as "regulatory adjustments", are complex, substantial, and have been used by some banks to inflate their regulatory capital (see, e.g., Gropp, Mosk, Ongena, Simac, and Wix, 2024).

[5]The article also disclosed that the banks' managers were under investigation by judicial authorities for obstructing bank supervisory functions, following an on-site inspection that uncovered the scheme and other corporate governance failures.

a second phase of heightened uncertainty regarding their viability.

In early 2016, the distressed banks proposed a recapitalization plan to raise the necessary €2.5 billion by listing on the Italian stock exchange.[6] Due to their continued financial deterioration, there was no interest from investors. In mid-2016, a private vehicle sponsored by the Italian government to assist troubled banks (Atlante), assumed control of the distressed banks (third spike in Figure 1), but ultimately failed to secure the necessary funding as by that time the banks' condition had deteriorated beyond repair. Hence, left with no viable alternatives, in the first half of 2017, the ECB declared the banks as "likely to fail". The banks were placed into liquidation and were eventually acquired by another financial institution.

In sum, the distress faced by the banks in our study stemmed from poor corporate governance practices, which gave rise to mismanagement and accounting frauds. The exposure of these problems undermined trust and confidence in the banks' integrity and viability, ultimately leading to their downfall. In our empirical analysis, we examine the period leading-up to their failure to understand their corporate clients' behavior on both sides of the banks' balance sheets as the banks' distress unfolded, from the first signs of trouble to the banks' eventual collapse.

3 Data and Summary Statistics

Our analysis combines two main datasets from the Bank of Italy: (i) detailed bank–firm credit data from the Credit Register (CR) and (ii) bank–province–level deposit data from supervisory reports. The sample covers 2014–2016, allowing us to trace the evolution of the distressed banks' problems from about one year before their problems became public to one year after the ECB's SREP.

[6]This step was required under a 2015 law mandating all mutual savings banks in Italy with assets over €8 billion to become publicly listed companies by 2016.

The CR records all borrowers with total loans exceeding €30,000 at any single intermediary and provides information on credit volumes, loan types (credit lines, term loans), interest rates, and loan applications. Following Greenwald et al. (2025), we exclude credit lines with no granted credit or with utilization above the granted amount. Loan applications capture information requests by banks for first-time borrowers and include information about the applicants' credit histories, repayment behavior, and borrowing activity with other intermediaries.

We obtain interest rate data from Taxia, a component of the CR maintained by the Bank of Italy for supervisory and research purposes. Taxia covers roughly 90 banks, representing more than 80% of aggregate credit. It contains both relationship-level interest rates, computed as the ratio of interest payments to average outstanding balances by loan type (Crawford, Pavanini, and Schivardi, 2018), and contractual interest rates on new term loans, allowing us to calculate risk-adjusted returns at origination.

The baseline sample includes the 10 Northern Italian provinces where the two distressed banks had the largest local presence and were systemically important within the province. These provinces account collectively for about 60% of the banks' corporate lending, encompassing about 135,000 bank–firm relationships across about 56,00 unique firms. As a robustness check, we expand the sample to a broader set of provinces, covering 90% of total corporate lending; results are unchanged (Table A1 and Figure A1 in Online Appendix A).

We merge the CR with annual bank and firm balance sheets from supervisory reports and Cerved, respectively. The firm data include a measure of firms' default probability based on Cerved's proprietary Z-score, which unlike internal credit ratings, cannot be directly manipulated by banks. The score is derived from firms' accounting data and credit line usage and is a key determinant of loan application success (Rodano, Serrano-Velarde, and Tarantino, 2018).

The deposit data are available at a monthly frequency and distinguish between household and firm deposits by province. They cover about 500 banking groups across 110 provinces. For the analysis, we exclude banks with less than €1 million in total deposits in a province to prevent banks with very small presence in a province from disproportionately influencing our estimates.

Descriptive statistics are reported in Table 1. Panel A summarizes bank characteristics at the start of the sample. The 477 banks in our final sample have an average capital ratio of 12.5%, with deposits accounting for about 42% of total assets (of which one-quarter in corporate deposits).[7] Panel B reports firm-level characteristics. The sample includes 56,505 firms with average assets of €4 million and 17 years of age. About 28% are classified as "High-Risk" (Z-scores ≥ 7), and 43% borrow from only one bank.[8] Roughly one-quarter are clients of the distressed banks, with an average share of credit from the distressed banks of 44%. Panels C and D present statistics on credit line usage, loan applications, and firm outcomes. The average probability of applying to a new bank is 5%, and the switching success rate is 27%.[9] On average, firms draw 23% of available credit lines, with high-risk firms drawing about twice as much as low-risk ones. During the event window, total bank credit declined by 3.3%, while investment grew modestly.

[7] Private-sector deposits account for a smaller share of bank funding in Italy than in the U.S., where they are about 60% of total assets. The difference reflects greater reliance on bank bonds, often placed with retail investors, which represent roughly 23% of the total assets of Italian banks (see, e.g., Carletti, De Marco, Ioannidou, and Sette, 2021).

[8] Firms maintain on average 2.5 lending relationships (median of 2). Multiple relationships are relatively more common in Italy than in other countries, a pattern largely driven by larger firms (see, e.g., Detragiache et al., 2000; Kosekova, Maddaloni, Papoutsi, and Schivardi, 2023).

[9] In the full CR dataset, the average switching rate during the sample period (i.e., the share of firms establishing new lending relationships conditional on applying) is 17%, comparable to estimates for France (Boualam and Mazet-Sonilhac, 2021) and Norway (Cao et al., 2024).

4 Empirical Strategy and Results

We use difference-in-differences (DiD) analyses at different levels of aggregation (bank, firm, and bank-firm) to track the behavior of the distressed banks' corporate clients as their problems become widely known. We first analyze the deposit dynamics to capture the behavior of corporate depositors and the timing of distress on the liability side. We then turn to the asset side, our main focus, to examine the behavior of their corporate borrowers, and assess their contribution to the banks' failure.

4.1 The Dynamics of Depositor Runs

The revelation of accounting fraud that inflated regulatory capital, together with negative media coverage, eroded confidence in the distressed banks' viability and triggered depositor runs. Figure 2 illustrates how deposits of the distressed banks evolved relative to all other ("non-distressed") banks during our event window. To facilitate comparison, all series are normalized to 1 as of end of January 2014.

As shown in Figure 2, the deposits of the distressed banks, which had been growing at the same rate as the rest of the banking system, began to decline and diverge in late 2014, following the ECB Comprehensive Assessment, which revealed minor capital shortfalls at both banks. Although public, these findings attracted relatively little attention (Figure 1), and outflows were modest.[10] The first sizable outflows occurred in February 2015, when the press article made the banks' problems widely known and Google search activity spiked. After this initial drop, deposits briefly stabilized and partly recovered. The turning point came at the end of 2015, when the SREP report revealed the extent of their problems,

[10] Figure 2 reports end-of-month data. The small early declines starting in November 2014 are consistent with withdrawals by a few informed depositors, as documented in other contexts (see, e.g., Iyer et al., 2016 and Michaelides, 2014).

triggering a second, and much larger wave of deposit withdrawals. In contrast, other banks continued to experience steady deposit growth throughout this period.

In what follows, we confirm the insights from Figure 2 using DiD analysis at the bank-month level, controlling for bank and time-fixed effects. We estimate:

$$\log(Dep)_{b,t} = \beta_1\ D_b \times \text{Post } 1 + \beta_2\ D_b \times \text{Post } 2 + \alpha_b + \alpha_t + \epsilon_{b,t}, \quad (1)$$

where $\log(Dep)_{b,t}$ denotes the log of (total, firm, or household) deposits at bank b in month t, D_b equals 1 if bank b is one of the distressed banks, and 0 otherwise, and Post 1 and Post 2 distinguish the 'distress period' in two sub-periods. The first sub-period begins in February 2015, when the distressed banks' problems became widely known, and ends in November 2015, just before the release of the SREP results. The second sub-period starts in December 2015 and runs through December 2016. The omitted period is 2014. Equation (1) includes both bank and year-month fixed effects, α_b and α_t. Observations are weighted by total assets and standard errors are clustered at the bank and year-month level.[11]

The results are reported in Table 2. During Post 1 and Post 2, the deposits of the distressed banks decreased relative to other banks by 6.8% and 34.4%, respectively, corresponding to outflows of roughly 22.2% and 112.3% of their initial liquidity.[12] Distinguishing between household and firm deposits in columns (2) and (3), we find that the outflows in Post 1 were mainly driven by firms. During this period, corporate deposits fell by 13.2% relative to other banks, while decreases in household deposits were smaller and only marginally significant (p-value = 0.098). Household deposits only began to fall markedly during Post 2, but even then with

[11]In robustness tests, we confirm that results are similar if we do not weight observations or if we contrast the distressed banks to banks of different sizes (small, medium, or large banks).

[12]Liquid holdings include reserves and government securities, which are eligible as collateral with the ECB. As of December 31, 2013 (i.e., just before the start of our event window), the distressed banks' combined liquidity totaled €7.6 billion.

much lower intensity than corporate deposits (22.4% vs. 58.8%).

Figure 3 reports the estimates from a dynamic DiD specification for firm and household deposits separately. The results confirm that firms began withdrawing deposits as soon as the banks' problems became widely known and with greater intensity than households. They also confirm that until December 2014, the deposits of the distressed banks moved in parallel to other banks.

Additional analysis, reported in Table B1 in Online Appendix B, shows that corporate deposits flowed primarily toward well-capitalized banks, regardless of size. Households instead did not appear to prioritize bank soundness: they shifted to large, systemically important banks irrespective of their capital levels.[13]

Our results thus far yield two key insights. First, deposit withdrawals affected banks' liquidity differently overtime: outflows in Post 1 drained about a quarter of their liquidity, creating a significant but still manageable strain, while the second wave in Post 2 exhausted all liquidity. Second, at the onset of distress, firms and households behaved very differently: firms reacted first and more sharply as soon as the banks' problems became public, and their choice of new banks differed. While corporate deposits flew primarily towards healthier banks, household deposits went to large systemically important banks.

These patterns likely reflect not only differences in deposit insurance and ability to assess fundamentals, but also the nature of services they seek from their banks (Egan, Hortacsu, and Matvos, 2017). Whereas households may be primarily seeking a safe "store of value" in systemically important banks, firms may be trying to ensure continued access to credit and liquidity. This implies that when firms withdraw deposits out of concern for a bank's viability, they may be also "running" on the asset side for the same reason.

[13]The results for households are similar to broader patterns in total deposit flows documented in other studies (Iyer, Jensen, Johannesen, and Sheridan, 2019; Acharya et al., 2023; Caglio, Dlugosz, and Rezende, 2024; Cipriani, Eisenbach, and Kovner, 2024).

4.2 The Asset-Side Dynamics

We now turn to the asset side to examine how these forces shaped the distressed banks' balance sheets and how they affected the banks' ultimate failure. We first explore two potential demand-side channels, both reflecting precautionary motives: "credit line run" on existing credit lines and "borrower flight" to outside banks. We then contrast these channels with alternative supply-side explanations.

The relative importance of demand and supply forces likely varied not only over time as the crisis deepened and outflows intensified, but also across different types of firms. Our tests aim to shed light on how the early dynamics, whether demand- or supply-driven, may have contributed to the weakening of the distressed banks in particular during the first, critical period leading up to the second wave of deposit outflows that precipitated their collapse.

4.2.1 Precautionary Drawdowns

We first examine whether the distressed banks began experiencing higher drawdowns on existing credit lines as their problems became public. Prior studies find that firms tend to draw their credit lines from banks facing funding shocks, either in anticipation of future credit supply restrictions or out of fear that their credit lines may be cut or revoked (Ivashina and Scharfstein, 2010; Ippolito et al., 2016; Chodorow-Reich et al., 2022; Greenwald et al., 2025). This phenomenon, known as a "credit-line run", occurs when firms preemptively draw on their credit lines to secure the committed liquidity. To test for such behavior, we estimate the following DiD specification at the bank-firm-quarter level:

$$ShareDrawn_{b,f,t} = \beta_1 \; D_b \times \text{Post } 1 + \beta_2 \; D_b \times \text{Post } 2 + \alpha_b + \mu_{f,t} + \epsilon_{b,f,t}, \qquad (2)$$

where $ShareDrawn_{b,f,t}$ is the share of drawn credit lines (i.e., drawn amount over granted amount) from bank b to firm f in quarter t. The dummy variable D_b equals 1 if bank b is one of the distressed banks, and 0 otherwise. Given the quarterly frequency, Post 1 equals 1 between 2015Q1 and 2015Q3, and 0 otherwise, while Post 2 equals 1 between 2015Q4 and 2016Q4, and 0 otherwise. The 'pre-period' (omitted group) spans from 2014Q1 to 2014Q4. Following Greenwald et al. (2025), we exclude bank-firm relationships that have already reached the credit line limit, as these borrowers cannot further adjust their drawdowns.

We include bank fixed effects, α_b, to control for time-invariant differences across banks. To control for time-varying firm-specific factors we include firm×year-quarter fixed effects, $\mu_{f,t}$, following Khwaja and Mian (2008). This allows us to determine whether the same firm, at the same time, draws more on credit lines from the distressed banks than from other banks.[14]

The results are reported in Table 3. At the onset of distress, we find higher drawdowns only among high-risk firms with single lending relationships, i.e., those with the strongest precautionary motives. During Post 1, these firms drew about 6% more on their credit lines than comparable high-risk borrowers at non-distressed banks (0.024/0.39). Firms with easier access to alternative funding sources (i.e., firms with multiple relationships or single-relationship firms with strong fundamentals), showed no increase in drawdowns during this period. By Post 2, as the banks' problems deepened, drawdowns broadened: all groups except low-risk single-relationship firms increased precautionary drawdowns. High- and low-risk firms with multiple relationships, raised drawdowns by roughly 5% (0.017/0.39 and 0.009/0.18, respectively), indicating that precautionary behavior became more

[14]This specification is very conservative, but it can only be estimated for firms with multiple banking relationships. To extend the analysis to the full sample of firms, we also estimate a specification that replaces $\mu_{f,t}$ with industry×province×size×year-quarter fixed effects, following Degryse, De Jonghe, Jakovljević, Mulier, and Schepens (2019). Firm size is determined based on quintiles of total assets at the end of 2013.

widespread as distressed deepened.

These results indicate that once the distressed banks' problems became public and corporate depositors began to flow out, their single-relationship riskier corporate borrowers started drawing more heavily on their credit lines. This behavior increased the share of risky loans in the distressed banks' portfolios and further strained their liquidity.[15] Economically, however, the aggregate impact of drawdowns in Post 1 was very small because the increase was confined to a relatively small segment of the banks' corporate borrowers. These precautionary drawdowns amounted to €12 million, corresponding to 17 bps of the banks' initial liquidity.[16]

The small and concentrated nature of drawdowns in Post 1 may seem at odds with the large, broad-based credit-line runs documented in prior studies. The key difference lies in the nature of the shock. Existing work (e.g., Ivashina and Scharfstein, 2010; Ippolito et al., 2016; Greenwald et al., 2025) focuses on aggregate liquidity shocks (e.g., the GFC and the COVID-19 pandemic), when many banks simultaneously face liquidity stress and firms have limited outside options, leading to widespread drawdowns. In our setting, by contrast, bank distress is idiosyncratic, and thus firms' responses differ accordingly.

In particular, when banks' liquidity problems are idiosyncratic, firms with strong fundamentals can turn to other banks. Instead of preemptively drawing on expensive credit lines and paying interest on the drawn amounts, these firms insure against future credit supply disruptions by establishing new lending relationships with healthier banks.[17] By contrast, high-risk single-relationship firms,

[15]While drawn funds are sometimes left on deposits in the same bank, mitigating liquidity pressures from drawdowns, this is unlikely in our setting, where firms concerned about the banks' viability were withdrawing deposits.

[16]These figures are calculated by multiplying the estimated coefficient for high-risk single relationship firms (0.024 in column 5 of Table 3) by the total amount of credit lines to this group in 2014Q4 (€510million).

[17]Firms aiming to establish new lending relationships may prefer not to make use of precautionary drawdowns also because high utilization is a signal of weaker credit quality (Chodorow-Reich et al., 2022). In our setting, credit line usage is observable to outside lenders through the credit

those least able to switch lenders, behave more like firms in systemic crises, preemptively drawing on their available credit lines once distress becomes public.

These results shed new light on the mechanisms underpinning banks' synergies in the joint provision of deposits and credit lines. Classic contributions such as Kashyap et al. (2002) and Gatev and Strahan (2006) show that deposit outflows and credit-line drawdowns tend to be negatively correlated, enabling banks to manage liquidity risk more efficiently. Consistent with this broad insight, we find that deposit outflows are not associated with credit line drawdowns from stronger firms who may be able to obtain credit from other banks. The absence of precautionary drawdowns from these firms reduces liquidity pressure on the distressed banks, generating a stabilizing force during periods of idiosyncratic distress. These results complement those in Bräuning and Ivashina (2024), who show that precautionary credit line drawdowns exhibit high interest rate sensitivity outside systemic crises.

4.2.2 Loan Applications to Outside Banks

Next we examine whether borrowers of distressed banks sought and secured new lending relationships as the banks' problems became public, and how these shifts influenced their liquidity and loan portfolios. Facing deposit outflows, the distressed banks may have reduced credit supply, forcing their corporate clients to seek financing elsewhere. Their clients may have also proactively sought new lending relationships to diversify funding sources and ensure stable access to credit.

Incentives to turn to other banks are strongest among firms with higher continuation values—those facing greater opportunity costs from potential credit supply disruptions—and among firms more dependent on the distressed banks (Detragiache et al., 2000).Because local "outside funding" capacity is limited, single-relationship firms, typically smaller firms reliant on local banks, have greater ur-

registry and negatively affects firms' publicly available Z-scores.

gency to diversify as soon as their banks' problems become widely known.[18]

For this analysis, we estimate the following linear probability model:

$$\begin{aligned} ApplOut_{f,t} = \beta_1 \; SD_{f,2013} \times \text{Post } 1 + \beta_2 \; SD_{f,2013} \times \text{Post } 2 \\ + \gamma' X_{f,t-4} + \alpha_{k,p,s,t} + Zscore(i)_{f,t} + \mu_f + \epsilon_{f,t} \end{aligned} \tag{3}$$

where $ApplOut_{f,t}$ equals 1 if firm f applied for a loan to an outside bank in quarter t, and 0 otherwise. A bank is defined as an outside bank to a firm if the firm has no outstanding loans from that bank in the year prior to the start of our event window. $SD_{f,2013}$ is the share of firm f's credit from the distressed banks in 2013, which takes values from 0 to 1. Post 1 and Post 2 are defined as in Eqn (2).

Controls in $X_{f,t-4}$ include lagged firm size, age, and profitability. We additionally include industry×province×size×year-quarter fixed effects ($\alpha_{k,p,s,t}$), Z-score ×year-quarter fixed effects for each risk category i ($Zscore(i)_{f,t}$ for $i = 1, ..., 9$), as well as firm fixed effects (μ_f). The firm fixed effects absorb the level effect of $SD_{f,2013}$ and other time-invariant borrower characteristics, including the initial strength of the borrower relationship with the distressed banks. Identification of the parameters of interest comes from *within* firm variation over time.[19] The key identifying assumption is that, conditional on controls and fixed effects, the pre-distress share of credit from the distressed banks does not correlate with firm-

[18] Local capacity constraints are more binding for smaller firms that tend to borrow from local banks (see, among others, Stein, 2002; Berger, Miller, Petersen, Rajan, and Stein, 2005; Degryse and Ongena, 2005; Agarwal and Hauswald, 2010). This incentive to switch is consistent with broader evidence on the costs of financial distress for firms' customers, who discount relationships with suppliers at greater risk of liquidation because of anticipated disruptions to future service (Titman, 1984). Similar strategic complementarities are thought to drive depositor runs (Diamond and Dybvig, 1983) and, more recently, "worker runs" (Hoffman and Vladimirov, 2025).

[19] To further enhance comparability between the two groups, we use entropy balancing regression weights (Hainmueller, 2012) based on firm size. Table A2 in Online Appendix A shows that while there are small differences in firm size between the two groups, they are otherwise well balanced across a range of characteristics. With the exception of firm size, all normalized differences fall below the conventional 0.25 threshold (Imbens and Wooldridge, 2018).

specific unobservables that influence the decision to apply for credit elsewhere.

We estimate the model separately for four groups of firms: low- and high-risk firms, and within each risk group, borrowers with single versus multiple lending relationships. The "borrower flight" channel predicts positive β_1 and β_2 coefficients, particularly during Post 1 and among low-risk firms with higher exposure to the distressed banks. As shown in Figure A2 in Online Appendix A, low-risk firms tend to be more profitable and more productive firms, with higher investment rates. In other words, these firms have higher continuation values and greater opportunity costs from credit supply disruptions, which have stronger incentives to diversify their relationships for precautionary motives (Detragiache et al., 2000).

Table 4 reports our findings. In column (1), where firm-fixed effects are not included in the specification, the coefficient of $SD_{f,2013}$ is very close to zero and statistically insignificant. This confirms that, during the pre-period, loan applications to outside banks were similar regardless of firms' reliance on the distressed banks. This changed sharply as information about the distressed banks' problems became public and began facing depositor runs. The coefficients on the interaction of $SD_{f,2013}$ with Post 1 and Post 2 are both positive and statistically significant, indicating that firms with higher credit dependence on the distressed banks were more likely to apply for outside loans during the distress period. The estimated coefficients are large and remain stable as we add firm fixed effects in column (2). For example, for firms fully dependent on the distressed banks (i.e., with $SD_{f,2013} = 1$), loan applications rose by about 24% in Post 1 (0.010/0.046) and 37% in Post 2 (0.017/0.046) relative to the average application rate.

Results of corresponding dynamic DiD specifications, reported in Figure 4, further show that applications to outside banks began rising precisely when the distressed banks' problems became public in 2015Q1 (i.e., at the start of Post 1).[20]

[20]In further tests, reported in Table A3 in Online Appendix A, we find that firms with stronger shareholder ties are less likely to apply to outside banks. We find instead no systematic difference

Distinguishing between low- and high-risk firms with single or multiple lending relationships (columns (3)–(6) of Table 4) shows that the Post 1 increase was entirely driven by low-risk firms with single lending relationships, i.e., those fully dependent on the distressed banks, in line with theoretical predictions under the "borrower flight" hypothesis. Other groups show no significant change at this stage. By Post 2, low-risk firms with multiple relationships also began applying elsewhere, suggesting that as distress deepened, even more diversified borrowers began seeking new lenders. Columns (7)–(8) further show loan applications to outside banks are strongest among firms with a larger share of maturing debt.

Additional analysis on new lending relationships, reported in Table 5, shows that low-risk firms were more likely to establish new relationships once the banks' problems became public. Conditional on applying for credit to an outside bank, low-risk firms that were fully dependent on the distressed banks ($SD_{f,2013}$=1) were about 12 pps more likely to form new lending relationships during Post 1. This is roughly a 46% increase relative to the mean (0.124/0.271). The corresponding increases in Post 2 are somewhat smaller (9 pps and 33%, respectively), indicating that early movers were, on average, more successful in securing new lenders.

The increase in the probability of forming a new relationship is higher than the probability of applying for credit (10 pps in column 1 of Table 5 vs. 1 pp in column 2 of Table 4), indicating that most loan applications from borrowers of distressed banks result in new lending relationships. Firms fleeing a failing bank, unlike typical switching borrowers, are less likely to be adversely selected, mitigating "winner's curse" concerns (Sharpe, 1990; von Thadden, 2004).

Additional results in columns (4)-(7) of Table 5 show that new relationships were primarily formed with better-capitalized and larger banks. Bank capitalization mattered more during the first wave of runs, when firm deposits moved toward

with respect to the length of the firm's lending relationship with the distressed banks.

better capitalized banks. Bank size became more important during the second wave, when households shifted toward large, systemically important banks.

Figure 5 offers a visual illustration of the "lost business" to outside banks. In particular, using the set of firms that that were borrowing exclusively from the distressed banks at the start of the event window (i.e., single-relationship firms), we compute cumulative value of new loans they obtained from outside banks over the event window, scaled by the distressed banks total loans at the start of the period.[21] For comparison, we compute the same measure for non-distressed banks.

Before the distressed banks' problems became widely known in 2015Q1, the share of lost business to outside banks was similar for both groups.[22] This changed sharply after 2015Q1, when the distressed banks began losing new loan business to outside banks at a significantly faster rate. The gap between the two figures indicates that by the end of the event window the lost loan business to outside banks was 10 pps larger for the distressed banks. Crucially, most of this loss occurred during Post 1 and, as shown in Figure A4, it was driven almost entirely by their most creditworthy borrowers (i.e., firms also attractive to other banks).[23]

Overall, our results show that as soon as the distressed banks' problems became public and they began experiencing outflows from corporate depositors, their most creditworthy clients also started seeking and establishing new lending relationships, setting in motion a process of endogenous deterioration of their loan portfolios. As shown in Figure 6, after adjusting for credit risk, loans to low-risk firms yield higher

[21] We restrict this computation to single-relationship firms because for multiple-relationship firms it is more challenging to attribute the lost business to existing or new lenders.

[22] Both series trend upward over time, as some borrowers naturally switch banks for reasons unrelated to distress.

[23] Figure A5 in the Online Appendix confirms these findings using the outstanding amount of drawn credit rather than the granted amount, indicating that credit lines with new lenders are actively used. This robustness check is important because a significant share of new lending relationships involve credit lines, which may not necessarily be utilized. Specifically, about 69% of new relationships include a credit line, while 60% include a term loan (many include both). However, since term loans are much larger on average, they account for a greater share of total new credit compared to credit lines (37% vs. 13%).

expected returns than loans to high-risk firms (Z-scores ≥ 7), indicating that low-risk borrowers are banks' most profitable customers.[24] Interestingly, returns peak for firms with good, but not perfect, credit scores. This is in line with models of relationship lending in which asymmetric information prevents creditworthy firms from credibly signaling their type to outside lenders, enabling incumbent banks to extract information rents (Sharpe, 1990; Rajan, 1992; von Thadden, 2004).[25]

4.2.3 Credit Demand vs. Credit Supply

Our results thus far suggest that the exit of low-risk borrowers in Post 1, when deposit outflows were still moderate, is more consistent with a decline in credit demand than in credit supply. In other words, these borrowers appear to have turned to other banks because they wanted to, likely for precautionary reasons, not because they were forced out. The departing low-risk borrowers are among banks' most profitable clients (Figure 6), making it unlikely that the distressed banks would have preferred to reduce lending to them rather than to riskier firms. In addition, from a capital perspective, cutting credit to high-risk borrowers is typically preferable as these loans carry higher risk weights in regulatory capital requirements (see, e.g., Gropp et al., 2019).

To examine how lending conditions at the distressed banks evolved relative to other banks during the event window, Table 6 presents estimates from the following

[24]Figure 6 reports risk-adjusted returns at loan origination for each rating, computed using contractual interest rates on new loans net of expected default probabilities for all borrowers during our sample period (2014-2016). This provides an ex-ante measure of loan profitability, not affected by ex-post shocks to borrower risk. Values above (below) zero indicate higher (lower) risk-adjusted returns relative to the omitted group (z-score = 1, the safest firms). Importantly, negative values for high-risk borrowers do not imply negative NPV loans; they reflect that high-risk loans are less profitable than the safest loans on a risk-adjusted basis.

[25]Robustness tests confirm similar results for new and existing customers, suggesting that the lower returns for high-risk firms do not reflect zombie lending (Online Appendix Figure A3).

DiD specification at the bank–firm–quarter level:

$$Y_{b,f,t} = \beta_1 \ D_b \times \text{Post } 1 + \beta_2 \ D_b \times \text{Post } 2 + \alpha_b + \mu_{f,t} + \epsilon_{b,f,t}, \tag{4}$$

where $Y_{b,f,t}$ denotes the log of total outstanding credit or the loan interest rate from bank b to firm f in quarter t, D_b equals 1 if bank b is one of the distressed banks and 0 otherwise, and Post 1 and Post 2 are defined as in Eqn. (2). In addition to bank-fixed effects, α_b, which control for time-invariant differences across banks, in our most conservative specifications we include firm×time fixed effects, $\mu_{f,t}$. The coefficients of interests, β_1 and β_2 reflect changes in credit and loan interest rates to the *same firm* in the *same quarter* for firms with multiple relationships (Khwaja and Mian, 2008).[26] Figure 8 reports the estimated coefficients and 95% confidence intervals from corresponding dynamic DiD specifications.

These specifications are used in the literature to identify credit supply effects under the assumption that borrowers are indifferent across lenders. However, this assumption is not appropriate in settings like ours where borrowers may be trying to diversify away from distressed banks. The inclusion of $\mu_{f,t}$ in this case can help absorb confounding factors, but it does not necessarily imply identification of credit supply effects.[27] We thus rely on the joint movement of credit volumes and loan interest rates to distinguish between demand and supply.

The results yield two key insights. First, the results for high-risk firms point to a tightening of credit conditions to these firms. Loan rates to high-risk borrowers increased already in Post 1 (Panel B of Table 6 and Figure 8), even though credit volumes decline more substantially only in Post 2. Facing funding pressures, the distressed banks may have begun charging higher interest rate to "captive" bor-

[26] For completeness, we also estimate less restrictive specifications for all firms by replacing firm×time fixed effects with industry×province×size×quarter fixed effects (Degryse et al., 2019). We weight these regressions by firms' total credit as of 2013Q4 and focus on performing exposures.

[27] See related discussion in Paravisini, Rappoport, and Schnabl (2023).

rowers to preserve margins. While this behavior may be consistent with "zombie lending", we caution against drawing such conclusion. First, during the pre-period the distressed banks were not charging lower rates to risky firms compared to other banks (Panel B of Figure 8). This suggests that, if zombie lending was occurring, it was not more pronounced among distressed banks. Second, incentives to evergreen risky loans likely diminished as the distressed banks came under greater market and supervisory scrutiny, in line with evidence in Bonfim, Cerqueiro, Degryse, and Ongena (2022).[28]

Second, consistent with the view that the departure low-risk borrowers at the onset of distress reflected a decline in credit demand rather than credit supply, we find that the decline in credit to these firms from the distressed banks during Post 1 was not accompanied by higher loan rates (Panel B of Table 6). Instead, as shown in Figure 8, during Post 1 the distressed banks began charging lower rates to these firms. This indicates that, at least initially, when their outflows were still moderate, the distressed banks were trying to retain their most creditworthy and profitable borrowers with cheaper credit. As the crisis deepened, these lower rates disappeared and lending volumes contracted further, reflecting the banks' funding pressure intensified and reduced ability to lend even to their best clients.

Overall, these results provide further support to the view that the departure of low-risk firms at the onset of distress was primarily demand-driven (i.e., these firms actively sought to reduce their exposure to troubled banks). The next two sections, on spillover effects and real outcomes, provide further evidence consistent with this interpretation. Before turning to these analyses, we examine the impact

[28] Weakly capitalized banks have stronger incentives to lend to "zombie" firms because the subsidies embedded in government guarantees and forbearance policies rise with leverage and asset risk (Acharya, Lenzu, and Wang, 2024). Since the seminal work by Peek and Rosengren (2005) and Caballero, Hoshi, and Kashyap (2008), a large body of empirical evidence has documented that weakly capitalized banks engage in zombie lending (see, e.g., Acharya, Eisert, Eufinger, and Hirsch, 2019; Schivardi, Sette, and Tabellini, 2022). The factors sustaining this "diabolical sorting" equilibrium may weaken once banks come under greater public and regulatory scrutiny.

of these asset-side dynamics on the banks' collapse.

4.2.4 Credit Reallocation and Impact on the Banks' Viability

In this section, we assess the economic magnitude of the credit reallocation during Post 1 and its impact on the distressed banks' viability. Our focus is on the change in the riskiness of their loan portfolios resulting from the exit of low-risk borrowers, and the consequent changes in their capital position.

While the reduction in outstanding credit may have alleviated liquidity pressures, it also changed the composition of distressed banks' loan portfolios. As the most creditworthy borrowers left, these banks became increasingly exposed to riskier borrowers, leading to a deterioration in average loan quality. This adverse deleveraging is visible in Figure 7, which shows that NPL ratios at the distressed banks begin to diverge sharply from the system average after 2014.

Table A4 confirms this deterioration in a regression framework. Column 1 shows that NPL ratios increased significantly at distressed banks from 2015 onward, consistent with the timing of borrower flight documented in Post 1. One concern with the NPL measure is that it may partly reflect banks' discretion in recognizing bad loans, rather than compositional changes in the borrower pool. This concern is particularly relevant around 2014, when the small increase in NPLs may reflect more aggressive recognition of bad loans under heightened regulatory scrutiny during the AQR exercise.

We therefore also examine an alternative measure of loan quality based on Cerved Z-scores. This measure is constructed from external credit ratings and is therefore not subject to banks' reporting discretion. Column 2 shows a similar deterioration in loan quality, but with a cleaner timing: risk-weighted credit increases significantly only from 2015 onward. These results make it unlikely that the divergence simply reflects more aggressive recognition of pre-existing bad credits.

The exit of low-risk borrowers has a significant impact on the distressed banks' capital position. Our back-of-the-envelope exercise focuses on the direct effect of this adverse deleveraging on risk-weighted assets, and therefore on the denominator of the CET1 ratio. It abstracts from any effects that the resulting change in portfolio composition may have on the numerator of the ratio through retained earnings. This latter effect is difficult to quantify without additional assumptions about loan pricing, banks' dynamic responses, and the profitability of marginal borrowers. Moreover, insofar as banks price loans to deliver similar marginal risk-adjusted returns across borrower types, the difference in retained earnings between losing low-risk rather than high-risk borrowers is likely to be small.

To measure the capital effect, we conduct a back-of-the-envelope counterfactual estimate of how much the distressed banks' CET1 ratio would have improved had the same volume of lost business in Post 1 come from high-risk rather than low-risk borrowers. To do this, we first calculate the amount of total lost loan business to other banks and then measure the change in risk-weighted assets (RWAs) in the counterfactual scenario by mapping Cerved Z-scores of each firm into risk weights. As explained in detail in Online Appendix C, we estimate that counterfactual RWAs would have been €44 billion, compared to the realized €48 billion. Under this "virtuous" deleveraging scenario, the banks' CET1 ratio would have reached 7.57% i.e., 62 bps higher than their actual CET1 ratio of 6.95% at the end of Post 1.

This difference in CET1 ratios is sizable. By way of comparison, the AQR exercise completed just before Post1 identified an aggregate CET1 shortfall in 25 euro-area banks of 40 bps. Going further back, the 2011 EBA Capital Exercise, which required capital increases during a crisis at 27 European banks that significantly reduced lending (Gropp et al., 2019), identified a shortfall of 49 bps.

Overall, these results suggest that the exit of the safest corporate clients in

Post 1 significantly weakened the distressed banks' capital position. The banks were left with weaker loan portfolios and diminished income prospects, factors that likely deterred potential investors and further eroded depositor confidence. Although this exercise does not quantify the broader profitability consequences of borrower flight, the regulatory-capital effect alone is economically meaningful. While it is impossible to determine whether the second wave of depositor runs could have been avoided, these adverse compositional effects certainly left the distressed banks more vulnerable when the second wave hit.

4.3 Spillover Effects on Other Banks' Loan Portfolios

In this section, we explore the effects of the flight of borrowers on other banks in the region. Specifically, we examine whether the influx of new low-risk borrowers from the distressed banks had negative spillover effects on existing borrowers of other banks (i.e., a potential crowding out effect due to capacity constraints).

For this analysis, we first compute the share of loan applications that each bank received from the borrowers of the distressed banks as a fraction of the total loan applications each bank received in a given quarter:

$$Exp_{b,t} = \frac{DistBorrAppl_{b,t}}{TotalAppl_{b,t}}, \tag{5}$$

where $DistBorrAppl_{b,t}$ indicates the number of loan applications to bank b in quarter t from the distressed banks' borrowers, where bank b refers to any other bank in the region, excluding the distressed banks. The variable $TotalAppl_{b,t}$ indicates the total number of loan applications to bank b in quarter t from new customers. Using $Exp_{b,t}$, we estimate the following specification:

$$\Delta \log(Credit)_{b,f,t} = \beta_1 \; Exp_{b,t} \times HighRisk_{f,2013} + \gamma' X_{f,t-1} + \alpha_{k,p,t} + \alpha_{b,t} + \epsilon_{b,f,t}, \tag{6}$$

where $\Delta \log(Credit)_{b,f,t}$ represents the quarterly growth rate of credit from bank b to firm f in quarter t. The dummy variable $HighRisk_{f,2013}$ equals 1 if existing borrower f is high-risk (i.e., Z-score ≥ 7), and equals 0 otherwise. To control for unobserved heterogeneity, we include both industry×province×quarter and bank×quarter fixed-effects, $\alpha_{k,p,t}$ and $\alpha_{b,t}$, respectively. For completeness, we also estimate baseline specifications without bank×quarter fixed-effects, which allow for the inclusion of $Exp_{b,t}$, both with and without interactions with $HighRisk_{f,2013}$.

The results are presented in Table 7. Column (1) shows that the coefficient of $Exp_{b,t}$ is statistically insignificant, indicating that, on average, the credit reallocation did not have significant spillover effects on the borrowers of other banks. However, a different pattern emerges once we distinguish by borrower type. In column (2), where $Exp_{b,t}$ is interacted with $HighRisk_{f,2013}$, we find that high-risk borrowers of banks that received applications only from distressed banks' borrowers ($Exp_{b,t} = 1$) experienced a 1.9 pps reduction in credit from these banks, roughly equal to 10% of the standard deviation of credit growth in the sample. This effect remains robust when we control for bank×quarter fixed effects in column (3). This selective reallocation away from high-risk firms provides further support to the idea that low-risk borrowers are the most desirable borrowers.

Column (4) explores the role of bank balance sheets by interacting $Exp_{b,t} \times HighRisk_{f,2013}$ with pre-determined key bank characteristics such as bank capital, size, and interbank borrowing (as of December 2013).[29] The interaction with bank capital is positive and statistically significant, showing that the reduction in credit to high-risk borrowers is stronger for banks with lower capital ratios. The larger and better borrower pool from the distressed banks may have enabled weakly capitalized banks to "cleanse" their loan portfolios and improve their capital ratios by reallocating credit away from their riskier customers towards low-risk firms from

[29]Among the control variables (not shown in the table for brevity), we also include double interactions between $HighRisk_{f,2013}$ and bank characteristics.

the distressed banks. In contrast, well-capitalized banks were able to accommodate new, creditworthy borrowers without curtailing credit to existing borrowers. Finally, we also find that exposed banks with greater reliance on wholesale interbank borrowing in 2013, which were more adversely affected by the sovereign debt crisis (De Marco, 2019), reduced credit to high-risk borrowers.

Overall, the results highlight the crucial role of bank capital in both initiating and facilitating credit reallocation during bank distress. The matching of bank-dependent creditworthy firms with well-capitalized lenders enhances the resilience of credit relationships, dampening cyclicality in aggregate credit provision and reducing the transmission of bank shocks to the real economy (Schwert, 2018).

4.4 Firm Outcomes: Total Credit and Investment

Finally, we examine how bank distress affects borrowers' overall credit access and investment. Our earlier results show that low-risk firms are more likely to apply and secure new lending relationships when their main bank becomes distressed. It remains unclear, however, whether these firms are able to obtain sufficient credit on comparable terms as to avoid a slowdown in investment. These firms are relatively small and may face switching frictions and information asymmetries, as emphasized by Chodorow-Reich (2014). At the same time, adverse selection and winner's curse concerns may be mitigated in this setting, as these firms proactively exit a distressed bank rather than being pushed out (Detragiache et al., 2000; Darmouni, 2020). To examine how their total credit and investment evolved over the event window, we estimate the following model at the firm-year level:

$$\begin{aligned} Y_{f,t} = {} & \beta_0 SD_{f,2013} + \beta_1 SD_{f,2013} \times \text{Post } 1 \\ & + \beta_2 SD_{f,2013} \times \text{Post } 2 + \alpha_{k,p,t} + \lambda_{j,t} + \epsilon_{f,t}. \end{aligned} \tag{7}$$

where $Y_{f,t}$ indicates either the growth of total granted credit, defined as the sum of term loans and granted credit lines, irrespective of whether the latter were drawn, or investment of firm f in quarter t. $SD_{f,2013}$ denotes the share of firm's f credit from the distressed banks in 2013. $\alpha_{k,p,t}$ and $\lambda_{j,t}$ denote industry×province×quarter and Z-score×quarter fixed effects.[30]

The results are reported in Table 8. Panel A reports results for total credit and Panel B for investment. The first three columns report a baseline specification, which studies the relationship between $Y_{f,t}$ and $SD_{f,2013}$ without distinguishing across the different sub-periods. In column (1) we find that over the entire event window, the coefficient of $SD_{f,2013}$ is negative but not statistically significant, indicating that, on average, firms with higher initial credit dependence on the distressed banks did not see their total credit growth and investment rates decline relative to firms with lower $SD_{f,2013}$.

However, when we distinguish between high-risk and low-risk firms in columns (2)-(3), we find that this is only true for low-risk firms. High-risk firms experienced significant declines in total credit growth and investment. In terms of economic significance, the coefficient of $SD_{f,2013}$ in column (2) indicates that high-risk firms that were fully dependent on the distressed banks (i.e., with $SD_{f,2013} = 1$) grew by 2 pps less than other high-risk firms and saw 0.25 pps lower investment rate, equivalent to a 40% decline relative to the average investment rate.[31]

Distinguishing across the three sub-periods (columns (4)-(6)), reveals that low-risk firms also saw declines in credit growth during Post 1. However, these were only temporary as their credit recovered in Post 2 (i.e., the interaction coefficient with Post 2 in column (6) of Panel A is positive and statistically significant, more than compensating for the Post 1 decline), leaving their investment rate unaffected.

[30] Growth-specifications absorb firm-fixed effects.

[31] Comparisons within high-risk firms are important as high-risk and low-risk firms may have systematically different credit demand and investment needs (Figure A2).

By contrast, high-risk firms, which were unable to switch, could not reverse the large declines in credit and investment rates they experienced in Post 1.

Overall, these results confirm that low-risk firms were able to substitute credit from other banks without experiencing a significant slowdown in investment. They also reinforce the demand-driven interpretation of low-risk borrowers' exit at the onset of distress: not only did other banks absorb these firms (by reallocating credit away from their own riskier clients, as shown in Table 7), but the absence of any adverse real effects suggests that these firms transitioned smoothly to new, well-capitalized lenders. In contrast, high-risk firms, unable to transition, experienced significant declines in credit growth and investment rates.

5 Conclusions

This paper provides new micro-level evidence on the early dynamics of bank distress and the dual role of corporate clients in amplifying bank fragility. Drawing on the 2017 failures of two Italian banking groups, we show that, as soon as signs of weakness emerge, firms react on both sides of the balance sheet by withdrawing deposits and reallocating credit. These shifts unfold before large-scale depositor runs and jointly accelerate the banks' deterioration. The deposit outflows drain liquidity, while the loss of most creditworthy and profitable borrowers increases asset risk, eroding confidence and making it more difficult to attract fresh capital.

Our analysis underscores the importance of the early phase of distress, a stage often overlooked in crisis management. The initial reallocation of credit toward stronger banks not only signals declining confidence but also weakens banks' capital position. Back-of-the-envelope estimates indicate that, had the same volume of deleveraging during this phase come from high-risk rather than low-risk borrowers, the distressed banks would have maintained substantially higher capital ratios.

We also document key differences between episodes of systemic and idiosyncratic bank distress. In contrast to the large and broad-based credit-line runs observed during aggregate shocks, precautionary drawdowns in our setting are much smaller and limited to high-risk, single-relationship firms, those least able to switch to alternative lenders. Creditworthy firms are instead able to secure funding from better-capitalized competitors. These findings offer new insights on synergies underlying banks' joint provision of deposits and credit lines.

From a policy perspective, our results show that bank distress undermines liquidity and solvency well before large depositor runs, implying that liquidity support or deposit guarantees alone may be insufficient. Supervisors should monitor loan application patterns by high-quality borrowers as early warning signals and act swiftly, especially through early recapitalization, to prevent the loss of top clients and restore confidence. Targeted instruments, such as liquidity facilities for affected banks, could also discourage the premature exit of high-quality borrowers, while preserving their access to credit elsewhere if needed.

Our results also highlight an additional role of bank capital beyond its traditional function of absorbing losses: it shapes which banks are able to retain and attract creditworthy borrowers. At the system level, the pairing of creditworthy firms with well-capitalized banks can help mitigate procyclicality and contain the transmission of banking sector shocks to the real economy.

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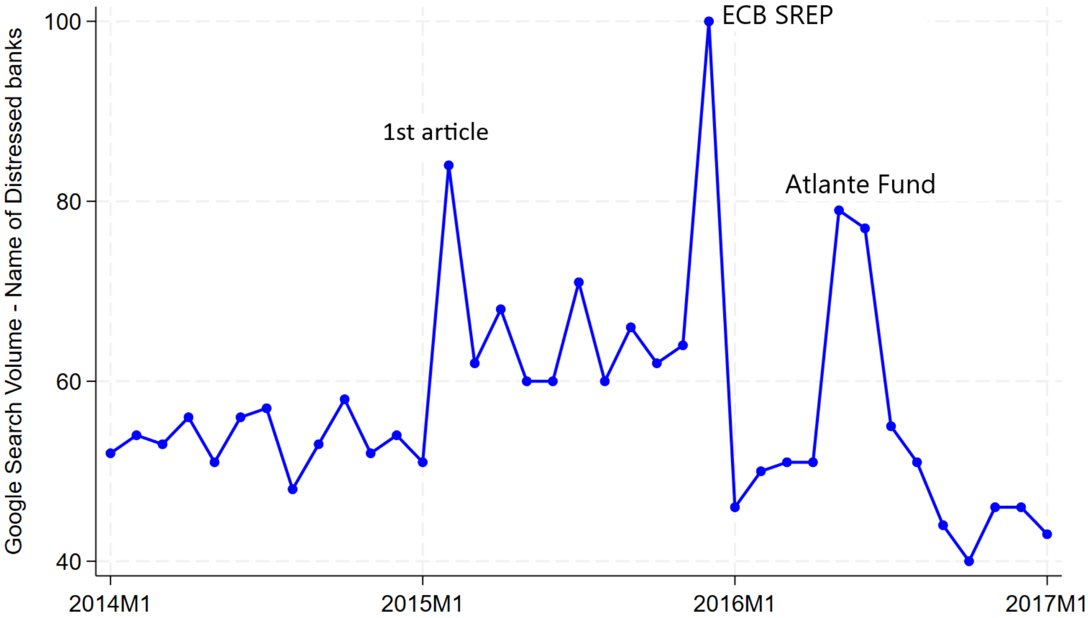
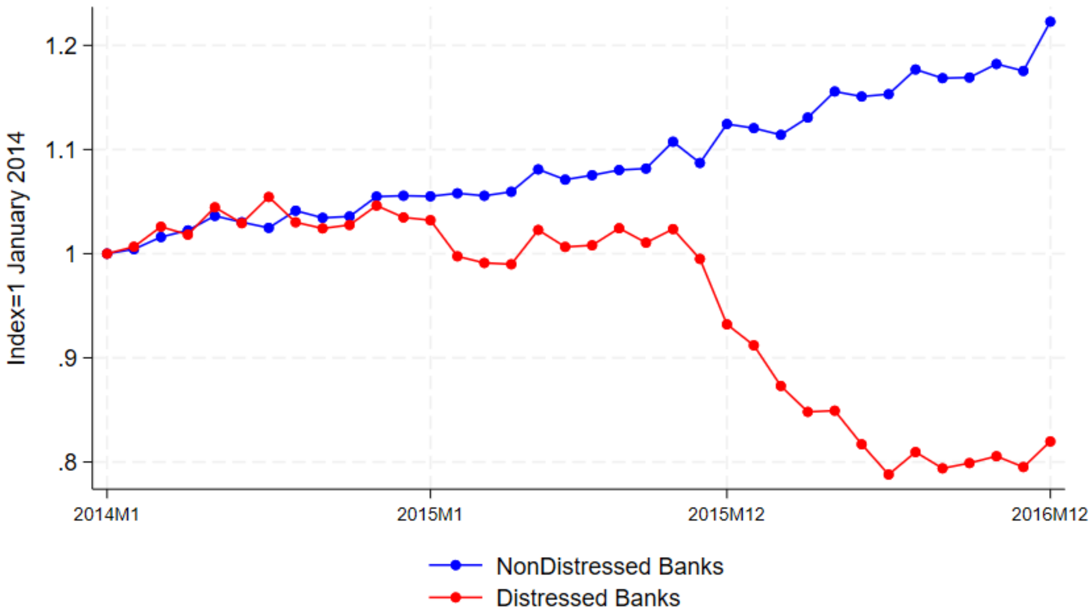
Figure 1: Google Trends



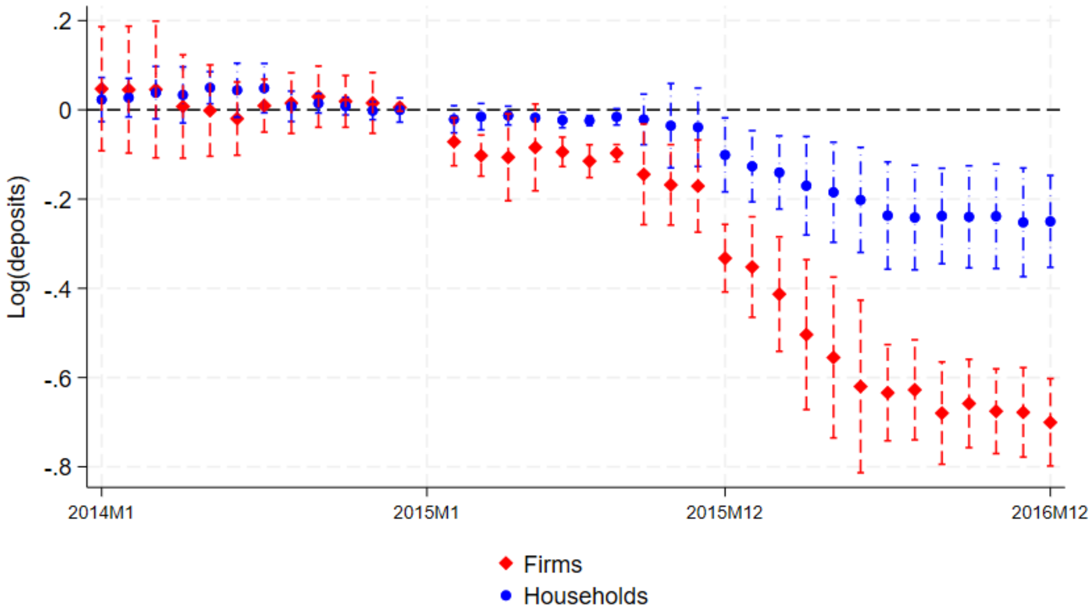
This figure shows the Google Trends searches for the name of the distressed banks between January 2014 and January 2017 (monthly data for the period January 2004-December 2022 downloaded as of December 2, 2022). Numbers represent search interest relative to a time period, with 100 indicating the peak number of searches. “1^{st} article” refers to the February 2015 article published in the Italian financial press containing interview with former bank employees about loans-for-share schemes; “ECB SREP” refers to the release of the ECB Supervisory Review (SREP) final results on November 30, 2015 announcing that the banks were under-capitalized; “Atlante Fund” refers to the recapitalization intervention by the publicly sponsored Atlante recapitalization fund which acquired the distressed banks in April 2016.

Figure 2: Total Deposits: Distressed vs. Non-Distressed Banks



This figure shows the evolution of total deposits of distressed and non-distressed banks from January 2014 to December 2016. All series are normalized to 1 as of January 2014.

Figure 3: Dynamic DiD: Firm vs. Household Deposits

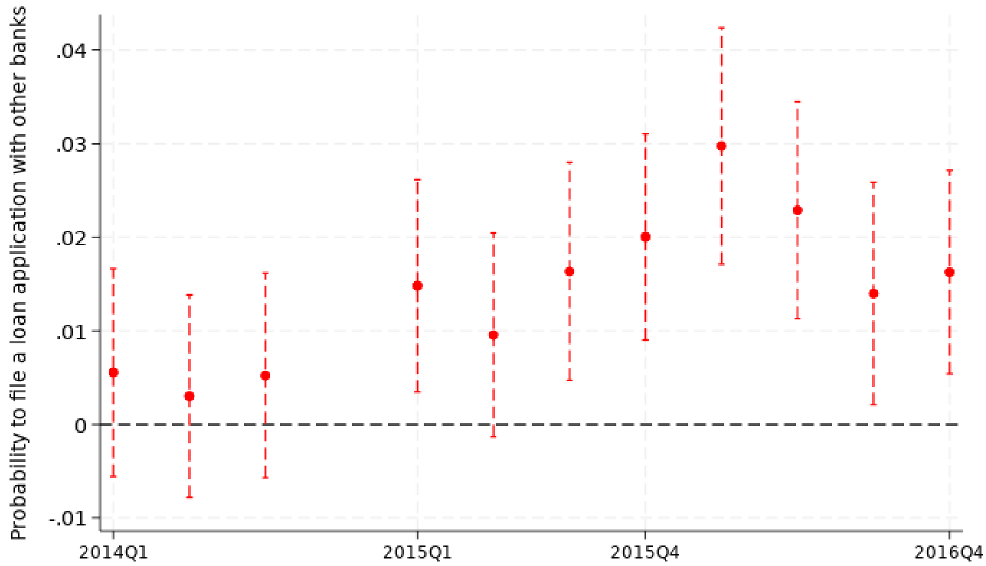


This figure plots the β_t coefficients and 95% confidence intervals from the following dynamic DiD specifications at the bank-month:

$$\text{Log(Dep)}_{b,t} = \sum_{t=2014M1}^{2016M12} \beta_t D_b \times I(t) + \alpha_b + \alpha_t + \epsilon_{b,t},$$

where $Log(Dep)_{b,t}$ denotes the log of firm or household deposits of bank b in month t. D_b is a dummy variable that $= 1$ if bank b is one of the distressed banks, and $= 0$ otherwise. $I(t)$ are calendar year-month dummy variables for the period between January 2014 and December 2016 (January 2015 is the omitted period). The specification includes bank and year-month fixed-effects, α_b and α_t, respectively. Standard errors are clustered at the bank and month level.

Figure 4: Dynamic DiD: Loan Applications to Outside Banks

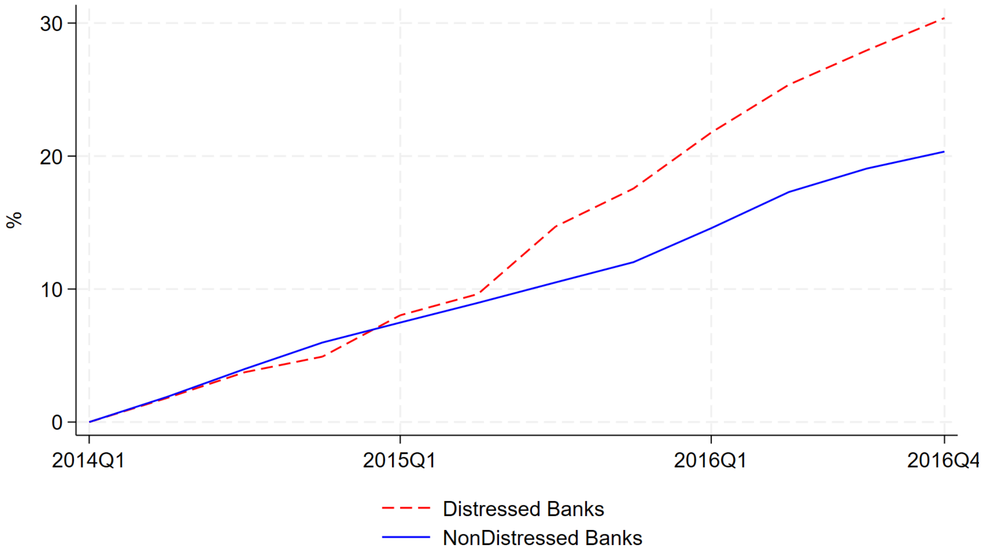


This figure plots the β_t coefficients and associated 95% confidence interval for the following equation:

$$\text{ApplOut}_{f,t} = \sum_{t=2014Q1}^{2016Q4} \beta_t I(t) \times \text{SD}_{f,2013} + \gamma' X_{f,t-4} + \mu_f + \alpha_{k,p,s,t} + \lambda_{j,t} + \epsilon_{f,t},$$

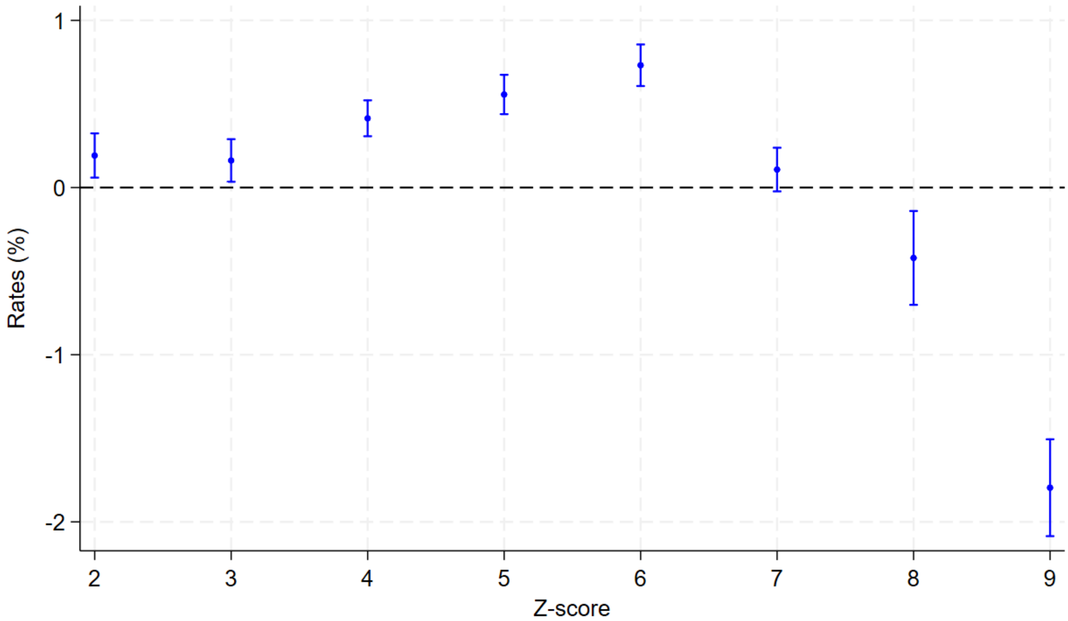
where $\text{ApplOut}_{f,t}$ is a dummy equal to one if firm f applies to an 'outside banks' with which the firm has no previous relationship (i.e., first-time borrowers). $SD_{f,2013}$ is the share of credit of firm f from distressed banks in 2013 and it is equal to zero if the firm was not borrowing from distressed banks. $I(t)$ are calendar year-quarter dummy variables for the period between 2014Q1 to 2016Q4 (2014Q4 is the omitted period). $X_{f,t-4}$ are lagged firm controls and include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. μ_f are firm-fixed effects $\alpha_{k,p,s,t}$ are industry×province×size×year-quarter fixed effects, where size denotes firms' asset quintiles at the end of 2013, and $\lambda_{j,t}$ are Z-score*year-quarter fixed effects. Estimates are weighted using entropy balance weight based on firm size. Standard errors are clustered at the firm-level.

Figure 5: Lost 'Loan Business' to Outside Banks



This figure plots the cumulative value of new credit that single-relationship firms of either distressed or non-distressed banks obtained from outside banks (i.e., new relationships) during the event window (2014Q1-2016Q4), expressed as a fraction of the total loan volume from each group of banks (distressed vs. non-distressed) at the start of the event window. Both series are normalized to zero as of 2014Q1.

Figure 6: Credit risk-adjusted interest rates



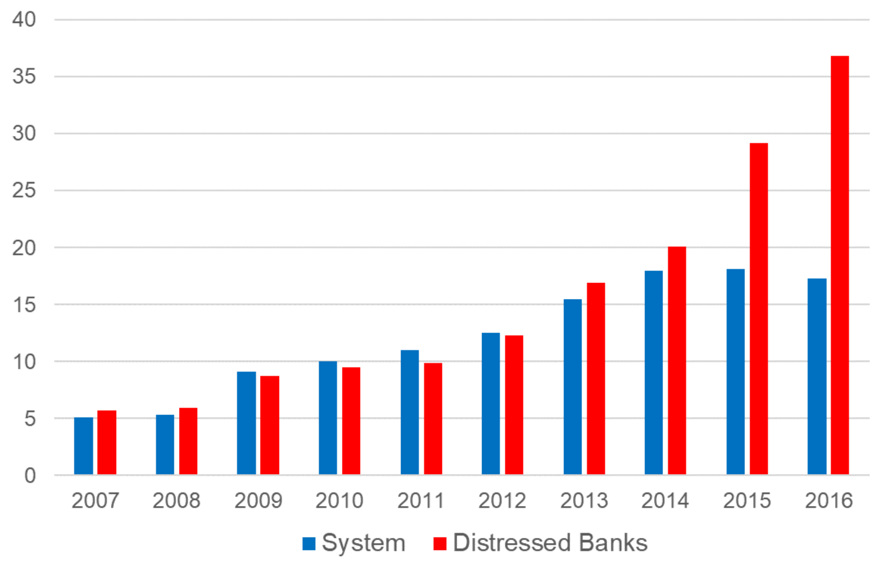
This figure plots the credit risk-adjusted interest rates, calculated as InterestRate-PD×(1-RR), where PD is the 1-year probability of default and RR is the average recovery rate. To compute the different parameters, we proceed as follows. We first set RR to 0.43, which is the average recovery rate for loans to non-financial firms in the period 2006-2013 (Bank of Italy, Table A6, Statistical Appendix to Notes on Financial Stability and Supervision, No. 13 - Bad Loan Recovery Rates). We then calculate credit risk-adjusted rates as $\alpha_i - \beta_i \times (1 - 0.43)$, where α_i and β_i are the estimated coefficients from two separate regressions:

$$\text{InterestRate}_{f,t} = \sum_{i=2}^{9} \alpha_i ZScore(i) + \lambda ShareCollateral_{f,t} + \gamma' X_{f,t-4} + \alpha_{k,p,s,t} + \epsilon_{f,t},$$

$$\text{BadLoan}_{f,t} = \sum_{i=2}^{9} \beta_i ZScore(i) + \lambda ShareCollateral_{f,t} + \gamma' X_{f,t-4} + \alpha_{k,p,s,t} + \epsilon_{f,t},$$

where $\text{InterestRate}_{f,t}$ is the contractual interest rates on new term loans paid by firm f at origination time t. $\text{BadLoan}_{f,t}$ is the 1-year probability of default, i.e. a dummy equal to one if at least one of the loans of firm f becomes a bad loan in year $t+1$. $ZScore(i)$ is a dummy for each firm-risk category (from 2 to 9, with 1, the safest group, as the omitted category). $ShareCollateral_{f,t}$ is the share of firm f's loans that are collateralized. $X_{f,t-4}$ are lagged firm controls and include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. $\alpha_{k,p,s,t}$ are industry×province×size×year-quarter fixed effects, where size denotes firms' asset quintiles at the end of 2013. Standard errors are clustered at the firm-level.

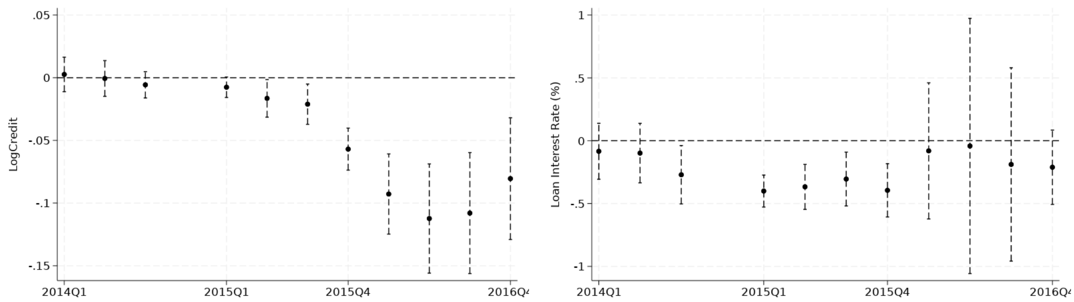
Figure 7: NPL over Loans ratio: Distressed Banks vs. System



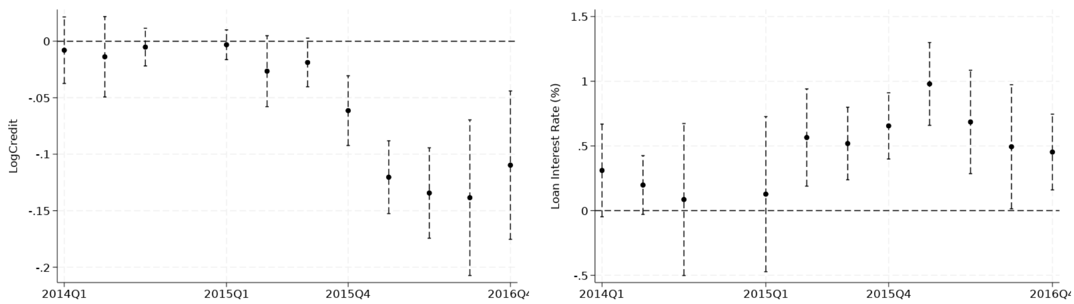
This figure shows the evolution of the Non-Performing Loans (NPL) to total loans ratio of the distressed banks vs. all Italian banks between 2007 and 2016.

Figure 8: Distressed vs. Non-Distressed Banks: Credit Volume & Interest Rates

A. Low-Risk Firms



B. High-Risk Firms



This figure plots the estimated coefficients and associate 95% confidence intervals of corresponding dynamic specifications of Eqn. (4) for loan volume and loan interest rates, respectively, where Post 1 and Post 2 are replaced with quarterly dummy variables (2014Q4 is the omitted period). Similar to Khwaja and Mian (2008), all specifications include firm×quarter fixed effects and are estimated for firms with multiple lending relationships. Regressions are weighted using firms' total credit as of 2013Q4. Panels A and B distinguish between Low-Risk (Z-score < 7) and High-Risk (Z-score ≥ 7) firms.

Table 1: Summary statistics

	Obs.	Mean	St. Dev.	Median	5th pct.	95th pct.
	Panel A. Bank characteristics as of 2013Q4					
Total Assets (€mil.)	477	6017.75	48594.95	495.58	73.56	9473.03
Capital Ratio (%)	477	12.47	4.00	12.06	6.70	19.69
Deposits/Assets (%)	477	42.12	12.41	42.01	20.33	61.85
Firm Deposit Share (%)	477	24.40	14.10	22.26	7.93	45.84
	Panel B. Firm characteristics as of 2013Q4					
	Obs.	Mean	St. Dev.	Median	5th pct.	95th pct.
Total Assets (€mil.)	56,503	4.001	9.687	1.061	0.063	70.668
Sales (€mil.)	56,164	4.007	9.874	1.025	0.019	70.917
Age (years)	56,041	17.334	11.816	14	2	54
EBITDA/Assets	56,291	0.072	0.129	0.069	-0.504	0.467
Altman Z-score	56,503	4.921	2.067	5	1	9
High-Risk	56,503	0.279	0.0448	0	0	1
Number of bank relationships	56,503	2.397	1.935	2	1	6
Single Relationship Firm	56,503	0.428	0.494	0	0	1
Rel. with Distressed Banks =1	56,503	0.266	0.442	0	0	1
Share Credit Distressed ($SD_{f,2013}$)	56,503	0.117	0.260	0	0	1
$SD_{f,2013}$ if Rel. with DBs=1	15,033	0.441	0.334	0.322	0.02	1
	Panel C. Loan Applications and Credit Line Drawdowns					
	Obs.	Mean	St. Dev.	Median	5th pct.	95th pct.
Loan Applications ($ApplOut_{f,t}$)	627,044	0.046	0.209	0	0	1
Distressed bank borrowers	160,425	0.061	0.239	0	0	1
Non-Distressed bank borrowers	473,435	0.041	0.197	0	0	1
New Relationship Dummy	20,791	0.273	0.445	0	0	1
Distressed bank borrowers	6,929	0.293	0.455	0	0	1
Non-Distressed bank borrowers	13,862	0.262	0.439	0	0	1
Share of Credit Lines Drawn	1,064,925	0.225	0.342	0	0	0.944
Low-Risk borrowers	857,002	0.183	0.317	0	0	0.922
High-Risk borrowers	207,923	0.396	0.388	0	0.314	0.975
	Panel D. Firm-year panel, 2014-2016					
	Obs.	Mean	St. Dev.	Median	5th pct.	95th pct.
Δlog(Credit) (%)	135,520	-3.348	44.572	0	-73.086	65.356
Investment Rate (%)	135,520	0.606	13.667	-0.456	-5.819	10.142

This table provides summary statistics for all variables used in the empirical analysis.

Table 2: Deposit Runs at the Distressed Banks

	All (1)	Firms (2)	Households (3)
$D_b\times$ Post1	-0.068**	-0.132***	-0.045*
	(0.0277)	(0.0369)	(0.0265)
$D_b\times$ Post2	-0.344***	-0.588***	-0.224***
	(0.0756)	(0.103)	(0.0729)
Fixed Effects			
Bank	Yes	Yes	Yes
Year-Month	Yes	Yes	Yes
Observations	16,804	16,804	16,804
R-squared (within)	0.109	0.072	0.024

This table provides the estimates for Eqn. (1). The sample period is January 2014-December 2016. The unit of observation is at the bank-month level, and the dependent variable is the log of total deposits by bank b in month t, $Log(Dep)_{b,t}$. D_b is a dummy variable that = 1 for deposits of the two distressed banks, and = 0 otherwise. Post 1 is a dummy equal to one between February 2015 and November 2015, and 0 otherwise. Post 2 is a dummy variable equal to one between December 2015 and December 2016, and 0 otherwise. Regressions are weighted by bank total assets. Standard errors are clustered at the bank and year-month level.

Table 3: Credit Line Drawdowns

	Share of Credit Lines Drawn					
	All Firms		Low-Risk		High-Risk	
			Single	Multiple	Single	Multiple
	(1)	(2)	(3)	(4)	(5)	(6)
$D_b\times$Post 1	0.003*	0.001	-0.006	0.001	0.024**	0.001
	(0.001)	(0.008)	(0.001)	(0.001)	(0.004)	(0.007)
$D_b\times$Post 2	0.019***	0.011***	-0.005	0.009***	0.030*	0.017**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.015)	(0.008)
Fixed Effects						
Bank	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Size						
×Province×Time	Yes	-	Yes	-	Yes	-
Firm×Time	No	Yes	No	Yes	No	Yes
Observations	1,064,925	862,530	119,196	703,444	28,952	159,084
R-squared	0.171	0.705	0.215	0.702	0.336	0.649

This table provides the estimates for Eqn. (2). The dependent variable is the share of drawn over total credit lines granted from bank b to firm f in quarter t, $ShareDrawn_{b,f,t}$. The unit of observation is at the bank-firm-quarter level, and the sample period is between 2014Q1 and 2016Q4. The variable D_b is a dummy variable that = 1 for deposits of the two distressed banks, and = 0 otherwise. Post 1 is a dummy = 1 between 2015Q1 and 2015Q3, and = 0 otherwise. Post 2 is a dummy variable = 1 between 2015Q4 and 2016Q4, and = 0 otherwise. Low-Risk (High-risk) indicates firms with Cerved Z-scores < 7 (≥ 7). Standard errors are clustered at the bank-level.

Table 4: Loan Applications to Outside Banks

	All Firms		Low-Risk		High-Risk		Maturing with 1-Year	
			Single	Multiple	Single	Multiple	$\geq$50%	$<$ 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SD_{f,2013}$	0.001							
	(0.002)							
$SD_{f,2013}$ × Post 1	0.010***	0.010***	0.014***	0.008	0.008	-0.004	0.013***	0.006
	(0.004)	(0.004)	(0.005)	(0.007)	(0.008)	(0.012)	(0.004)	(0.008)
$SD_{f,2013}$ × Post 2	0.017***	0.017***	0.014***	0.029***	0.009	0.006	0.024***	0.004
	(0.003)	(0.003)	(0.005)	(0.006)	(0.008)	(0.012)	(0.004)	(0.007)
Fixed Effects								
Firm	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Size								
×Province×Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CreditScore×Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	627,044	627,044	145,820	314,343	44,880	98,208	473,966	121,526
R-squared	0.084	0.213	0.304	0.223	0.424	0.342	0.179	0.227

This table reports estimation results for Eqn. (3). The unit of observation is at the firm-quarter level, and the sample period is 2014Q1-2016Q4. The dependent variable is $ApplOut_{f,t}$, a dummy = 1 if firm f applies to an outside bank in quarter t, and =0 otherwise. $SD_{f,2013}$ is the share of firm's f total credit from the distressed banks in 2013 (this variable = 0 if the firm was not borrowing from distressed banks in 2013). Post 1 is a dummy equal to one between 2015Q1 and 2015Q3, Post 2 is a dummy equal to one between 2015Q4 and 2016Q4. Lagged firm-controls include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. Credit score dummies, which range from 1 (safest) to 9 (riskiest), are interacted with the year-quarter indicator. Low-Risk (High-risk) indicates firms with Cerved Z-scores < 7 (≥ 7).

Table 5: New Lending Relationships

	Firms			Banks			
				Bank Capital		Bank Size	
	All (1)	Low-Risk (2)	High-Risk (3)	Low (4)	High (5)	Small (6)	Large (7)
$SD_{f,2013}$	0.003	0.004	-0.002	-0.037	0.032	0.020	-0.054
	(0.029)	(0.035)	(0.068)	(0.042)	(0.041)	(0.036)	(0.048)
$\text{SD}_{f,2013}$ × Post 1	0.102**	0.124**	0.025	0.081	0.169***	0.098*	0.168**
	(0.041)	(0.050)	(0.093)	(0.060)	(0.059)	(0.055)	(0.067)
$\text{SD}_{f,2013}$ × Post 2	0.062	0.090*	-0.065	0.093	0.036	0.055	0.119*
	(0.042)	(0.051)	(0.096)	(0.064)	(0.059)	(0.059)	(0.066)
Fixed Effects							
Industry×Size×Province×Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CreditScore×Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,791	15,426	3,736	10,533	10,565	12,584	8,051
R-squared	0.182	0.190	0.330	0.231	0.232	0.212	0.261

This table provides the estimates for Eqn. (2). The unit of observation is at the firm-year level. The sample period is 2014-2016 and the sample is restricted to firms that file at least one loan application to an outside bank in a given year. The dependent variable is $NewRel_{f,t}$, a dummy variable that equals 1 if a new bank-firm relationship with an outside bank is created in the quarter after a loan application by borrower f during year t, and equals 0 otherwise. $\text{SD}_{f,2013}$ is the share of firm's f total credit from the distressed banks in 2013 (this variable = 0 if the firm was not borrowing from distressed banks in 2013). Post 1 is a dummy equal to one in 2015, Post 2 is a dummy equal to one in 2016. Lagged firm controls include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. Column (1) reports estimation results of Eqn. (2) for all firms. Columns (2) and (3) report results for "Low-Risk" (z-score < 7) and "High-Risk" (z-score ≥ 7) firms separately. Columns (4) and (5) distinguish banks with respect to bank capital $\text{HighCapital}_{b,2013}$, a dummy variable that = 1 if the bank had an above the median capital ratio in 2013, and = 0 otherwise. Columns (6) and (7) distinguish banks with respect to bank capital using $\text{LargeBank}_{b,2013}$ is a dummy variable that = 1 if the bank had total assets above €100 billion in 2013 (i.e., if it was one of the top five banks in the country), and = 0 otherwise. Standard errors are clustered at the firm level.

Table 6: Credit volume and Loan Interest Rates

			Low-Risk		High-Risk	
	All	Multiple	All	Multiple	All	Multiple
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Credit volume ($Log(Credit)$)						
$D_b \times$ Post 1	-0.020**	-0.014**	-0.021***	-0.014*	-0.014	-0.009
	(0.008)	(0.006)	(0.007)	(0.008)	(0.009)	(0.012)
$D_b \times$ Post 2	-0.099***	-0.094***	-0.098***	-0.089***	-0.101***	-0.105***
	(0.022)	(0.020)	(0.020)	(0.020)	(0.023)	(0.021)
Observations	1,449,628	1,238,980	1,125,291	970,376	318,657	268,603
R-squared	0.604	0.756	0.615	0.762	0.586	0.604
Panel B. Loan interest rates						
$D_b \times$ Post 1	-0.049	-0.078	-0.090	-0.123	0.260***	0.234**
	(0.158)	(0.134)	(0.162)	(0.137)	(0.086)	(0.097)
$D_b \times$ Post 2	0.236	0.165	0.189	0.113	0.531***	0.555**
	(0.391)	(0.347)	(0.411)	(0.358)	(0.192)	(0.221)
Fixed Effects						
Bank	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Size ×Province×Time	Yes	No	Yes	No	Yes	No
Firm×Time	No	Yes	No	Yes	No	Yes
Observations	1,048,612	868,675	950,491	791,004	94,754	77,671
R-squared	0.189	0.616	0.187	0.608	0.342	0.569

This table provides the estimates for Eqn. (4). The unit of observation is at the bank-firm-quarter level and the sample period is 2014Q1-2016Q4. In Panel A, the dependent variable is the log of total granted credit from bank b to firm f in quarter t. In Panel B, dependent variable is the average interest rates on total credit form b to firm f in quarter t. The variable D_b is a dummy variable that equals 1 if bank b is one of the distressed banks, and equals 0 otherwise. Post 1 is a dummy = 1 between 2015Q1 and 2015Q3, and = 0 otherwise. Post 2 is a dummy = 1 between 2015Q4 and 2016Q4, and = 0 otherwise. Low-Risk (High-risk) indicates firms with Cerved Z-scores < 7 (≥ 7). Standard errors are clustered at bank-level.

Table 7: Credit Spillovers Effects on Other Banks in the Region

	(1)	(2)	(3)	(4)
$\text{Exp}_{b,t}$	-0.0062	-0.001		
	(0.0119)	(0.0077)		
$\text{Exp}_{b,t} \times \text{HighRisk}_{f,2013}$		-0.019***	-0.019***	-0.111***
		(0.0034)	(0.0036)	(0.0369)
$\text{Exp}_{b,t} \times \text{HighRisk}_{f,2013} \times \text{CapitalRatio}_b$				0.010***
				(0.0045)
$\text{Exp}_{b,t} \times \text{HighRisk}_{f,2013} \times \text{Log(Ass)}_b$				-0.023
				(0.0404)
$\text{Exp}_{b,t} \times \text{HighRisk}_{f,2013} \times \text{Interbank}_b$				-0.299**
				(0.144)
Fixed effects				
Industry×Province×Time	Yes	Yes	Yes	Yes
Bank	Yes	Yes	-	-
Bank×Time	No	No	Yes	Yes
BankCharacteristics×High-Risk	No	No	No	Yes
Firm controls	Yes	Yes	Yes	Yes
Observations	661,016	661,016	661,016	661,016

This table provides the estimates for Eqn. (6). The unit of observation is at the bank-firm-quarter level. The sample excludes credit relationships with the distressed banks. The dependent variable is $\Delta \log(Credit)_{b,f,t}$, the quarterly growth rate of credit at the bank-firm level. $Exp_{b,t}$ is the share of loan applications from distressed bank borrowers received by bank b at time t. Lagged firm controls include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. Credit score dummies, which take values from 1 (safest) to 9 (riskiest), are interacted with the year-quarter indicator. Standard errors are clustered at the bank level.

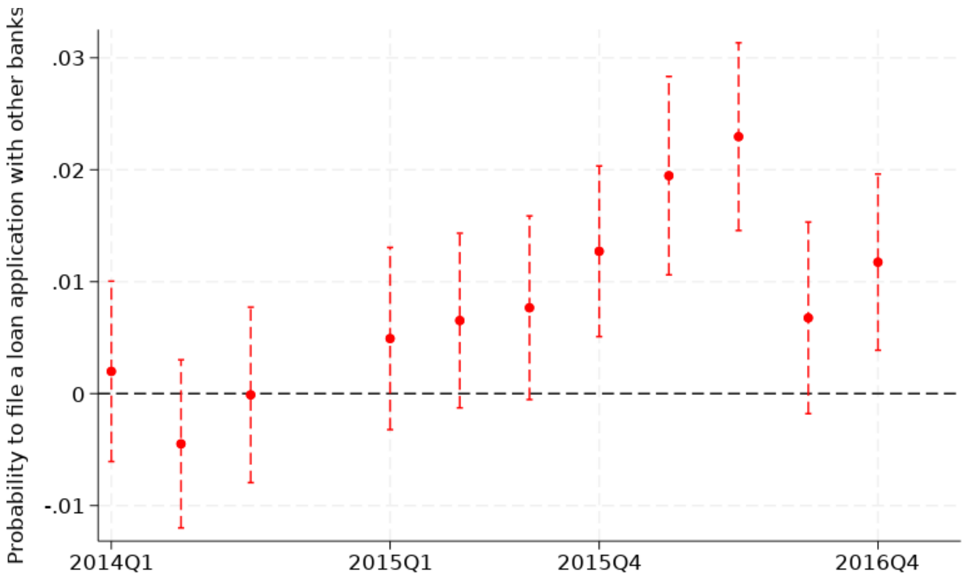
Table 8: Firm Outcomes: Total Credit and Real Effects

	All (1)	High-Risk (2)	Low-Risk (3)	All (4)	High-Risk (5)	Low-Risk (6)
Panel A. Total Credit						
$SD_{f,2013}$	-0.130	-2.029*	0.703			
	(0.551)	(1.150)	(0.626)			
$SD_{f,2013}\times$Pre				1.199	0.568	1.489
				(0.918)	(1.826)	(1.059)
$SD_{f,2013}\times$Post 1				-3.184***	-6.084***	-1.947*
				(1.018)	(2.114)	(1.162)
$SD_{f,2013}\times$Post 2				1.573	-1.251	2.649**
				(1.044)	(2.195)	(1.197)
Observations	135,520	31,715	103,519	135,520	31,715	103,519
R-squared	0.055	0.105	0.047	0.055	0.105	0.047
Panel B. Investment Rate						
$SD_{f,2013}$	-0.124	-0.254*	-0.094			
	(0.075)	(0.142)	(0.089)			
$SD_{f,2013}\times$Pre				-0.011	-0.165	0.067
				(0.111)	(0.206)	(0.134)
$SD_{f,2013}\times$Post 1				-0.214*	-0.355*	-0.174
				(0.119)	(0.215)	(0.144)
$SD_{f,2013}\times$Post 2				-0.170	-0.275	-0.201
				(0.131)	(0.269)	(0.150)
Fixed-effects						
Province×Industry×Time	Yes	Yes	Yes	Yes	Yes	Yes
I(CreditScore)×Time	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135,520	31,715	103,519	135,520	31,715	103,519
R-squared	0.035	0.069	0.040	0.035	0.069	0.040

This table provides the estimates for Eqn. (7). The unit of observation is at the firm-year level and the sample period is 2014-2016. In Panel A, the dependent variable is the annual growth rate of credit, while and in Panel B it is the investment rate ((i.e., the change in total fixed assets over lagged total fixed assets). $SD_{f,2013}$ is the share of credit of firm f from the distressed banks in 2013 ($SD_{f,2013} = 0$ if the firm was not borrowing from the distressed banks). Pre is a dummy = 1 in 2014, Post 1 is a dummy = 1 in 2015, and = 0 otherwise. Post 2 is a dummy = 1 in 2016, and = 0 otherwise. Lagged firm controls include the log of total assets, the log of firm age, the ratio of EBITDA over assets. Credit score dummies, which take values from 1 (safest) to 9 (riskiest), are interacted with year-quarter indicator. Standard errors are clustered at the firm-level.

Online Appendix A - Robustness Tests

Figure A1: Loan Applications to Outside Banks. Robustness 90% lending



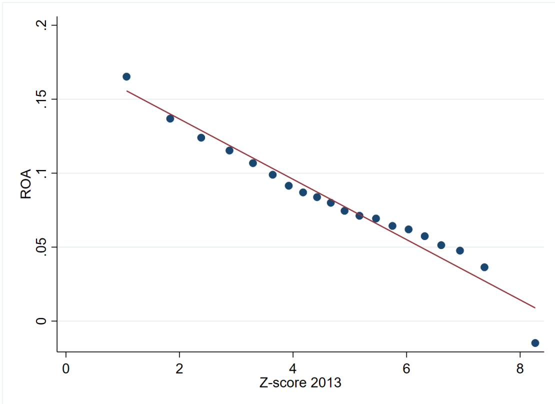
This figure plots the β_t coefficients and associated 95% confidence interval for the following equation using a sample of 42 provinces where the distressed banks make 90% of lending:

$$\text{ApplOut}_{f,t} = \sum_{t=2014Q1}^{2016Q4} \beta_t I(t) \times \text{SD}_{f,2013} + \gamma' X_{f,t-4} + \mu_f + \alpha_{k,p,s,t} + \lambda_{j,t} + \epsilon_{f,t},$$

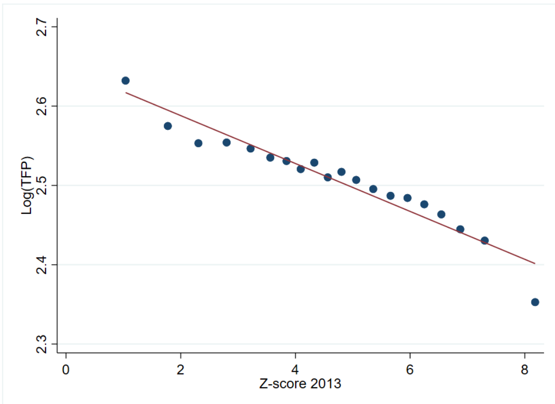
where $\text{ApplOut}_{f,t}$ is a dummy equal to one if firm f applies to an 'outside banks' with which the firm has no previous relationship (i.e., first-time borrowers). $SD_{f,2013}$ is the share of credit of firm f from distressed banks in 2013 and it is equal to zero if the firm was not borrowing from distressed banks. $I(t)$ are calendar year-quarter dummy variables for the period between 2014Q1 to 2016Q4 (2014Q4 is the omitted period). $X_{f,t-4}$ are lagged firm controls and include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. μ_f are firm-fixed effects $\alpha_{k,p,s,t}$ are industry×province×size×year-quarter fixed effects, where size denotes firms' asset quintiles at the end of 2013, and $\lambda_{j,t}$ are z-score*year-quarter fixed effects. Regressions are weighted using entropy balance weight based on firm size. Standard errors are clustered at the firm-level.

Figure A2: Firm Credit-Risk and Other Firm Characteristics

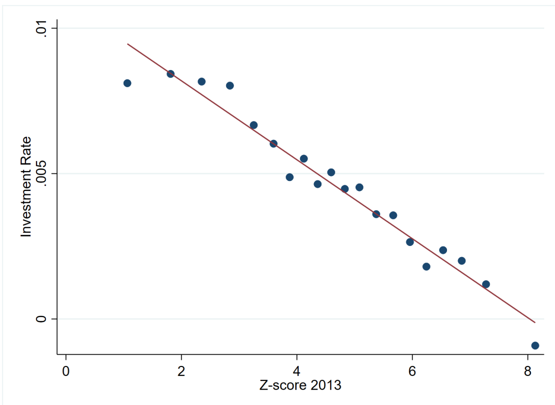
A. Firm Profitability & Credit-Risk



B. Total Factor Productivity & Credit-Risk



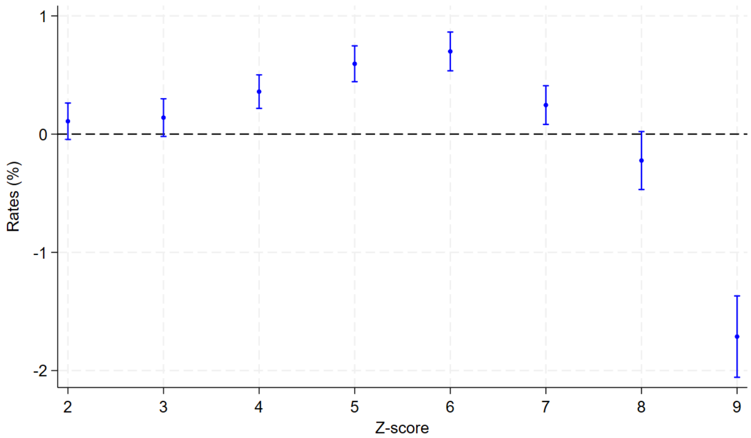
C. Investment Rate & Credit-Risk



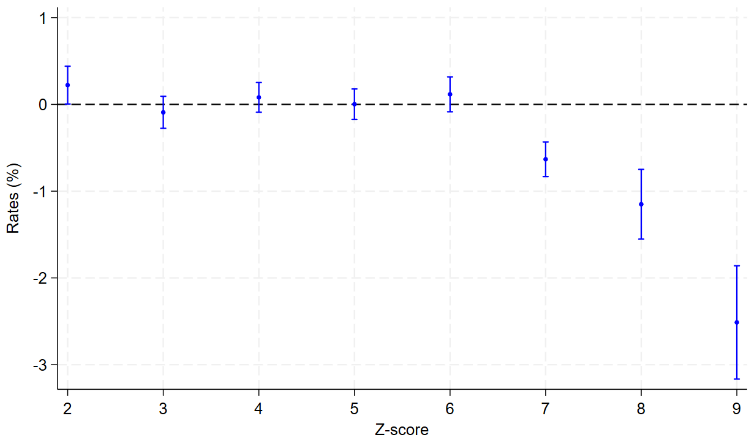
This figure shows the relationship between firms' Cerved Z-score and: profitability (EBITDA over total assets), productivity (TFP), and investment rate (change in total fixed assets over lagged total assets) in 2013 using a binscatter plot controlling for the log of total assets, the log of firm age, lagged profitability and industry×province×size×year-quarter fixed effects $\alpha_{k,p,s,t}$. A higher z-score value indicates higher credit risk.

Figure A3: Credit risk-adjusted interest rates: New and Existing borrowers

A. Existing borrowers



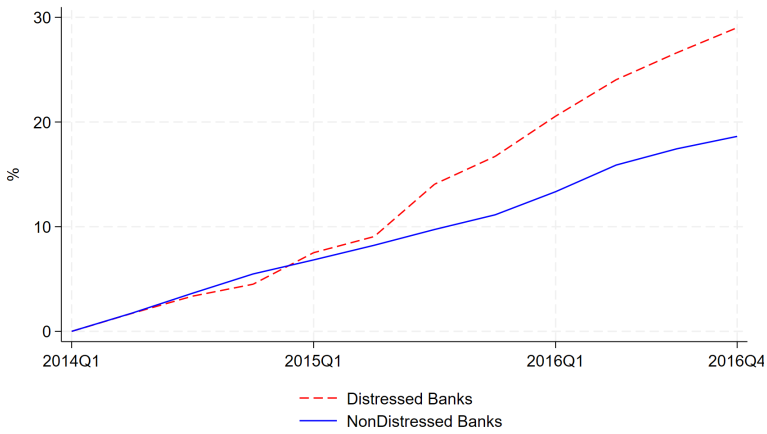
B. New borrowers



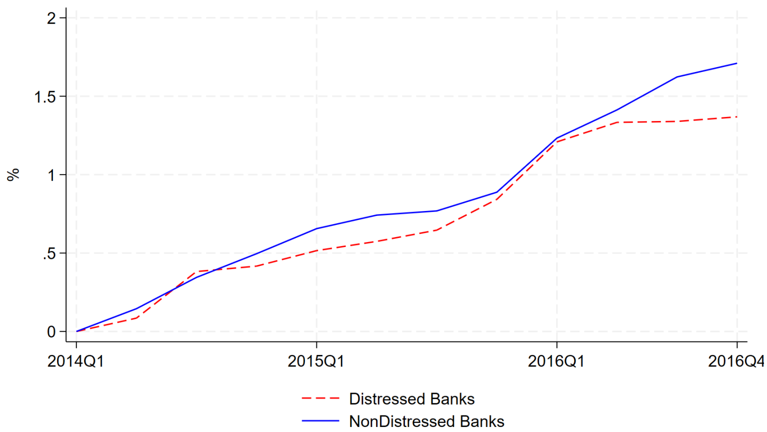
This figure plots the credit risk-adjusted interest rates, calculated as InterestRate-PD$\times$(1-RR), where PD is the 1-year probability of default and RR is the average recovery rate, by firm-risk category separately for new and existing borrowers. See Figure 6 for a description of how to compute the different parameters.

Figure A4: Lost 'Loan Business' to Outside Banks

A. Low-Risk Firms



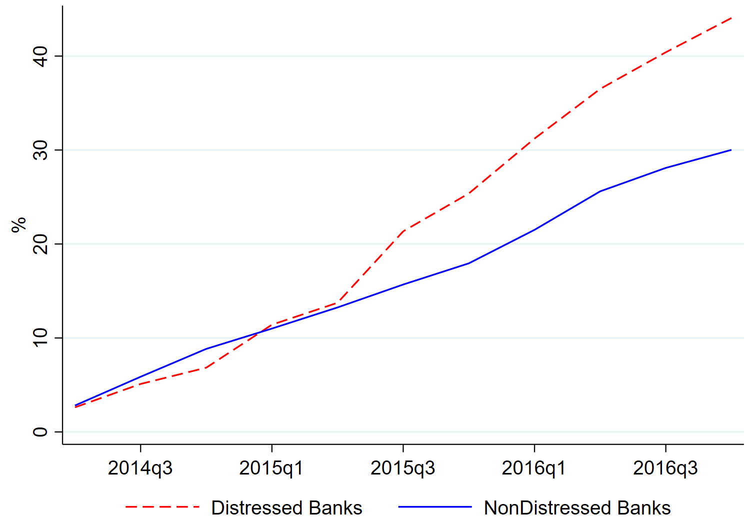
B. High-Risk Firms



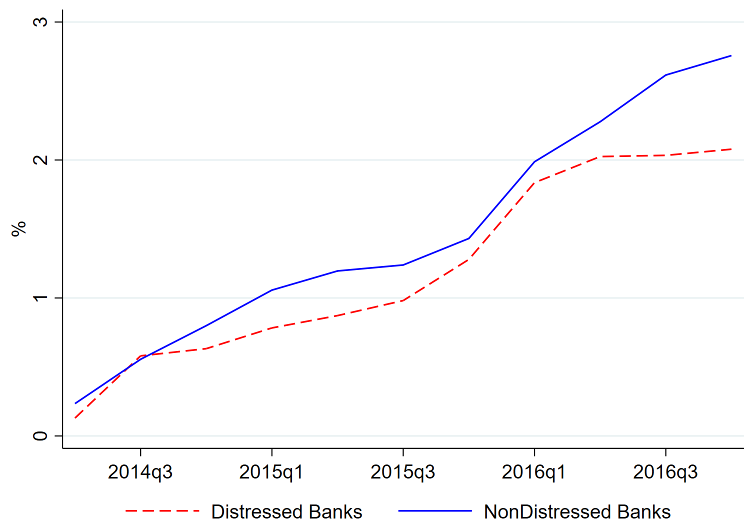
This figure plots the cumulative value of new credit that single-relationship firms of either distressed or non-distressed banks obtained from outside banks (i.e., new relationships) during the event window (2014Q1-2016Q4), expressed as a fraction of the total loan volume from each group of banks (distressed vs. non-distressed) at the start of the event window. Both series are normalized to zero as of 2014Q1. Panels A and B distinguish between Low-Risk (z-score < 7) and High-Risk firms (z-score ≥ 7) with single-relationships firms as of 2013Q4.

Figure A5: Lost 'Loan Business' to Outside Banks: Outstanding Drawn Credit

A. Low-Risk Firms



B. High-Risk Firms



This figure plots the cumulative value of loans that single-relationship firms of the distressed (non-distressed) banks received from outside banks during the event window (2014Q1-2016Q4) as a fraction of their total outstanding drawn credit from the distressed (non-distressed) banks at the start of the event window. Panels A and B distinguish between Low-Risk (z-score < 7) and High-Risk firms (z-score ≥ 7) with single-relationships firms in 2013.

Table A1: Credit volume and Loan Rates: Robustness 90% lending

			Low-Risk		High-Risk	
	All	Multiple	All	Multiple	All	Multiple
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Credit volume ($Log(Credit)$)						
$D_b\times$ Post 1	-0.022**	-0.019**	-0.023**	-0.019*	-0.015*	-0.014
	(0.009)	(0.008)	(0.011)	(0.011)	(0.008)	(0.010)
$D_b\times$ Post 2	-0.109***	-0.102***	-0.104***	-0.099***	-0.116***	-0.109***
	(0.026)	(0.024)	(0.027)	(0.027)	(0.024)	(0.019)
Observations	4,959,827	4,091,690	3,777,648	3,152,437	1,157,259	939,253
R-squared	0.591	0.751	0.604	0.757	0.585	0.707
Panel B. Loan interest rates						
$D_b\times$ Post 1	0.009	-0.030	-0.011	-0.061	0.160	0.149
	(0.154)	(0.129)	(0.162)	(0.135)	(0.119)	(0.104)
$D_b\times$ Post 2	0.291	0.203	0.255	0.160	0.487***	0.500***
	(0.347)	(0.309)	(0.373)	(0.329)	(0.150)	(0.164)
Fixed Effects						
Bank	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Size						
×Province×Time	Yes	No	Yes	No	Yes	No
Firm×Time	No	Yes	No	Yes	No	Yes
Observations	3,497,978	2,813,708	3,115,003	2,521,687	358,565	292,021
R-squared	0.248	0.631	0.249	0.626	0.389	0.570

This table provides the estimates for Eqn. (4) using a sample of 42 provinces where the distressed banks make 90% of lending. The unit of observation is at the bank-firm-quarter level and the sample period is 2014Q1-2016Q4. In Panel A, the dependent variable is the log of total granted credit from bank b to firm f in quarter t. In Panel B, dependent variable is the average interest rates on total credit form b to firm f in quarter t. The variable D_b is a dummy variable that equals 1 if bank b is one of the distressed banks, and equals 0 otherwise. Post 1 is a dummy = 1 between 2015Q1 and 2015Q3, and = 0 otherwise. Post 2 is a dummy = 1 between 2015Q4 and 2016Q4, and = 0 otherwise. Low-Risk (High-risk) indicates firms with z-scores < 7 (≥ 7). Standard errors are clustered at bank-level.

Table A2: Firm Characteristics Balance

	Existing Borrowers	
	Distressed banks (1)	Non-distressed banks (2)
Total Assets (€mil.)	6.62	3.05
	(0.23)	(-0.23)
Revenues (€mil.)	6.88	2.96
	(0.25)	(-0.25)
Age (years)	18.72	16.83
	(0.16)	(-0.16)
Z-score	5.15	4.84
	(0.15)	(-0.15)
High-Risk	0.30	0.27
	(0.07)	(-0.07)
Profitability	0.06	0.07
	(-0.08)	(0.08)
Manufacturing	0.38	0.28
	(0.16)	(-0.16)
Retail & Wholesale Trade	0.24	0.23
	(0.02)	(-0.02)
Construction	0.05	0.06
	(-0.03)	(0.03)

This table reports the average values of firm characteristics as of December 2013 for distressed and non-distressed bank borrowers. Numbers in parentheses are normalized differences, calculated as the difference between the averages in the two groups, normalized by the square root of the sum of the corresponding variances (Imbens and Wooldridge, 2018). Values in parentheses exceeding 0.25 indicate an unbalanced sample in that covariate. $Manufacturing$, $Retail\&WholesaleTrade$, and $Construction$ are dummy variables equal to 1 if the firm belongs to one of these sectors, and 0 otherwise.

Table A3: Loan Applications to Outside Banks: Relationship Length and Breadth

	All Firms	
	(1)	(2)
$SD_{f,2013} \times$ Post 1	0.010***	0.013***
	(0.0036)	(0.0038)
$SD_{f,2013} \times$ Post 2	0.017***	0.019***
	(0.0032)	(0.0034)
LongRel × Post 1	-0.001	
	(0.0167)	
LongRel × Post 2	0.001	
	(0.0019)	
Shareholder × Post 1		-0.018***
		(0.0053)
Shareholder × Post 2		-0.013***
		(0.0049)
Fixed Effects		
Firm	Yes	Yes
Industry × Province × Size × Year-Quarter	Yes	Yes
CreditScore × Year-Quarter	Yes	Yes
Firm Controls	Yes	Yes
Observations	627,044	627,044
R-squared	0.213	0.213

This table reports estimation results for Eqn. (3). The unit of observation is at the firm-quarter level, and the sample period is 2014Q1-2016Q4. The dependent variable is $\text{ApplOut}_{f,t}$, a dummy = 1 if firm f applies to an outside bank in quarter t, and =0 otherwise. $SD_{f,2013}$ is the share of firm's f total credit from the distressed banks in 2013 (this variable = 0 if the firm was not borrowing from distressed banks in 2013). Post 1 is a dummy equal to one between 2015Q1 and 2015Q3, Post 2 is a dummy equal to one between 2015Q4 and 2016Q4. LongRel is a dummy equal to one for above the median relationship length (86 months) and zero otherwise. Shareholder is a dummy equal to one if the firm owns any shares of the distressed banks, measured using available data as of 2016. Lagged firm-controls include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. Credit score dummies, which range from 1 (safest) to 9 (riskiest), are interacted with the year-quarter indicator. Firms with a credit score <7 are classified as "Low-Risk". Conversely, firms with a credit score ≥ 7.

Table A4: Loan Quality: NPL and Share of Risk-weighted Credit

	(1) NPL	(2) RiskWCredit
$D_b \times 2013$	-0.004	0.017
	(0.008)	(0.030)
$D_b \times 2014$	0.013**	0.043
	(0.006)	(0.026)
$D_b \times 2015$	0.023***	0.054**
	(0.005)	(0.025)
$D_b \times 2016$	0.043***	0.080***
	(0.005)	(0.027)
$D_b \times 2017$	0.071***	0.105***
	(0.005)	(0.031)
Bank Controls	Yes	Yes
Year FE	Yes	Yes
Observations	1343	1341
R^2	0.211	0.090

This table estimates the following equation: $Y_{b,t} = \sum_{t=2014}^{2017} \beta_t D_b + \gamma' X_b + \mu_t + \varepsilon_{b,t}$, where $Y_{b,t}$ is either: (i) the ratio of non-performing loan (NPL) to total loans, constructed as a weighted average at the bank-year level from the loan-level data; or (ii) the share of risk-weighted credit out of total credit for bank b in year t. D_b is a dummy equal to one for distressed banks, and X_b is a vector of pre-determined bank-level controls as of end-2013 (size deciles, capital ratio, ROA, and interbank over assets). The share of risk-weighted credit is constructed as follows (0.42× LowRiskCredit+ 1.5× HighRiskCredit)/TotCredit where LowRiskCredit, HighRiskCredit and TotCredit refer to total bank credit given to low-risk, high-risk firms or both. Low-risk and high-risk exposures are assigned 42% and 150% risk-weights, approximated by mapping the Cerved Z-score to the Basel II risk-weighting framework (see Online Appendix C).

Online Appendix B - Deposit Reallocation

To better understand the corporate depositors' behavior, we study where they move their funds and compare their choices to households. Because we cannot track individual depositors in our data, we exploit the bank-province heterogeneity in the data by estimating the following model for non-distressed banks:

$$\log(Dep)_{b,p,t} = \beta_1 \; HS_{p,2013} \times \text{Post } 1 + \beta_2 \; HS_{p,2013} \times \text{Post } 2 + \alpha_p + \alpha_{b,t} + \epsilon_{b,t}, \quad \text{(B1)}$$

where $\log(Dep)_{b,p,t}$ indicates the log of (firm or household) deposits of non-distressed bank b in province p in month t. $HS_{p,2013}$ equals one if the distressed banks had an above median share of (corporate or household) deposits in province p at the start of the event window, and equals zero otherwise. Equation (B1) includes province and bank-month fixed effects, α_p and $\alpha_{b,t}$, respectively. Identification is obtained by comparing changes in the deposit volumes of the same bank at the same time across different provinces, depending on the distressed banks' ex-ante share of deposits.

The results are presented in Table B1. Column (1) shows that in regions where the distressed banks held a larger-than-median share of the local deposit market, other banks experienced a larger average increase in deposits during both Post 1 and Post 2 by 13% and 21%, respectively. In columns (2)-(4), we introduce interaction terms with bank capital and bank size. We find that the increase in firm deposits during Post 1 is larger for banks with stronger capital positions.

In contrast, the results for household deposits, reported in columns (5)–(7), reveal a markedly different pattern. Unlike firms, households do not appear to prioritize bank soundness: they run towards large, systemically important banks, irrespective of capital levels. These findings are consistent with Iyer et al. (2019), Acharya et al. (2023), Caglio et al. (2024) and Cipriani et al. (2024).

Table B1: Deposit Re-allocation

	Firms				Households		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{HS}_{p,2013} \times$ Post	0.128***						
	(0.037)						
$\text{HS}_{p,2013} \times$ Post 2	0.208***						
	(0.060)						
$\text{HS}_{p,2013} \times$ Post 1 $\times$ $\text{HighCapital}_{b,2013}$		0.223**		0.222**	-0.182**		-0.060
		(0.089)		(0.088)	(0.070)		(0.091)
$\text{HS}_{p,2013} \times$ Post 2 $\times$ $\text{HighCapital}_{b,2013}$		0.271*		0.265*	-0.188		-0.062
		(0.137)		(0.141)	(0.130)		(0.148)
$\text{HS}_{p,2013} \times$ Post 1 $\times$ $\text{LargeBank}_{b,2013}$			-0.158**	-0.024		0.444***	0.539***
			(0.071)	(0.060)		(0.152)	(0.162)
$\text{HS}_{p,2013} \times$ Post 2 $\times$ $\text{LargeBank}_{b,2013}$			-0.158*	-0.024		0.463***	0.561***
			(0.093)	(0.086)		(0.154)	(0.170)
Fixed Effects							
Bank×Year-Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province×Year-Month	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	166,160	166,160	166,160	166,160	147,745	147,745	147,745
R-squared	0.459	0.464	0.464	0.464	0.406	0.406	0.407

This table provides the estimates for Eqn. (B1). The sample period is 2014M1-2016M12. The unit of observation is at the bank-province-month level, and the dependent variable $Log(Dep)_{b,p,t}$ is the log of total deposits by bank b in province p in month t. $\text{HS}_{p,2013}$ is a dummy that = 1 if the distressed banks had an above median share of (corporate or household) deposits in province p in 2013, and = 0 otherwise. Post 1 is a dummy that = 1 between 2015M2 and 2015M11, and = 0 otherwise. Post 2 is a dummy variable that = 1 between 2015M12 and 2016Q4, and = 0 otherwise. $\text{HighCapital}_{b,2013}$ is a dummy variable that = 1 if the bank had an above the median capital ratio in 2013, and = 0 otherwise. $\text{LargeBank}_{b,2013}$ is a dummy variable that = 1 if the bank had total assets above €100 billion in 2013 (i.e., if it was one of the top five banks in the country), and = 0 otherwise. Standard errors are clustered at the bank and year-month level.

Online Appendix C - Back of the Envelope Calculation

In this section, we quantify the effect of the adverse reallocation on the distressed banks' capital position. Our focus is on the change in the riskiness of their loan portfolio resulting from the exit of low-risk borrowers. To do this, we conduct a counterfactual exercise measuring how much their capital ratio (CET1 ratio) would have improved had the high-risk borrowers left during Post 1 instead of the low-risk borrowers. We proceed in three steps.

First, we calculate the amount of total lost loan business to other (inside or outside) banks. Specifically, we estimate a specification similar to Eq. (4), where we collapse total outstanding credit from distressed and non-distressed banks, and include bank$\times$borrower-type fixed effects to account for differences in loan-portfolio composition. Table C1 shows that distressed banks lost 11% of outstanding credit, or €3.58 billion relative to €32.5 billion of total corporate loans at the beginning of Post1. The loss was primarily concentrated among their low-risk borrowers.

Table C1: Quantification of Lost Business

	Log(Outstanding Credit)		
	(1) All	(2) Low-Risk	(3) High-Risk
$D_b \times$Post1	-0.111***	-0.113***	-0.053
	(0.027)	(0.034)	(0.036)
$D_b \times$Post2	-0.625***	-0.660***	-0.479***
	(0.038)	(0.046)	(0.052)
Observations	687003	522596	164333
Year-Quarter	Yes	Yes	Yes
Bank×Industry ×Size×Province	Yes	Yes	Yes

The unit of observation is a firm-quarter-bank group (i.e., distressed or non-distressed) and the sample period is 2014Q1–2016Q4. The dependent variable is the log of total outstanding credit from bank group b to firm f in quarter t. The variable D_b is a dummy variable that equals 1 if bank b is one of the distressed banks, and equals 0 otherwise. Post 1 is a dummy = 1 between 2015Q1 and 2015Q3, and = 0 otherwise. Post 2 is a dummy = 1 between 2015Q4 and 2016Q4, and = 0 otherwise. Standard errors are clustered at firm level.

Second, we measure the change in RWAs in a counterfactual scenario where the high-risk borrowers exit. To do this, we map the Cerved Z-score of each firm into risk weights under the Basel II Standardized Approach which the distressed banks were using at the time. We attribute an average risk weight of 42% to low-risk borrowers and of 150% to high-risk borrowers. This is obtained as follows. We assign 20% risk weight to firms with scores 1–4, 50% risk weight to those with scores 5, 100% risk weight to those with score 6, and 150% risk weight to firms with scores 7–9.[32] The mapping between Cerved scores and risk weights is based on the reported Cerved average 1-year Probability of Default (PD) and

[32]The risk-weights for corporate exposures are found on p.7 of the Basel II Standardised Approach to Credit Risk.

follows consultation with industry experts. Given that the portfolio of low-risk borrowers (scores 1–6) at distressed banks consists of approximately two-thirds of firms with scores 1–4 and the remainder equally split between scores 5 and 6, we assign a weighted-average risk weight of 42% to low-risk borrowers and 150% to high-risk borrowers. The latter is consistent with the definition of firms with scores above 7 as sub-standard, with a PD exceeding 3% (Rodano et al., 2018). Table C2 summarizes the mapping between Cerved scores, PD and risk weights. Accordingly, the difference in risk weights applied to the reallocated loan portfolio between the counterfactual and the realized scenarios is 108% (150%-42%).

Table C2: Cerved Scores and Risk Weights

Cerved Score	Cerved PD	Risk Weights
1	0.13%	20%
2	0.18%	20%
3	0.25%	20%
4	0.49%	20%
5	1.06%	50%
6	1.88%	100%
7	3.60%	150%
8	7.58%	150%
9	14.19%	150%
Average (1–6)	0.78%	42%

Third, we compute the change in the CET1 ratio in the counterfactual scenario. For simplicity, we keep the numerator (CET1 capital) constant and equal to €3.34 billion at the end of Post1. To calculate the changes in the denominator, we subtract from the actual RWAs at the end of Post 1, as reported in the banks' balance sheets and supervisory documents, the 108% difference in risk-weight times the amount of lost business ($48 - 3.58 \times 1.08$). This yields counterfactual RWAs of €44.13 billion and a counterfactual CET1 ratio of 7.57%. Compared to the actual CET1 ratio of 6.95%, this represents an improvement of 62 basis points.