Corporate Runs and Credit Reallocation*

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November 19, 2025

We study how corporate clients' behavior on both sides of the balance sheet shapes the early dynamics of bank distress. Using granular data from Italy's 2017 regional bank failures, we show that firms react to emerging signs of weakness by simultaneously withdrawing deposits and reallocating credit. Riskier firms draw down existing credit lines, while creditworthy borrowers move to healthier banks, leaving distressed banks with weaker portfolios and eroded capital buffers. These endogenous adjustments amplify bank fragility well before large depositor runs and supervisory intervention, highlighting the importance of early recapitalization and strong bank capital in containing distress.

JEL classification: G21, G28

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

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Conflict-of-interest disclosure statement

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I am the Deputy Vice Chair of the Board of Directors of Unicredit S.p.a. and a member of the Expert Panel on banking supervision at the European Parliament.

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I have nothing to disclose.

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I am an officer of the Bank of Italy. The paper has been reviewed by the management of the Department of Economics and Statistics of the Bank of ltaly prior to its circulation, in line with the policy of the Bank of ltaly. I have no other potential conflict to disclose.

1 Introduction

Bank failures carry significant economic and social costs, 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 has examined the fragility of bank liabilities—particularly the risk of depositor runs—as the trigger of bank failures (Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005), studying depositors' incentives to withdraw funds and contagion across banks (Iyer and Puri, 2012; Martin, Puri, and Ufier, 2023). Much less is known, however, about fragility on the asset side, especially that arising from borrower behavior in the period leading up to large-scale depositor runs and bank collapses.

This paper examines the early-stage dynamics of bank distress, focusing on how corporate clients respond to emerging signs of weakness. Corporations can amplify fragility not only because their deposits tend to be 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). Because creditworthy firms are better positioned to secure outside credit, distressed banks may be left with weaker borrower pools, triggering an endogenous process of asset-side deterioration that makes it harder to attract fresh capital and heightens vulnerability to runs.

We study these mechanisms using the 2017 failures of two regional banking groups in Italy, which provide a clear window into the unfolding dynamics of distress. Our aim is to trace how corporate clients' behavior on both sides of the balance sheet—from the first public signals of weakness to the final supervisory

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

action declaring the banks "likely to fail"—shaped the evolution of distress. Using granular data from the Bank of Italy, we track firms' deposit withdrawals, credit line drawdowns, and loan applications to other banks, examining how their corporate clients simultaneously weakened both sides of the banks' balance sheets and generated spillovers to other banks and firms in the region.

Two pivotal events mark the timeline. The first, in early 2015, started when the financial press revealed that the two banks had been inflating their regulatory capital using improper accounting practices, triggering an initial wave of deposit outflows. The second, at the end of 2015, followed the ECB's Supervisory Review, which revealed that the banks failed to meet minimum capital requirements and precipitated a second and much larger wave of depositor runs.

Our analysis focuses on the period between these two events—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 ultimately sealed their fate. 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, our paper's main focus, to study how credit line drawdowns and credit reallocation during this first phase of distress contributed to the banks' deterioration and ultimate failure.

We find that the early reactions of corporate clients weakened the banks not only on the liability side but also on the asset side—through deposit withdrawals, credit line drawdowns, and the reallocation of new borrowing to other banks. These simultaneous pressures reduced deposit funding, worsened loan quality, and compressed income prospects, eroding capital buffers at a critical moment. By undermining both liquidity and asset quality, these compositional shifts made it harder to attract fresh capital needed to restore confidence, leaving the banks more fragile and exposed to the second, larger wave of depositor runs that followed. Several pieces of evidence indicate that, at the onset of distress—when deposit outflows were still fairly moderate—the deterioration in their loan portfolios was driven primarily by demand rather than supply forces.

Turning first to deposits, we find that corporate clients began withdrawing deposits as soon as the banks' problems became public. Following the initial press revelations, deposits at the distressed banks declined by about 10% during the first phase of distress. This first wave of outflows, concentrated among firms, drained roughly a quarter of the banks' initial liquidity buffers. The second wave, following the publication of the ECB's SREP report, was broader and far more severe, driven by both firms and households, reducing total deposits by about 26% and fully exhausting liquidity buffers. We find that firms moved toward better-capitalized banks regardless of size, while households sought safety in large systemically important banks, regardless of capital.

On the asset side, during this first phase—after the initial press revelations but before the second run—their riskiest corporate borrowers began drawing more heavily on existing credit lines from the distressed banks. By contrast, their most creditworthy and profitable clients began applying and establishing new lending relationships with healthier banks. Although this reallocation temporarily eased funding pressure, it left the distressed banks with weaker and riskier portfolios.

The increase in credit line drawdowns was small in aggregate, concentrated among high-risk firms with single-bank relationships and already high utilization rates. The loss of new loan business to "outside banks" was instead quite substantial.[2] Conservative estimates indicate that the total value of loans that was lost to outside banks amounts to about 10% of the distressed banks' initial loan portfolios, driven almost entirely by their most creditworthy borrowers. Notably, most of this loss occurs already *before* the second wave of runs.

During this first phase, the loss of low-risk borrowers increased balance-sheet

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

risk and undermined confidence in the banks' capital position. Back-of-the-envelope calculations indicate that these shifts raised the ratio of risk-weighted assets to total assets by 2.6 percentage points (pps)—equivalent to about 31% of their CET1 capital at the start of the event window, roughly a year before their problems became public. When the ECB's report confirmed that the banks had fallen below minimum capital requirements, confidence collapsed, triggering a second, larger wave of depositor runs. A counterfactual exercise underscores the importance of the composition effect: had the deleveraging come from riskier rather than their most creditworthy clients, the banks would have nearly doubled their buffer above the 4.5% regulatory minimum, leaving them considerably more resilient.

Several pieces of evidence suggest that the departure of the banks' best corporate clients during the first phase of distress was primarily demand-driven, reflecting precautionary motives rather than a contraction in credit supply. First, loan applications to outside banks are concentrated among single-relationship firms with high continuation values, those facing greater opportunity costs from potential credit disruptions, consistent with theoretical predictions (Detragiache et al., 2000). Second, these firms are among the banks' most profitable customers, delivering higher risk-adjusted returns. Third, within-firm analysis (Khwaja and Mian, 2008) shows that during the first phase of distress, lending rates to these clients do not increase; if anything, they decline, indicating that the distressed banks initially tried to retain these customers with lower rates. Fourth, consistent with these being highly desirable customers, other banks in the region absorb them and reduce credit to their own high-risk borrowers. As a result, these firms transition smoothly to healthier banks without significant declines in credit or investment, whereas riskier borrowers, unable to switch, experience marked reductions in both.

Our paper offers new valuable insights into the early-stage dynamics of bank distress, contributing to several strands of the literature. First, our paper 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; Martin et al., 2023; 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 disruptions to liquidity and credit prompt early runs by corporate clients, triggering an endogenous process of deterioration on both sides of balance sheet that begins as soon as their problems become public.

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, 2023). While prior studies document large, broad-based drawdowns during systemic crises and aggregate liquidity shocks, we show that in episodes of idiosyncratic bank distress, where creditworthy firms can switch to other banks, precautionary drawdowns are far more contained—limited mainly to high-risk firms with single relationships. These findings shed new light on the mechanisms underpinning banks' synergies in the joint provision of deposits and credit lines (Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006). Our results suggests that the stabilizing mechanism identified by Bräuning and Ivashina (2024)—where higher rates dampen precautionary drawdowns—also operates during idiosyncratic distress, explaining why drawdowns are more price-elastic when creditworthy firms have outside options.

Our findings carry important lessons for supervision and crisis management. They show that early-stage distress erodes both sides of the balance sheet well before large-scale depositor runs occur, implying that liquidity support or deposit guarantees alone may be insufficient. Swift supervisory action to address solvency weaknesses—particularly through early recapitalization—is essential to restore confidence and prevent loss of best borrowers. Bank capital plays a dual role: beyond absorbing losses, it determines which institutions can retain and attract creditworthy firms when market discipline intensifies. At the same time, the market forces that destabilize weak banks can strengthen sound ones, supporting the reallocation of credit across the system. Ensuring timely intervention and credible resolution frameworks is therefore critical to containing distress at its source and preserving credit continuity during periods of financial turmoil. 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 under examination and a chronological account of the events which ultimately let 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

[3] Following Bank of Italy disclosure rules, we combine the two banking groups and refer to them jointly as the "distressed banks" throughout the paper. The banks' identities or statistics based on fewer than three institutions cannot be disclosed under these regulations.

equity at the time, some banks, including the distressed banks, resorted to "loan for shares" schemes, requiring loan applicants use part of their loan proceeds to purchase shares of the lending bank. While not illegal, equity raised through such schemes should receive approval from an extraordinary shareholders' meeting and, crucially, must be excluded from the computation of regulatory capital.[4]

The first signs of trouble surfaced in November 2014, when the ECB–SSM 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

[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.

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 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" and underwent 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 (Centrale dei Rischi, hereafter

[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.

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, when they faced large-scale depositor runs and collapsed.

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. (2023), we exclude credit lines with zero granted exposure 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.

Interest rate data (available for roughly 90 banks covering over 80% of aggregate credit) are computed as the ratio of interest payments to average outstanding balances by type of loan (Crawford, Pavanini, and Schivardi, 2018). We complement these with the Taxia dataset, which provides 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 56,505 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 (Online Appendix Table A1 and Figure A1).

We complemented the credit registry data 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 bank 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 dataset have an average capital ratio of 12.5%, with deposits accounting for about 42% of total assets (of which one-quarter from firms).[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 $\geq$ 7), and 43% borrow from only one bank.[8] Roughly one-quarter of firms are clients of the distressed banks, with an average credit dependence of 44%. Panels C and D present statistics on credit line usage, loan applications, and firm outcomes. On average, firms draw 23% of available credit lines, with high-risk firms drawing about twice as much as low-risk ones. The average probability of applying to a new bank is 5%, and the switching success rate is 27%.[9] During the event window, total bank credit declined by 3.3%, while investment, sales, and wages grew modestly.

[7] Private-sector deposits account for a smaller share of bank funding in Italy than in the U.S., where they account for 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 information about the banks' problems became widely known. The event window spans January 2014 to December 2016, covering roughly one year before the onset of distress and extending until the banks' eventual collapse. We first analyze the deposit dynamics to capture behavior of their 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, assess their contribution to the banks' failure, and explore possible alternative explanations.

4.1 The Dynamics of Depositor Runs

The revelation of accounting fraud to inflate regulatory capital, together with negative media coverage, eroded confidence in the distressed banks' viability and triggered depositor runs. Figure 2 illustrates how the total deposits of the distressed banks evolved relative to all other ("non-distressed") banks during this period. 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 increasing at the same rate as other banks, began to decline and diverge from other banks in late 2014, following the ECB–SSM 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 for their names spiked.

[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, Puri, and Ryan, 2016 and Michaelides, 2014).

After this initial drop, deposits briefly stabilized and partly recovered. Between the end of November 2014 and the end of November 2015, the distressed banks lost about 10% of total deposits. The turning point came at the end of 2015, when the SREP report exposed the greater extent of their problems, triggering a second, and much larger wave of deposit withdrawals that precipitated their collapse. By December 2016, they lost about 26% (€6.43 billion) of total deposits. Other banks instead saw increases in their deposits, especially during the second wave of runs.

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:

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

where $\log(Dep)_{b,t}$ denotes the log of (total, firm, or household) deposits at bank b in month t. The variable D_b equals 1 if bank b is one of the distressed banks, and equals 0 otherwise. 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-level.[11]

The results are reported in Table 2. During Post 1 and Post 2, the deposits of the distressed banks decrease 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 buffers.[12] Distinguishing between household and firm deposits in columns

[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] Liquidity buffers 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

(2) and (3), we find that the outflows in Post 1 are mainly driven by firms. During this period, the 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 begin to fall markedly during Post 2, but even then with much lower intensity than corporate deposits (22.4% vs. 58.8%).

Figure 3 shows results 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. Importantly, we also observe that until December 2014, the deposits of the distressed banks move in parallel to other banks.[13]

Additional analysis of deposit reallocation (Online Appendix Table B1) shows that corporate deposits flowed primarily toward well-capitalized banks, regardless of their size. Unlike firms, households do not appear to prioritize bank soundness: they run toward large, systemically important banks irrespective of their capital levels. These findings for household deposits are consistent with results for total deposits reported by Iyer, Jensen, Johannesen, and Sheridan (2019), Acharya et al. (2023), Caglio, Dlugosz, and Rezende (2024) and Cipriani et al. (2024).

The deposit analysis yields two key insights. First, the scale of withdrawals severely strained the banks' liquidity: outflows in Post 1 drained about a quarter of their liquidity buffer, creating a significant but still manageable strain, while the second wave in Post 2 exhausted all liquidity and sealed their fate. 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. These patterns likely reflect not only differences in deposit

distressed banks' combined liquidity buffers totaled €7.6 billion.

[13]The omitted period is January 2015. In the second half of Post 1, household deposits recover somewhat: they are no longer significantly below pre-distress levels. Combined with Figure 2, this suggests that the distressed banks partly offset corporate outflows by attracting new household deposits, consistent with Martin et al. (2023) and Cipriani, Eisenbach, and Kovner (2024).

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 are also likely to "run" on the asset side for the same reasons.

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 the impact they had on the distressed banks' ultimate failure. We explore two potential demand-side channels, both reflecting precautionary motives: "credit line runs" on existing credit lines and "borrower flights" to outside banks. We 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 during the first, critical period leading up to the second and much larger 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 liquidity shocks, either in anticipation of future credit supply restrictions or out of fear that banks may cut or revoke existing lines (Ivashina and Scharfstein, 2010; Ippolito et al., 2016; Chodorow-Reich et al., 2022; Greenwald et al., 2023). 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. Following Greenwald et al. (2023), we exclude bank-firm relationships that have already reached the credit line limit, as these borrowers cannot further adjust their drawdowns. 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.

We include bank fixed effects, α_b, to control for time-invariant differences across banks. To control for time-varying firm-specific factors, we follow Degryse, De Jonghe, Jakovljević, Mulier, and Schepens (2019) and include industry × province × size × year-quarter fixed effects, which can be estimated for all firms.[14] For multiple relationship firms, we also report a more conservative specification, that replaces these with 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.

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—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 multiple relationships and single-relationship firms

[14] Firm size is determined based on quintiles of total assets at the end of 2013.

with stronger fundamentals, with easier access to alternative funding sources, show 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 usage. High- and low-risk firms with multiple relationships raised drawdowns by roughly 5% (0.017/0.39 and 0.009/0.18, respectively).

These results indicate that once the distressed banks' problems became public and corporate depositors began to flow out, their riskier corporate borrowers also began drawing more heavily on existing credit lines, increasing the share of risky loans in their portfolios and further straining liquidity.[15] Economically, however, the aggregate magnitude of drawdowns during Post 1 was very small: about 0.02% of total loans and 0.11% of the banks' initial liquidity buffers. By Post 2, the coefficient in column (1) implies a somewhat larger increase—about 0.06% of total loans and 0.44% of initial liquidity—as a broader set of borrowers began drawing.

The small and concentrated nature of drawdowns in Post 1 may seem at odds with the large, broad-based credit-line runs documented in other studies. A crucial difference lies in the nature of the shock. Previous studies (Ivashina and Scharfstein, 2010; Ippolito et al., 2016; Greenwald et al., 2023), examine aggregate liquidity shocks (e.g., GFC, COVID-19) when many banks and firms simultaneously face liquidity stress and firms have few outside options, leading to widespread drawdowns. In contrast, bank distress in our setting is idiosyncratic. Firms' behavior may differ significantly between these two very different contexts.

When banks' liquidity problems are idiosyncratic, firms with strong fundamentals can turn to other banks. Instead of preemptively drawing on costly credit lines and paying interest on the drawn amounts, these firms may prefer to insure against future credit supply disruptions by establishing new lending relationships

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

with healthier banks. As shown in Bräuning and Ivashina (2024), precautionary credit line drawdowns exhibit high interest rate sensitivity (price elastic), particularly outside systemic crises.[16] By contrast, high-risk single-relationship firms (i.e., those least able to switch lenders) behave more like firms in systemic crises, preemptively drawing on their available credit lines once distress becomes public.

Importantly, these results shed new light on the mechanisms underpinning banks' synergies in the joint provision of deposits and credit lines (Kashyap et al., 2002; Gatev and Strahan, 2006). Our results indicate that the stabilizing mechanism identified by Bräuning and Ivashina (2024), where the price elasticity of precautionary drawdowns curbs liquidity stress when rates rise and deposits flow out of the banking system, extends to periods of idiosyncratic bank distress. This also helps explain why the price elasticity of precautionary drawdowns is higher outside systemic crises when creditworthy firms have other options.

4.2.2 Loan Applications to Outside Banks

We next 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 (Detra-

[16]For firms aiming to establish new lending relationships, precautionary drawdowns may be undesirable 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 registry and negatively affects firms' publicly available Z-scores.

giache et al., 2000). Because local "outside funding" capacity is limited, single-relationship firms, typically smaller firms reliant on local banks, have greater urgency to diversify as soon as their banks' problems become widely known.[17] Similar strategic complementarities are thought to drive depositor runs (Diamond and Dybvig, 1983) and, more recently, "worker runs" (Hoffman and Vladimirov, 2025).

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 start of our event window. $SD_{f,2013}$ is the share of firm's f credit from the distressed banks in 2013, which takes values from 0 to 1. Post 1 and Post 2 are defined as before.

Controls $X_{f,t-4}$ 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 firm's relationship with distressed banks. Identification of the parameters of interest, thus comes from *within* firm variation over time.[18]

[17] Local capacity constraints are more binding for smaller firms that tend to borrow from smaller local banks (see, among others, Stein, 2002; Berger, Miller, Petersen, Rajan, and Stein, 2005; Degryse and Ongena, 2005; Agarwal and Hauswald, 2010).

[18] To further enhance comparability between the two groups, we use entropy balancing regression weights (Hainmueller, 2012) based on firm size, as Online Appendix Table A2 indicates small differences in firm size between the two groups. Firms borrowing from distressed and non-distressed banks were otherwise very similar at the start of the event window. Normalized differences across observable characteristics are all below the conventional 0.25 threshold for balance (Imbens and Wooldridge, 2018).

The key identifying assumption is that, conditional on these controls and granular fixed effects, the ex-ante (pre-distress) share of credit from the distressed banks does not correlate with firm-specific unobservables that influence the decision to apply for credit elsewhere. To test this assumption and rule-out potential pre-trends, we estimate specifications without firm fixed effects. These specifications allow us to estimate the level effect of $SD_{f,2013}$ and verify whether borrowers with a higher credit dependence on the distressed banks were not more likely to apply to outside banks also during the pre-period (parallel trends assumption).

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" hypothesis 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 the Online Appendix, low-risk firms tend to be more profitable and more productive firms, with higher investment rates. In other words, firms with 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, 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 coefficients are large and remain stable as we add firm fixed effects in column (2). For a fully dependent firm ($SD_{f,2013} = 1$), 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 mean application rate. The results of corresponding dynamic DiD specifications, reported in Figure 4, confirm 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).[19]

Distinguishing between low- and high-risk firms with single or multiple lending relationships (columns (3)–(6)) shows that the Post 1 increase is 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 sought new lenders. Columns (7)–(8) further show that increases in loan applications to outside banks are strongest among firms with a larger share of maturing debt.

Additional analysis of credit reallocation (Online Appendix Table A4) shows that low-risk firms were more likely to start new lending relationships once the banks' problems became public. Conditional on applying for credit to an outside bank, fully dependent low risk firms ($SD_{f,2013}$=1) were about 12 pps more likely to form new relationships during Post 1, roughly a 46% increase relative to the mean (0.124/0.271), and 9 pps (33%) more likely in Post 2, suggesting that early movers were more successful in securing new lenders. The probability of forming a new relationship among fully dependent borrowers is therefore higher (+12pps) than their probability of applying for credit (+1.4pp as in column (3) of Table 4), indicating that loan applications from borrowers of distressed banks are accepted at a much higher rate as they mostly come from low-risk borrowers. The new

[19] In further tests, reported in Table A3 in the Online Appendix, we find that firms with stronger shareholder ties are less likely to apply to outside banks. Ownership data for these banks are only available as of 2016. We find instead no systematic difference with respect to the length of the firm's lending relationship with the distressed banks.

relationships were primarily formed with better-capitalized and larger banks. Bank capitalization matters more during the first wave of runs, when firm deposits moved toward better capitalized banks, while bank size became more important in the second wave, when households shifted toward large, systemically important banks.

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 5, after adjusting for credit risk, loans to low-risk firms yield higher expected returns than loans to high-risk firms (z-scores ≥ 7), indicating that low-risk borrowers are banks' most profitable customers. The figure reports risk-adjusted returns at loan origination for each rating category, computed using contractual interest rates on new loans net of expected default probabilities. This provides an ex-ante measure of loan profitability that is not affected by ex-post shocks to borrower risk. Values above (below) zero indicate higher (lower) returns relative to the omitted group (z-score = 1). Interestingly, returns peak for firms with good—but not perfect—credit scores, consistent 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).[20]

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. These borrowers appear to have turned to other banks because they wanted to, likely for precautionary reasons, not because they

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

were forced out. As shown in Figure 5, accounting for credit risk, low-risk borrowers are among banks' most profitable clients, making it unlikely that the distressed banks would have preferred to reduce lending to them rather than to higher-risk 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, Mosk, Ongena, and Wix, 2019).

However, as the distressed banks began facing depositor runs, their incentives may have shifted. Their effective market power was stronger over high-risk firms, which could not easily switch to other lenders (Dell'Ariccia and Marquez, 2004), allowing them to protect margins by charging higher interest rates to these borrowers. At the same time, reducing credit to high-risk borrowers could have increased default risk and further weakened already thin capital buffers. Limiting lending to low-risk borrowers may have appeared less immediately damaging.

Hence, to examine how lending conditions at the distressed banks evolved relative to other banks during the event window, Table 5 presents estimates from the following 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 at time t. D_b equals 1 if bank b is one of the distressed banks and 0 otherwise. 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).[21] Figure 8 reports the estimated coefficients and 95%

[21]For completeness, we also estimate less restrictive specifications for all firms by replacing

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.[22] We thus rely on the joint movement of credit volumes and loan interest rates to distinguish between demand and supply. Finally, as in Khwaja and Mian (2008) we focus on performing exposures.

The results yield two key insights. First, the results for high-risk firms point to tightening of credit conditions. Loan rates to high-risk borrowers rise already in Post 1 (Panel B of Table 5 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" borrowers to preserve margins. In addition, to the extent that these banks had previously engaged in "zombie lending" to avoid recognizing nonperforming loans and maintain regulatory capital requirements (Caballero, Hoshi, and Kashyap, 2008), incentives to evergreen risky loans likely shifted once their fragility became public and began experiencing depositor runs. As banks came under greater market and regulatory scrutiny, they tighten terms and eventually cut credit to risky borrowers, in line with evidence in Bonfim, Cerqueiro, Degryse, and Ongena (2022).[23]

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.

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

[23]Weakly capitalized banks have stronger incentives to lend to low-productivity "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 et al. (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 have weaken once banks come under greater public and regulatory scrutiny. It is worth noting that during the pre-period the distressed banks were not

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 is not accompanied by higher loan rates (Panel B of Table 5). Instead, as shown in Figure 8, during Post 1, the distressed banks began charging lower rates to these firms. This result 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 indicate that, at the onset of distress, the adjustment was primarily demand-driven, as low-risk borrowers reduced their exposure to troubled banks. The last two sections—on spillover effects and real effects—provide additional evidence consistent with this interpretation.

4.2.4 Credit Reallocation and Impact on the Banks' Viability

We next assess the aggregate magnitude of credit reallocation during Post 1 and its likely impact on the banks' distress and eventual collapse. Because credit-line drawdowns are quantitatively small, we focus on the more sizable asset-side adjustment—the credit reallocation—to assess how the early departure of low-risk firms weakened the distressed banks at a critical moment.

Scale of Credit Reallocation To quantify the aggregate "lost business" to outside banks, we focus on firms that were borrowing exclusively from the distressed banks at the start of the event window (i.e., existing single-relationship firms) and

charging lower rates to risky firms compared to other banks (Panel B, Figure 8). Since zombie lending is typically associated with "unusually cheap" credit to troubled borrowers, this result suggests that if zombie lending was occurring, it was not to a greater extent than other banks.

compute the cumulative value of loans received from outside banks over the event window, scaled by total loans from the distressed banks at the start of the period.[24] We also compute the corresponding figure for non-distressed banks.

Figure 6 provides a visual illustration. Until the distressed banks' problems became widely known in 2015Q1, the share of new loan business lost to outside banks was similar for both distressed and non-distressed banks.[25] This changed sharply in 2015Q1, when the distressed banks began losing new loan business to outside banks at a much faster rate. The gap between the two groups indicates that, by the end of Post 2, distressed banks had lost about 10 pps more business to outside banks, corresponding to €2 billion of their total corporate loan portfolio as of December 2013 (€20.2 billion). Importantly, most of this loss occurred during Post 1 and it was driven almost entirely by their most profitable, low-risk borrowers, who were also attractive to other banks (Online Appendix Figure A4).[26]

Impact of Credit Reallocation on Banks' Viability From a funding perspective, the departure of low-risk borrowers initially alleviated liquidity pressure. The value of the "lost business" from departing low-risk borrowers in Post 1 amounted to roughly 2% of the banks' initial total loans and 66% of deposit outflows during that period. In essence, the exit of low-risk firms in Post 1 temporarily eased funding strains by shrinking both sides of the balance sheet. However,

[24]We compute values only for single-relationship firms, as for multiple-relationship firms it is more challenging to attribute the lost business to any one of their existing lenders. Since multiple-relationship firms are typically larger firms and take out bigger loans, our estimates provide a lower bound of the distressed banks' lost business to other banks.

[25]Both figures trend upward because, over time, a fraction of banks' existing customers switch to outside banks for reasons other than bank distress.

[26]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%).

the composition of this deleveraging was strongly adverse: the departing firms were among the banks' most creditworthy and profitable borrowers, leaving behind weaker and riskier loan portfolios at a critical moment.

To assess the overall impact on the banks' solvency, we compute a back-of-the-envelope estimate of the banks' risk-weighted assets to total assets (RWA/TA) ratio at the end of Post 1. This ratio summarizes how the combined effects of asset-side deleveraging and deposit outflows altered the banks' balance-sheet risk:

$$\frac{RWA_1}{TA_1} = \frac{RWA_0 - 0.5 \times \textit{Lost Business}_1}{TA_0 - \textit{Deposit Outflows}_1}, \tag{5}$$

where the subscript 0 denotes December 31, 2013 (just before the start of the event window), and subscript 1 refers to the end of Post 1. We set $RWA_0 =$ €54.05 billion and $TA_0 =$ €82.40 billion, corresponding to the distressed banks' combined balance sheets at the start of the event window. $\textit{Lost Business}_1$ denotes the reduction in lending to low-risk firms during Post 1 of €1.11 billion. This amount is assigned a 0.5 risk weight, consistent with the treatment of loan exposures to firms rated A+ to A- under the Basel II standardized approach in place at the time. The denominator adjusts total assets for the reduction associated with deposit outflows during Post 1, reflecting the mechanical balance-sheet contraction.

Applying Eqn. (5) indicates that, by the end of Post 1, the banks' RWA/TA ratio would have risen by about 2.6 pps relative to its initial level. To isolate the role of loan composition, we conduct a counterfactual exercise in which all else remains equal but the same amount of credit reduction comes from high-risk rather than low-risk borrowers. The "lost business" term in the numerator is assigned a 1.5 risk weight (as exposures below BB- ratings), instead of 0.5, reducing the banks' total RWA by about €1.11 billion. Due to banks' thin capitalization levels, this modest decline corresponds to 31% of their initial CET1 capital (€3.62 billion) and 93% of their initial buffer over Basel II's 4.5% minimum requirement.[27]

This exercise illustrates how the composition of credit reallocation eroded the banks' resilience. The disproportionate loss of low-risk borrowers increased balance-sheet risk and weakened the credibility of their capital position at a time when market confidence was already fragile. Shortly after the ECB's SREP report revealed that the banks had failed to meet minimum capital requirements, market confidence collapsed, triggering a second, much larger wave of depositor runs that accelerated their downfall. Under the counterfactual, the distressed banks would have nearly doubled their initial buffer over the 4.5% threshold, leaving them in a considerably stronger position and, arguably, less vulnerable to that trigger.

Overall, the exit of their best corporate clients during Post 1 left the banks with smaller capital buffers, poorer loan quality, and weaker income prospects, further undermining confidence and deterring potential investors. While it is impossible to know whether the second wave of runs could have been avoided, our results suggest that the adverse compositional effects during Post 1 brought the banks significantly closer to the trigger that ultimately sealed their fate.

4.3 Spillover Effects on Other Banks' Loan Portfolios

In this section, we explore spillover effects on the borrowers of 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

[27] These estimates are conservative, as they are based in their initial capital positions at the start of the event window. During Post 1 equity values fell sharply as problems mounted and boards marked down their capital. Extending Eqn. (5) to incorporate the increase in credit line drawdowns by high-risk firms (by adjusting the numerator to $RWA0 + 1.5 \times Drawdowns_1 - 0.5 \times Lost\ Business_1$) does not materially change the results.

loan applications each bank received in a given quarter:

$$Exp_{b,t} = \frac{DistBorrAppl_{b,t}}{TotalAppl_{b,t}}, \quad (6)$$

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:

$$\Delta \log(Credit)_{b,f,t} = \beta_1\ Exp_{b,t} \times HighRisk_{f,2013} + \gamma' X_{f,t-1} + \alpha_{k,p,t} + \alpha_{b,t} + \epsilon_{b,f,t}, \quad (7)$$

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 a larger influx of applications from distressed banks' borrowers experienced a 1.9 pps reductions 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 banks' 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).[28] 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 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 the banks' distress affected their borrowers' overall financing and investment, as is common in the literature (Chodorow-Reich, 2014; Huber, 2018). Our earlier evidence shows that low-risk firms were more likely to

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

apply and secure new lending relationships. It remains unclear, however, whether they were able to secure sufficient credit on comparable terms as to avoid a slow-down in investment. To assess how their total bank credit and investment evolved over the event window, we estimate the following model at the firm-year level:

$$\begin{aligned} Y_{f,t} = {} & \beta_0 SD_{f,2013} + \beta_1 SD_{f,2013} \times \text{Post 1} \\ & + \beta_2 SD_{f,2013} \times \text{Post 2} + \alpha_{k,p,t} + \lambda_{j,t} + \epsilon_{f,t}. \end{aligned} \tag{8}$$

where $Y_{f,t}$ indicates the growth of total credit or investment of firm f in quarter t, where total credit is defined as the sum of term loans and granted credit lines, irrespective of whether the latter were drawn. Thus, declines in total credit capture reductions in the overall amount of credit granted to the firm. $SD_{f,2013}$ 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.[29]

The results are reported in Table 6. Panel A reports results for total credit and Panel B for investment. The first three columns (columns (1)-(3)), report a baseline specification, which studies the relationship between $Y_{f,t}$ and $SD_{f,2013}$ without distinguishing across the different sub-periods. We find that over the entire event window and across all firms (column (1)), the coefficients of $SD_{f,2013}$ are 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, we find that this is only true for low-risk firms (columns (2) and (3)). High-risk firms, saw significant declines in total credit growth and investment rate. In terms of economic significance, the coefficient of $SD_{f,2013}$ in column (1) indicates that high-risk firms

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

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.[30]

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. By contrast, high-risk firms, which were unable to switch, could not reverse the large declines in credit and investment rates they saw in Post 1 (i.e., the interaction coefficients with Post 2 in column (5) are negative and statistically insignificant).

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) 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 fragility. Using the 2017 failures of two Italian banking groups, we show that as soon as signs of weakness emerge, firms run on both sides of the balance sheet—withdrawing deposits and

[30]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).

reallocating credit. These unfold before large-scale depositor runs and jointly accelerate their downfall. The withdrawal of deposits drains liquidity, while the loss of creditworthy and profitable borrowers increase asset risk and compress income, making it harder to attract new capital precisely when it is most needed.

Our analysis highlights that the first stage of distress—often overlooked in crisis management—plays a decisive role in determining banks' fate. The early reallocation of credit toward stronger banks not only signals weakening confidence but also amplifies solvency pressures. Back-of-the-envelope estimates show that the compositional changes in lending during this phase raised risk-weighted assets, eroding roughly one-third of the banks' initial capital. Under a counterfactual scenario in which deleveraging came from riskier clients instead, the distressed banks would have nearly doubled their capital buffer over the regulatory minimum, leaving them more resilient to future shocks.

We also uncover important differences between episodes of systemic and idiosyncratic bank distress. In contrast to the broad-based credit-line runs observed during aggregate liquidity shocks, precautionary drawdowns in this setting were limited to high-risk, single-relationship firms unable to switch banks. Creditworthy firms instead secured financing from better-capitalized competitors, revealing that precautionary drawdowns are highly price-elastic outside systemic crises. This finding offers new insights into the synergies underpinning banks' joint provision of deposits and revolving credits.

From a policy perspective, our results underscore that early-stage distress erodes both liquidity and solvency, long before large-scale depositor runs occur. Liquidity support or deposit guarantees alone are insufficient. Swift supervisory action—particularly early recapitalization—is essential to prevent the loss of banks' best corporate clients and to restore confidence. Beyond absorbing losses, bank capital determines which institutions can retain and attract creditworthy firms when market discipline tightens. At the system level, the matching of bank-dependent, creditworthy borrowers with well-capitalized lenders dampens procyclicality and limits the transmission of banking shocks to the real economy.

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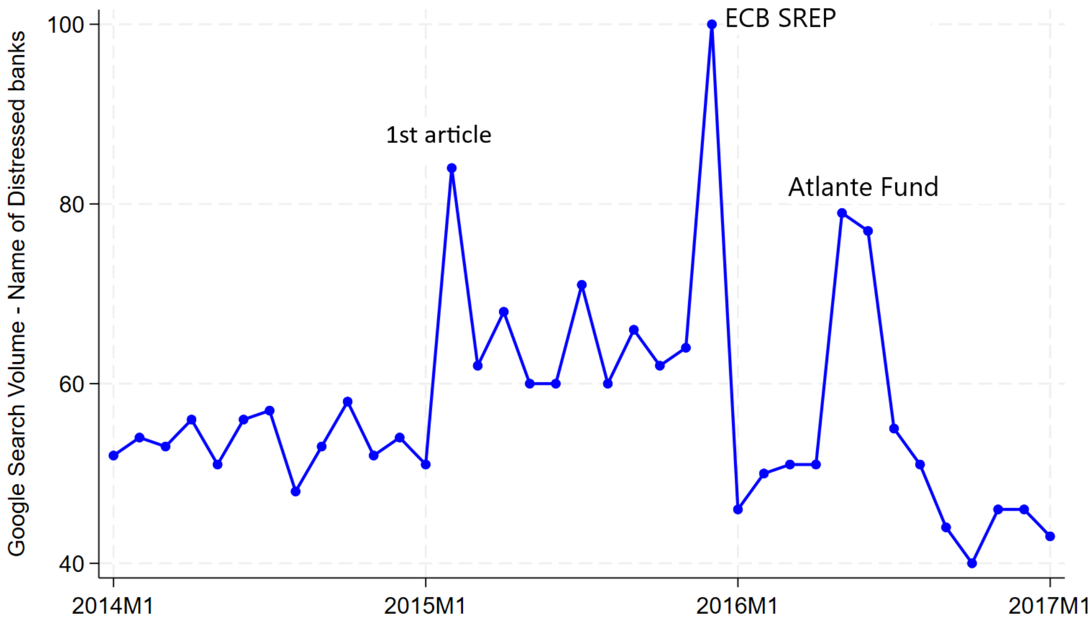
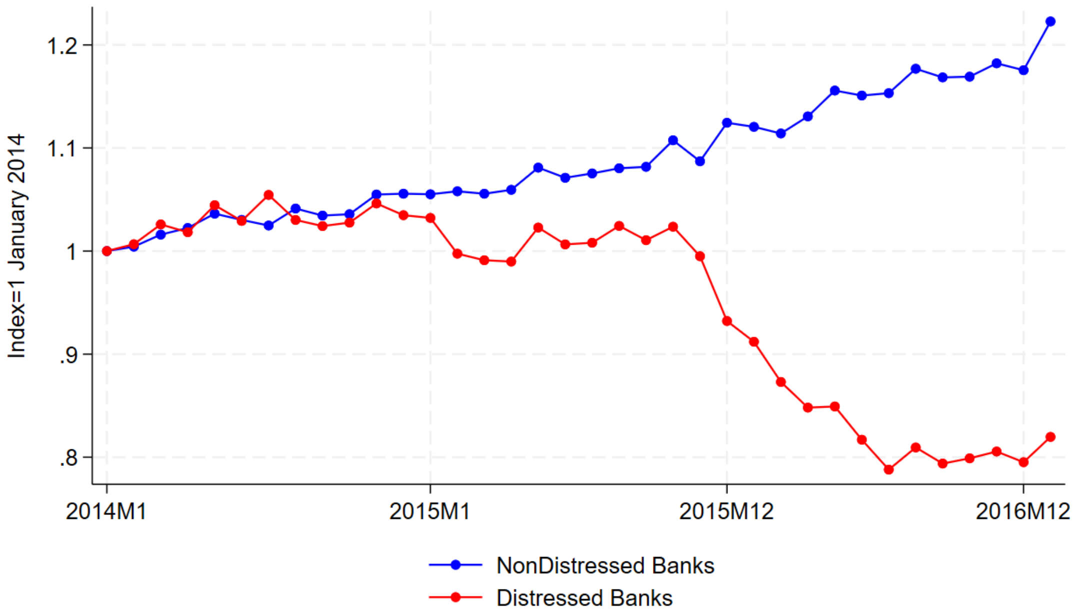
Figure 1: Google Trends



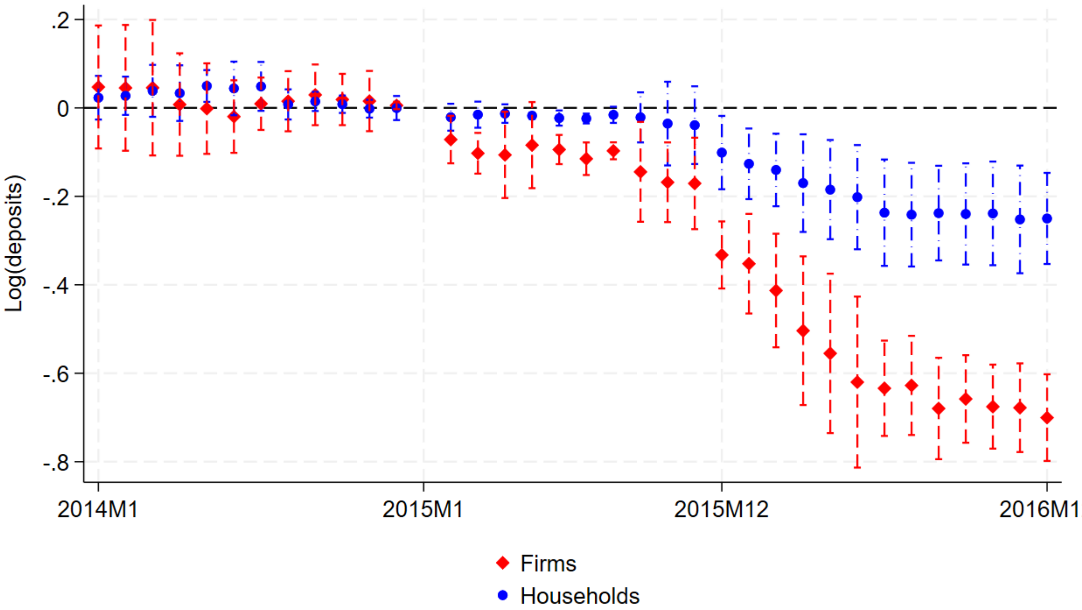
This figure shows the Google searches for the name of the distressed banks between January 2014 and January 2017. Numbers represent search interest relative to a time period, with 100 indicating the peak number of searches during the event period. "1st article" refers to the February 2015 article published 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 are 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 2014M1 to 2016M12. All series are normalized to 1 as of 2014M1.

Figure 3: Dynamic DiD: Firm vs. Household Deposits

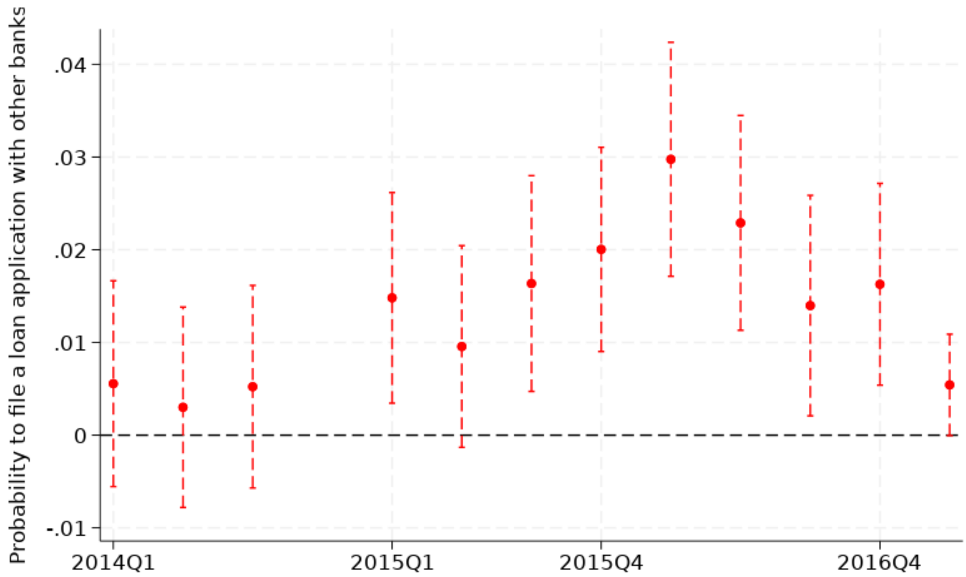


This figure plots the β_t coefficients and 95% confidence intervals from the following dynamic DiD specifications at the bank-month:

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

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 2014M1 to 2016M12 (2015M1 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

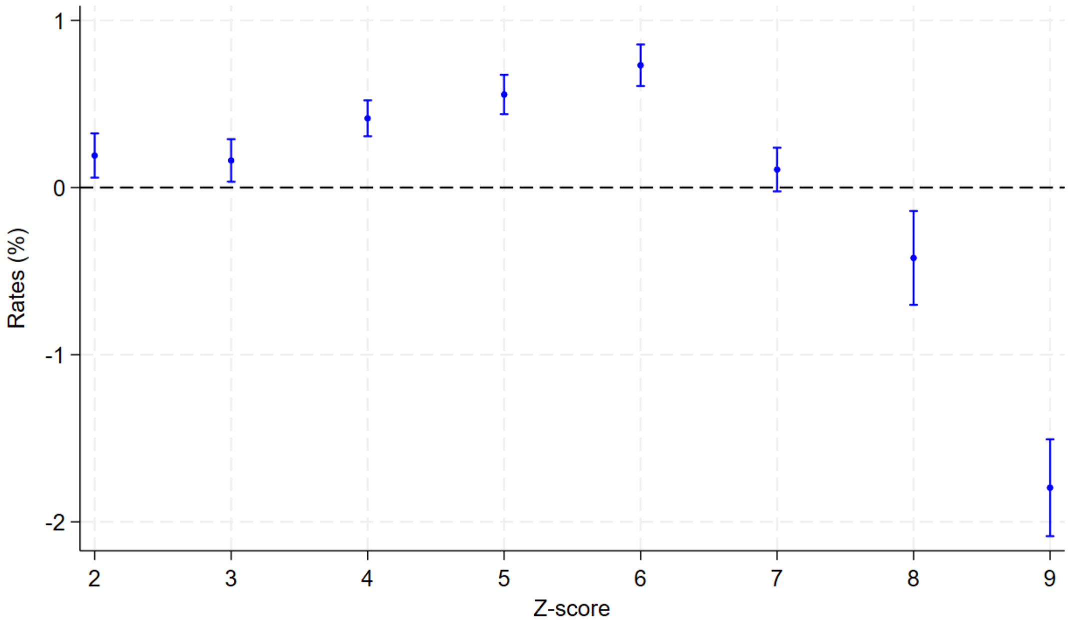


This figure plots the β_t coefficients and associated 95% confidence interval for the following equation:

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

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: Credit risk-adjusted interest rates



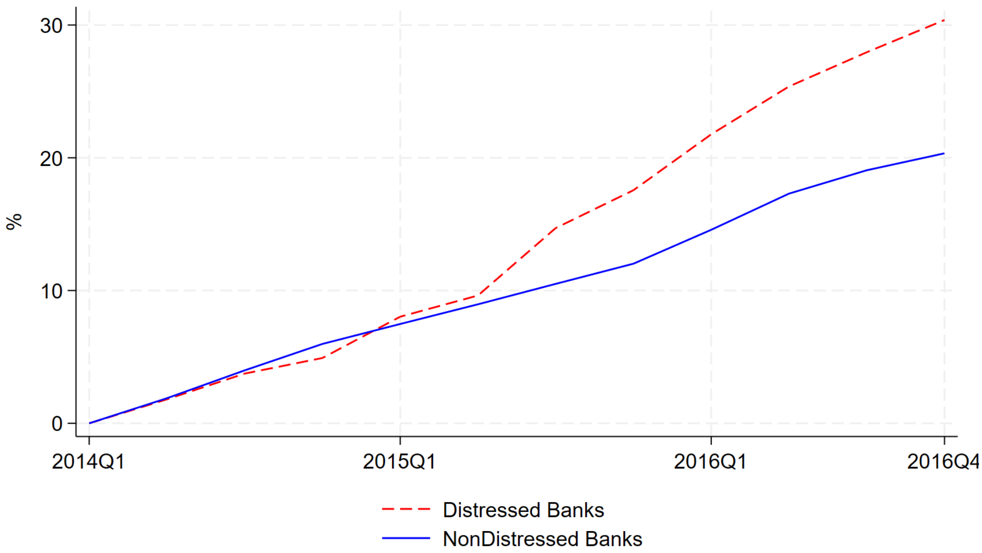
This figure plots the credit risk-adjusted interest rates, calculated as InterestRate-PD×(1-RR), where PD is the 1-year probability of default and RR is the average recovery rate, by firm-risk category. To compute the different parameters, we proceed as follows. We first set RR to 0.43, which is the average recovery rate for secured loans to non-financial firms (obtained from Table A6, Statistical Appendix to Notes on Financial Stability and Supervision, No. 13 - Bad Loan Recovery Rates in 2017). 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:

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

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

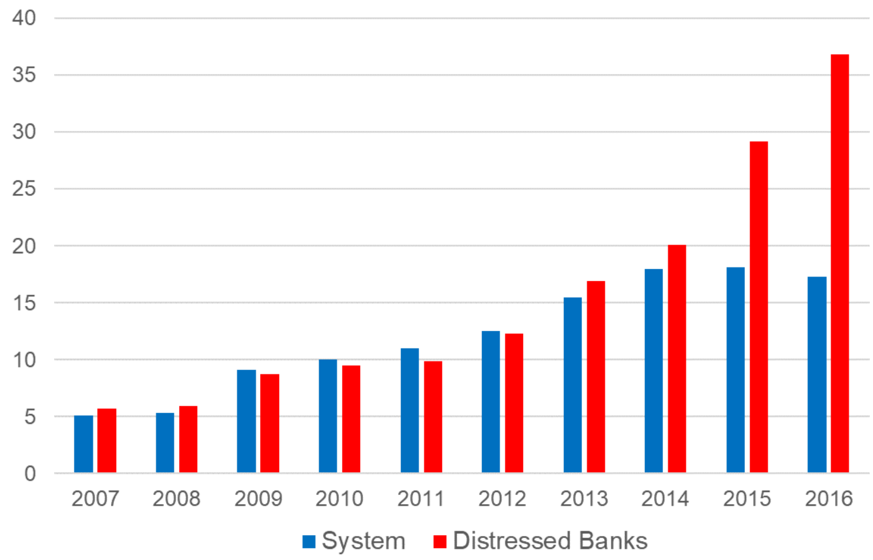
where $\text{InterestRate}_{f,t}$ is the contractual interest rates on new term loans paid by firm f at origination time t. $\text{BadLoan}_{f,t}$ is the 1-year probability of default, i.e. a dummy equal to one if at least one of the loans of firm f becomes a bad loan in year $t+1$. $ZScore(i)$ is a 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 6: 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.

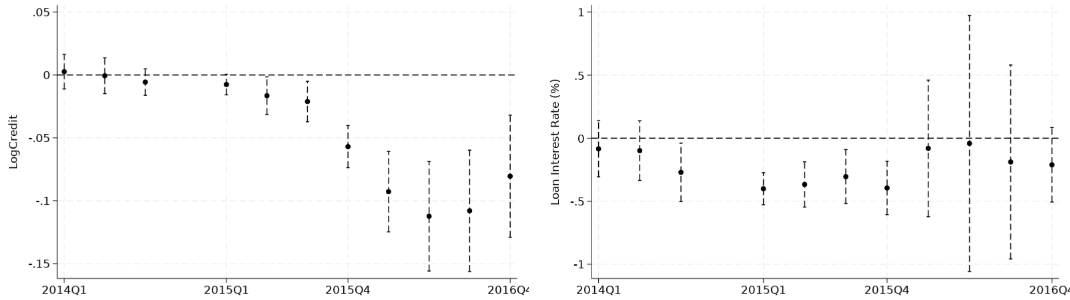
Figure 7: NPL over Loans ratio: Distressed Banks vs. System



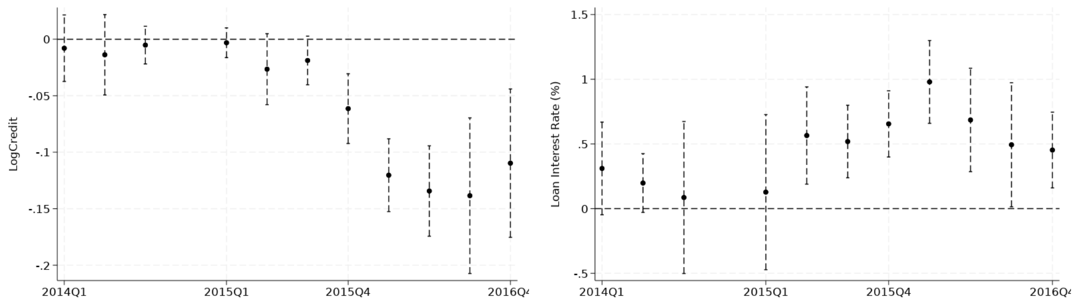
This figure shows the evolution of the Non-Performing Loans (NPL) to total loans ratio of the distressed banks vs. all Italian banks between 2007 and 2016.

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

	Panel A. Bank characteristics as of 2013Q4					
	Obs.	Mean	St. Dev.	Median	5th pct.	95th pct.
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	854,714	0.183	0.317	0	0	0.922
High-Risk borrowers	203,229	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 2014M1-2016M12. 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 that = 1 between 2015M2 and 2015M11, and = 0 otherwise. Post 2 is a dummy variable that = 1 between 2015M12 and 2016Q4, 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	No	Yes	No	Yes	No
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. 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	≥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 × Province × Size								
× Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CreditScore × Year-Quarter	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. Firms with a credit score <7 are classified as "Low-Risk". Conversely, firms with a credit score ≥7.

Table 5: 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	-0.047	-0.078	-0.085	-0.123	0.250**	0.234**
	(0.155)	(0.134)	(0.159)	(0.137)	(0.097)	(0.097)
$D_b\times$ Post 1	0.237	0.165	0.189	0.113	0.532***	0.555**
	(0.384)	(0.347)	(0.406)	(0.358)	(0.190)	(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	1,044,822	868,675	946,647	791,004	92,366	77,671
R-squared	0.218	0.616	0.217	0.608	0.403	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 z-scores < 7 (≥ 7). Standard errors are clustered at bank-level.

Table 6: Firm Outcomes: Total Credit and Real Effects

	All	High-Risk	Low-Risk	All	High-Risk	Low-Risk
	(1)	(2)	(3)	(4)	(5)	(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×Year	Yes	Yes	Yes	Yes	Yes	Yes
I(CreditScore)×Year	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. (8). 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.

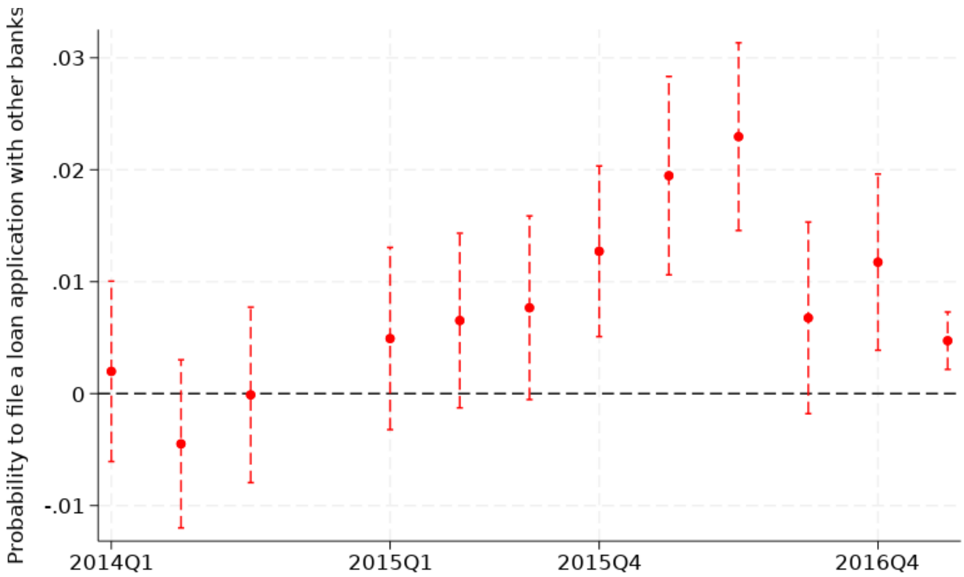
Table 7: Credit Spillovers Effects on Other Banks in the Region

	(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*Quarter	Yes	Yes	Yes	Yes
Bank	Yes	Yes	-	-
Bank*Quarter	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. (7). 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.

Online Appendix A - Robustness Tests

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



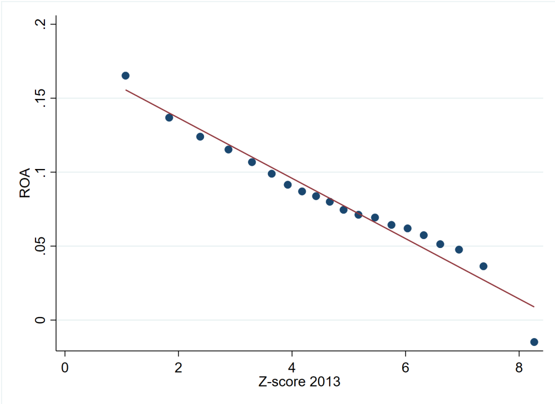
This figure plots the β_t coefficients and associated 95% confidence interval for the following equation using a sample of 42 provinces where the distressed banks make 90% of lending:

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

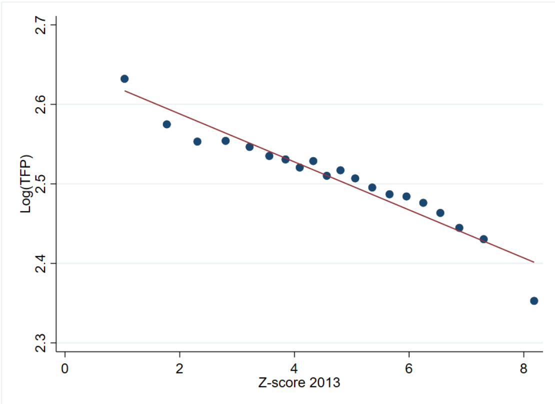
where $\text{ApplOut}_{f,t}$ is a dummy equal to one if firm f applies to an 'outside banks' with which the firm has no previous relationship (i.e., first-time borrowers). $SD_{f,2013}$ is the share of credit of firm f from distressed banks in 2013 and it is equal to zero if the firm was not borrowing 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

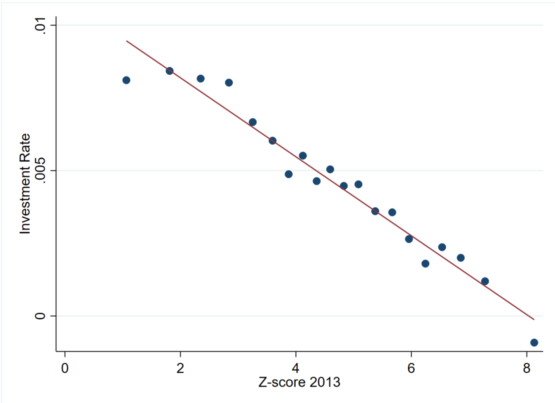
A. Firm Profitability & Credit-Risk



B. Total Factor Productivity & Credit-Risk



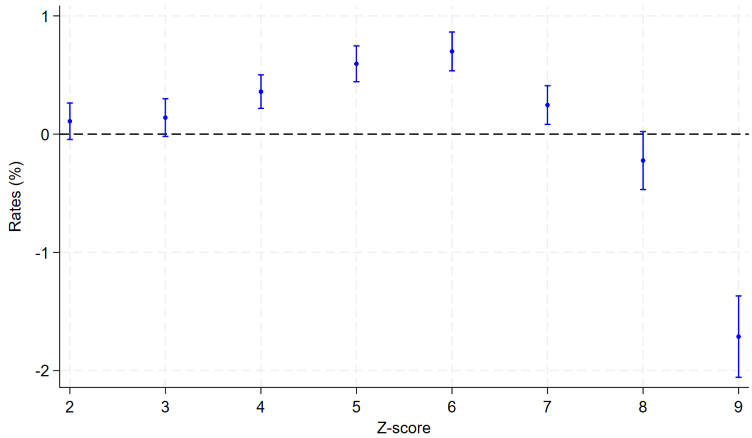
C. Investment Rate & Credit-Risk



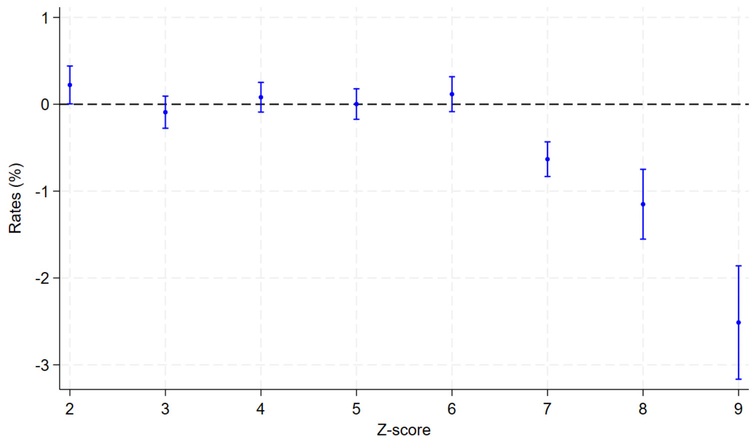
This figure shows the relationship between firms' Cerved Z-score and: profitability (EBITDA over total assets), productivity (TFP), and investment rate (change in total fixed assets over lagged total assets) in 2013 using a binscatter plot controling for $X_{f,t-4}$ (the log of total assets, the log 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



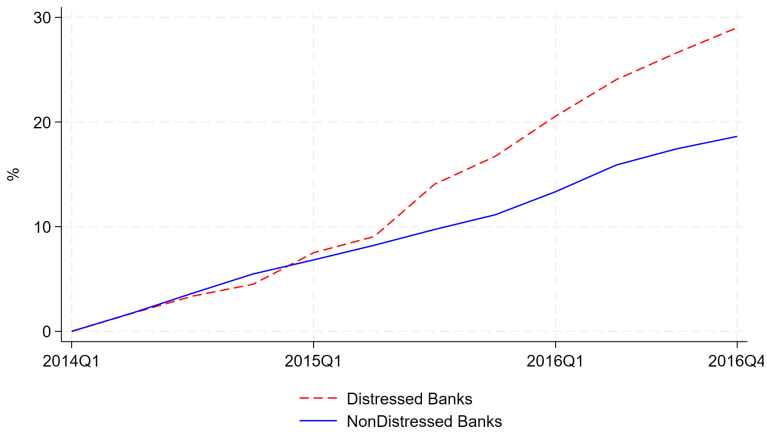
B. New borrowers



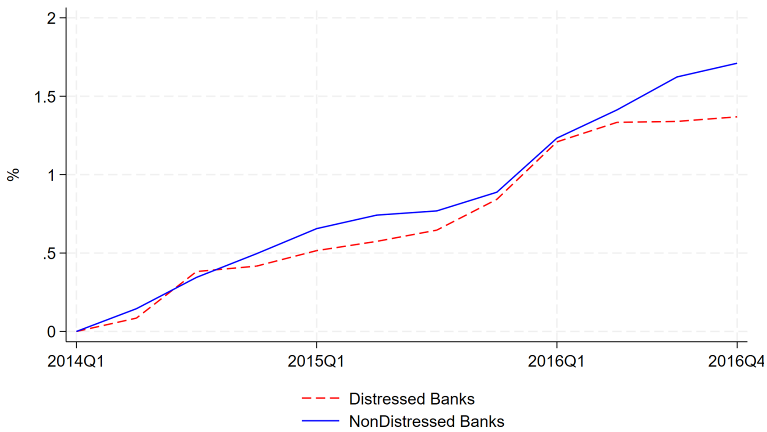
This figure plots the credit risk-adjusted interest rates, calculated as InterestRate-PD×(1-RR), where PD is the 1-year probability of default and RR is the average recovery rate, by firm-risk category separately for new and existing borrowers. See Figure 5 for a description of how to compute the different parameters.

Figure A4: Lost 'Loan Business' to Outside Banks

A. Low-Risk Firms



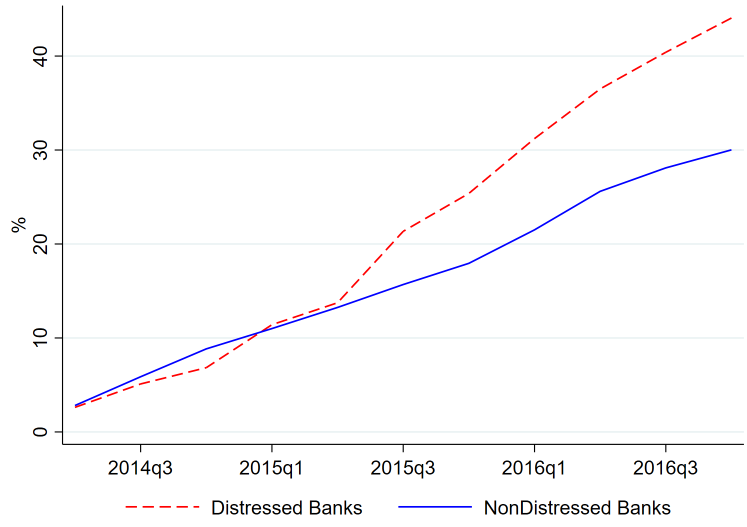
B. High-Risk Firms



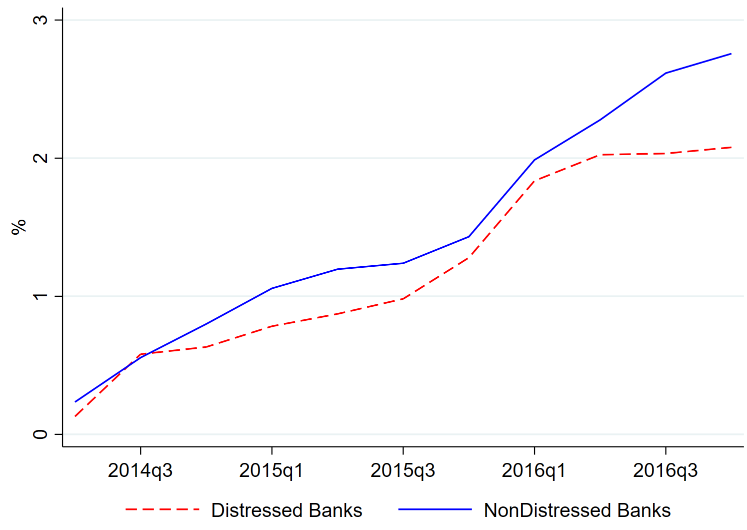
This figure plots the cumulative value of new credit that single-relationship firms of either distressed or non-distressed banks obtained from outside banks (i.e., new relationships) during the event window (2014Q1-2016Q4), expressed as a fraction of the total loan volume from each group of banks (distressed 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 = 1 if the firm belongs to one of these 1-digit sectors, and = 0 otherwise.

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

	All Firms	
	(1)	(2)
$SD_{f,2013}$ × Post 1	0.010***	0.013***
	(0.0036)	(0.0038)
$SD_{f,2013}$ × 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 distressed banks. 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: 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)
$\text{SD}_{f,2013} \times$ 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)
$\text{SD}_{f,2013} \times$ 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 × Province × Size × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CreditScore × Year	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.

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. The latter are important insofar as different time-varying shocks or spillover effects affect banks in the same provinces differently. Identification of β_1 and β_2 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. The smaller estimated coefficient for Post 1 is consistent with our earlier finding that deposit runs on the distressed banks were less severe during this period. 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 for household deposits are consistent with results for total deposits reported, for example, by 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	149,421	149,421	149,421
R-squared	0.459	0.464	0.464	0.464	0.420	0.419	0.420

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.