Corporate Runs and Credit Reallocation*

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October 4, 2024

Abstract

We study the reaction of corporate clients to bank distress on both sides of banks' balance sheet, exploiting the 2017 failure of two Italian regional banks. We find that firms initiate deposit runs before households, as soon as the banks' distress becomes public. At the same time, an endogenous deterioration unfolds on the asset side: while risky firms draw down existing credit lines from distressed banks, creditworthy firms seek new lending relationships with healthier banks. Only the riskier firms reduce investment, as creditworthy firms successfully switch to other banks, which in turn reallocate credit away from riskier firms.

JEL classification: G21, G28

Keywords: bank runs; bank failures; loan applications; credit reallocation

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1 Introduction

Bank failures impose significant economic and social costs, eroding public trust in the financial system and causing widespread declines in credit availability and economic activity (see, e.g., Bernanke (1983); Calomiris and Mason (2003); Ashcraft (2005); Huber (2018); Peek and Rosengren (2000)). Complementing the theoretical literature on bank runs (see, e.g., Diamond and Dybvig (1983); Goldstein and Pauzner (2005)), the empirical literature has focused predominantly on understanding the factors influencing depositors'—particularly households'—incentives to run and how contagion spreads to other banks (see, e.g., Iyer and Puri (2012); Iyer, Puri, and Ryan (2016); Blickle, Brunnermeier, and Luck (2023); Martin, Puri, and Ufier (2023)).

The U.S. banking turmoil in the Spring of 2023 showed once more that bank runs continue to pose a critical threat to bank stability. Unlike previous crises, this episode was distinct, characterized by rapid, large-scale withdrawals of corporate deposits. Corporations can significantly amplify bank distress for two key reasons. First, corporate deposits constitute a substantial and largely uninsured portion of bank funding, making them highly sensitive to negative news regarding their banks' financial health, especially in this digital age (see, e.g., Cookson, Fox, Gil-Bazo, Imbet, and Schiller (2023); Rose (2023); Koont, Santos, and Zingales (2023).[1] A second and more subtle reason is that corporate depositors are often also borrowers (see, e.g., Cao, Garcia-Appendini, and Huylebroek (2024)). Concerns about a bank's solvency may lead corporate clients to seek to diversify their credit sources by establishing new lending relationships with stronger, healthier banks (Detragiache, Garella, and Guiso (2000)).[2] More creditworthy borrowers are more likely to succeed, leaving distressed banks with the riskier and more constrained borrowers, who are also more likely to drawn down their credit lines early (see, e.g., Ivashina and Schrfstein (2010); Ippolito, Peydrò, Polo, and Sette (2016)). The reaction of their corporate clients can set off a process of gradual, endogenous deterioration of the bank's asset-side, undermining its long-term viability. While the existing empirical literature offers many valuable insights into depositors' behavior during bank distress, much less is known about how these asset-side dynamics interact with, and potentially exacerbate, depositor runs.

In this paper, we address this gap by analyzing the behavior of distressed banks' corporate

[1] In Europe, deposits from non-financial corporations account for about a quarter of total customer deposits from firms and households (ECB data portal). In the U.S., corporate deposits are even more substantial.

[2] It is important to note that this does not necessarily imply that the distressed banks' corporate clients will terminate their lending relationships or prepay their outstanding loans with the distressed banks, but rather that they may direct new loan business to other banks. In addition, this reallocation does not require that the same firm is active on both sides of a bank's balance sheet, although there are good theoretical reasons to expect this may happen in practice (Kashyap, Rajan, and Stein (2002); Mester, Nakamura, and Renault (2007)).

clients on both sides of the banks' balance sheets—from the first public signs of distress until their eventual collapse. We focus on the 2017-failure of two regional banking groups in Italy, consisting of six mutual banks, to examine their clients' behavior during the unfolding crisis (we refer to these banks as the "distressed banks" and use the terms banking groups and banks interchangeably). Specifically, we track their corporate client's deposit outflows, credit line drawdowns, and loan applications to other banks, assessing their impact on the distressed banks' loan portfolios and spillover effects on other banks in the region. We rely on granular credit registry and loan application data from the Bank of Italy, supplemented by bank-province level data on deposit volumes and financial statements for both the banks and their corporate clients.

The failure of these banks provides a compelling setting for empirical analysis. First, the banks' distress is largely idiosyncratic, triggered by media reports exposing accounting fraud and governance failures, allowing us to isolate the impact of bank distress on corporate clients. Second, although the banks are not large enough nationally to pose systemic risk, they are regionally important for their collapse to have spillover effects in the region, with a quarter of local firms maintaining lending relationships with these banks at the onset of distress.

The timeline of distress is marked by two pivotal events. The first event occurs in early 2015, when articles in the financial press reveal that these institutions are inflating their regulatory capital using improper accounting practices. These articles, featuring interviews with former bank employees, attracted significant public attention and triggers deposit outflows at the distressed banks. After these initial outflows, their deposits appear to stabilize until the end of 2015, when the ECB's Supervisory Review reveals that they are not meeting the minimum capital requirements. This is followed by a second and more severe wave of depositor runs.

We investigate the behavior of the distressed banks' corporate clients on both sides of the banks' balance sheet around these two critical events. We begin by analyzing the deposit outflows at the distressed banks. We find that deposit withdrawals from firms begin as soon as information about the banks' impending distress becomes public in early 2015. In contrast, deposit withdrawals from households only start during the second distress event, and with less intensity. Over the entire sample period, the distressed banks lose about 20% of their total deposits—amounting to over 40% of their firm deposits and 15% of their household deposits.

To understand which types of banks attract their deposits, we study the deposit inflows at other banks. These analyses rely on within-bank-time variation, leveraging the granularity of the deposit data at the bank-province level. The results show that firms and households behave quite differently not only in terms of the timing and intensity of their withdrawals, but also in their choice of new banks. We find that households seek safety in large, systemically important banks, regardless of their capital, in line with the results from Iyer, Jensen, Johannesen, and Sheridan (2019), Acharya, Das, Kulkarni, Mishra, and Prabhala (2023), and Caglio, Dlugosz, and Rezende (2024). In contrast, firms turn to better capitalized banks, regardless of size. These differences underscore the importance of distinguishing between these two classes of deposits and are likely due to differences in incentives, ability to evaluate bank fundamentals, and the nature of services they seek from their banks (see, e.g., Egan, Hortacsu, and Matvos (2017)).

Our credit analysis reveals a gradual, endogenous deterioration of the distressed banks' loan portfolios, starting as soon as their financial problems become public. While previous studies (e.g., Ivashina and Schrfstein (2010); Chodorow-Reich, Darmouni, Luck, and Plosser (2022); Greenwald, Krainer, and Paul (2023)), including one on Italy (Ippolito et al. (2016)), document the occurrence of "credit-line runs" on distressed banks, we extend this finding by showing that these runs are triggered by riskier clients with single lending relationships. Fearing future credit supply disruptions and the possible revocation of their credit lines, these clients begin drawing down their available credit lines as soon as the banks' problems become public. In contrast, creditworthy clients with single lending relationships pursue a different strategy: rather than drawing on their available credit lines, they apply to 'outside banks'—those with no prior lending relationships—in line with predictions in Detragiache et al. (2000). These clients successfully establish new lending relationships with larger, better-capitalized banks.[3] These novel findings demonstrate how this distinct borrower behavior contributes to the progressive decline in the distressed banks' loan portfolios. Firms with imminent liquidity needs (e.g., with over 50% of their credit maturing within the next twelve months) are more likely to apply to outside banks, whereas firms with deeper ties to the distressed banks, such as those holding equity stakes, are less likely to do so.

Importantly, the overall 'lost business' to outside banks during this initial period is quite substantial. Our conservative estimates indicate that the cumulative value of loans that is lost to outside banks accounts for about 10% of the distressed banks' initial loan portfolios, with the majority occurring *before* the second distress event and driven by the banks' most creditworthy borrowers.[4] As we show, these are more profitable and productive firms, with higher investment rates, and are among banks' most profitable borrowers, delivering higher risk-adjusted returns.

[3] A similar phenomenon occurs in the labor market, where skilled workers leave distressed companies in what is referred to as 'worker runs' (see, e.g., Baghai, Silva, Thell, and Vig (2021); Hoffmann and Vladimirov (2023)).

[4] We confirm that results are robust to computing the volume of lost business using the amount drawn rather than granted for credit lines, indicating that the credit lines with new lenders are actively used.

While the distressed banks initially appear to be trying to retain these creditworthy clients offering cheaper loans than other lenders, over time, their outstanding credit to these firms declines relatively more. Instead, we find that once their difficulties became public, the distressed banks begin reducing credit supply to riskier firms, charging relatively higher interest rates to these firms compared to other lenders. This is in line with prior research showing that banks' incentives to lend to riskier firms or engage in "zombie lending" decrease when they are subject to stricter supervisory and public scrutiny (Caballero, Hoshi, and Kashyap (2008); Bonfim, Cerqueiro, Degryse, and Ongena (2022)). Shifting away from these riskier borrowers could help the distressed banks, operating under Basel II's standardized approach, to preserve or raise their regulatory capital (Peek and Rosengren (1997); Gropp, Mosk, Ongena, and Wix (2019)).[5]

As we show, the distressed banks' more creditworthy borrowers are able to adequately substitute credit from the other banks without facing significant declines in investment rate. In contrast, high-risk firms, which are unable to switch lenders, see significant declines in their total credit and investment rates. We also find that the influx of new, low-risk borrowers from the distressed banks has significant spillover effects on other banks in the region. Faced with an influx of low-risk applicants from the distressed banks, other banks reduce credit to their existing high-risk borrowers. The larger and better borrower pool may thus enable other banks in the region to "cleanse" their loan portfolios and improve their capital ratios by reallocating credit away from their riskier clients towards more profitable and productive firms.

Our paper offers new insights into the dynamics of bank distress, contributing to two strands of the literature. First, the paper contributes to the empirical literature on bank runs (see e.g., Iyer and Puri (2012); Iyer et al. (2016); Artavanis, Paravisini, Robles-Garcia, Seru, and Tsoutsoura (2022); Blickle et al. (2023); Acharya et al. (2023); Martin et al. (2023)). This body of work finds that large uninsured depositors, concerned about a bank's fundamentals, are more likely to withdraw their funds, seeking safety in deposit insurance and implicit government guarantees (e.g., too-big-to-fail banks or publicly-owned banks).[6] Our results reveal a simultaneous process of endogenous deterioration on the asset-side, driven by their corporate clients, which begins well before the larger, more widespread depositor run and the banks' collapse.

Recent evidence from Correia, Luck, and Verner (2023), based on a large sample of U.S. bank

[5]Under Basel II's standardized approach, firms with better ratings receive significantly lower risk weights, sometimes as low as 20% (see paragraph 20.43 of the Basel Accord). During the peak of their distress in late 2015, the distressed banks applied to the ECB for approval to use the Internal Ratings-Based (IRB) model, which potentially allows for greater discretion in calculating regulatory capital. This application was not approved.

[6]Other studies have examined the effects of introducing or changing deposit insurance limits on depositor and bank behavior (Calomiris and Jaremski (2019); Iyer et al. (2019); De Roux and Limodio (2023)).

failures from 1863 to 2023, shows that a significant and escalating decline in loan portfolio quality is consistently observed in the years leading up to bank failures, even those involving depositor runs. Our paper shows that part of this deterioration comes from a flight of safer borrowers to other, healthier, banks operating in the same area. We provide a detailed micro-level account of how the distressed banks' corporate clients contribute to the erosion of the distressed banks' loan portfolios and document the broader effects of bank distress on firms' investment, as well as spillover effects on other banks in the region. Both our findings and those of Correia et al. (2023) underscore the critical importance of timely and well-targeted interventions that go beyond providing deposit insurance and liquidity support. Addressing the solvency issues quickly is essential, especially in an era where online banking and social media can accelerate the speed of bank runs (Cookson et al. (2023); Rose (2023); and Koont et al. (2023)).

Second, the paper contributes to the empirical literature on the impact of bank distress on credit supply and the real economy (see e.g., Bernanke (1983); Calomiris and Mason (2003); Ashcraft (2005); Schnabl (2012); Huber (2018); Darmouni (2020); Beck, Da-Rocha-Lopes, Samuel, and Silva (2021)). Unlike these studies, which focus on crisis periods, our results show that in the absence of widespread banking sector problems, the negative effects of bank distress are concentrated among the least profitable and productive firms, with positive spillover effects for healthier banks.[7] While these forces are destabilizing for the distressed banks, they may contribute to the overall stability of the banking system by facilitating more efficient credit allocation.

2 Timeline of Distress

In this section, we provide an overview of the distressed banks under examination and a chronological account of the events that led to their eventual collapse. Comprising of six mutual banks within two banking groups, the distressed banks were prominent regional banks in Northern Italy—one of Italy's wealthiest and most economically powerful regions. During the sample period, the regional GDP growth was 1.7%, nearly twice larger than the 1% national growth rate. These banks were predominantly owned by local households and entrepreneurs and were not publicly listed. Despite a relatively modest size on a national scale (ranked 10^{th} and 11^{th} by total assets in 2013), these banks were significant lenders in the region. About a quarter of the region's firms had an active lending relationship with the distressed banks at the time.

[7] All else equal, borrowers leaving a failing bank are less adversely selected and thus have a higher chance of receiving credit from other banks (see, e.g., Darmouni (2020); Dell'Ariccia and Marquez (2004)).

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. Lacking direct access to capital markets and with local private markets depressed from the sovereign debt crisis, unlisted mutual banks found it challenging to attract fresh capital. As a result, the distressed banks resorted to "loan-for-share" schemes, whereby loan applicants were asked to use a portion of their loan proceeds to acquire shares of the distressed banks. While not illegal, equity raised through such schemes must receive approval from an extraordinary shareholders' meeting and, crucially, must be excluded from the computation of regulatory capital.[8]

The first signs of trouble at the distressed banks surfaced in November 2014 when the ECB-SSM Comprehensive Assessment revealed a minor capital shortfall at both institutions. Initially, it appeared that both banks could address this shortfall adequately. However, in mid-February 2015, about two and a half months later, an article in the Italian financial press containing interviews with former bank employees, revealed that the distressed banks had been inflating their capital ratios since 2012 using "loan-for-share" schemes. 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. The publication of this article marked the first public disclosure of the banks' impending distress, drawing significant public attention—as evidenced by the sharp spike in Google searches for the banks' names in Figure 1 (first spike)—and initiating a period of intense scrutiny and uncertainty surrounding their future viability.

Over the subsequent two months, the situation escalated further as negative press-coverage continued, with articles pointing to excessive remunerations for directors and favourable financing deals for members of their boards. As we show later, this also triggered an endogenous deterioration in their borrower pool, which until the end of 2013, had been similar to other banks in the region. Shortly after these articles were published, the stock prices of the distressed banks were also devalued by their respective boards by approximately 23%. Between August and September 2015, a series of new articles and the initial findings of the ECB's Supervisory Review (SREP) unveiled that the "loan-for-share" practices were more widespread than initially believed, causing significant capital shortfalls relative to the required regulatory minimum.

By the end of November 2015, with the release of the final SREP findings, it became clear

[8]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 enable banks to systematically inflate their regulatory capital (see, e.g., Gropp, Mosk, Ongena, Simac, and Wix (2024)).

that the banks' survival hinged on raising fresh capital. During this period, 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 financial health and future 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. 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. However, due to continued financial deterioration, poor 2015 results, and a loss of credibility amid negative publicity, investors did not participate in the capital increase.

Subsequently in mid-2016, Atlante, a private vehicle sponsored by the Italian government to assist troubled banks, assumed control of the distressed banks (third spike in Figure 1). This recapitalization attempt ultimately failed to secure the necessary funding as by that time the banks' condition had deteriorated beyond repair. Left with no viable alternatives, in the first half of 2017, the ECB declared the banks as "failing" or "likely to fail". As a result, the banks underwent liquidation and were eventually acquired by another financial institution.

Overall, 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

The empirical analysis relies on two key datasets, maintained by the Bank of Italy. The first dataset includes deposit volumes at the bank-province level, obtained from bank supervisory reports. The second dataset includes detailed bank-firm credit data from the Italian Credit Register ("Centrale dei Rischi"; thereafter CR). Our empirical analysis focuses on the period between the beginning of 2014 till the end of 2016. This event window allows us to examine the unfolding of events, starting one year before the distressed banks' problems became public until one year after the ECB SREP results, when the distressed banks collapsed.

The data on bank deposits are reported on a monthly frequency and are available by type of counter-party (households or non-financial firms) and province of residence. This data is available for approximately 500 banking groups across 110 Italian provinces.[9] For our empirical analysis, we exclude banks with less than €1 million in total deposits in a single province to prevent provinces with limited bank presence from disproportionately influencing our estimates.

The CR contains credit information for borrowers with total outstanding loans from a single intermediary in excess of €30,000. It includes information on credit volumes, credit lines, interest rates, and loan applications at the bank-firm level. For additional information on both firms and banks, we merge the credit registry data with: i) annual balance sheet data on non-financial firms from Cerved, providing insights into firms' financial condition, including profitability, productivity, investment rate, and default likelihood, based on Cerved's proprietary Z-score, which is similar to the Altman Z-score[10]; and ii) annual data on individual and consolidated bank balance sheets from the Italian Supervisory Reports of the Bank of Italy.

Regarding credit volumes, CR tracks the amount of credit granted and drawn at the bank-borrower level on a quarterly basis, differentiating between broad types of loans such as credit lines and term loans. For credit lines, following Greenwald et al. (2023), we exclude observations where granted exposures are zero and those where utilized exposures exceed the granted amounts. We also focus on performing loan exposures as in Khwaja and Mian (2008). Finally, for identification purposes, we focus our credit analysis in the areas where the distressed banks concentrate their lending activities the most.[11] These include 10 provinces in Northern Italy, where the two distressed banks allocate 60% of their total loan portfolios, yielding a sample of 135,000 bank-firm relationships to 56,505 unique firms.

The subsection "Richiesta di prima informazione" in CR contains data on information requests made by banks following loan applications from borrowers, which we use for our loan applications analysis. The information from these requests allows banks to observe the borrowers' credit history and repayment performance with other banks over the past three years. It also includes detailed information on outstanding loans (e.g., number of bank relationships, utilization of granted credit lines) as well as the number of loan applications made to other banks.

In addition, the subsection "Taxia" in CR includes quarterly data on loan interest rates for a sub-sample of about 90 banks, accounting for over 80% of aggregate credit. Interest rates are calculated as the ratio of interest payments to the average outstanding loan amount and are

[9]Italy is divided in 20 regions and each region is further subdivided into provinces, each surrounding a city. In terms of population, Italian provinces are about the size of US Metropolitan Statistical Areas (MSAs).

[10]For more details on the Cerved Z-score see Rodano, Serrano-Velrde, and Tarantino (2018).

[11]While the advent of online banking may have reduced the importance of geographical distance for deposits and credit products to households, geographical distance remains crucial for the provision of credit to SMEs (see, e.g., Degryse and Ongena (2005); Agarwal and Hauswald (2010); Nguyen (2019)).

available by type of loan (Gobbi and Sette (2015); Crawford, Pavanini, and Schivardi (2018)).

Descriptive statistics for our sample are reported in Table 1. Panel A provides an overview of bank characteristics at the start of the sample period. The sample consists of 480 banks, with an average asset size of about €6 billion and an average capital ratio of 12.5%.[12] Deposits from both households and non-financial firms collectively account for 42% of total assets, with firms contributing 25% of total deposits. The share of private sector deposits in Italy is significantly lower than in the US, where core deposits account for about 60% of total assets. This difference is due to funding from bank bonds, which, in Italy, are often placed with retail investors and account for 22.5% of total assets (Carletti, De Marco, Ioannidou, and Sette (2021)).

Panel B of Table 1 provides an overview of key firm characteristics. On average, firms in the sample have total assets and sales of approximately €4 million, an average age of 17.3 years, and an EBITDA to assets ratio of 7.2%. The Cerved Z-score, ranging from 1 to 9 with higher values indicating higher credit risk, averages 4.9. About 27.9% of firms are classified as "High-Risk" with Z-scores ≥ 7 (Rodano et al. (2018)).

Each firm in the sample maintains an average of 2.5 bank-lending relationships, with a median of 2. A significant fraction of firms in our sample (42.8%) has a lending relationship with only one bank. While multiple relationships are generally more common in Italy than in other countries (see e.g., Detragiache et al. (2000)), this pattern is predominately driven by larger firms (see, e.g., Kosekova, Maddaloni, Papoutsi, and Schivardi (2023)). About 26.6% of firms have loans from the distressed banks, with a 44% average credit dependence on these banks.

Panel C of Table 1 presents summary statistics on bank credit at the bank-firm-quarter level. During the sample period, the average probability of applying for a loan to an 'outside bank', *ApplOut*, is 4.6%. Borrowers of the distress banks are more likely to apply to an outside bank than borrowers of non-distressed banks (6.1% vs. 4.1%). Among those who apply, the probability of establishing a new relationship averages approximately 27%.[13] As observed in Table 1, the distressed banks' borrowers have a higher likelihood of starting a new lending relationship than borrowers of other banks (29.3% vs. 26.2%). This could be because other banks may be more willing to accept borrowers of the distressed banks due to lower adverse selection and "winner's curse" concerns (von Thadden (2004); Sharpe (1990)) and because fleeting borrowers may be more inclined to accept their offers (Darmouni (2020); Bonfim, Nogueira, and Ongena (2021)).

[12]Because many of the banks in the sample are small (400 have less than €2 billion in total assets) all regressions at bank level are weighted by total assets.

[13]In the full CR dataset, the average switching rate during the sample period (i.e., the fraction of firms that establishes new lending relationships) is 17%, comparable to estimates for other countries such as France (Boualam and Mazet-Sonilhac (2021)) and Norway (Cao et al. (2024)).

Finally, in Panel D of Table 1, we report summary statistics on changes in total bank credit and various real outcomes (investment, sales, and wages) at the firm-year level. We observe that, on average, during the event window, firms experienced a 3.3% decline in total bank credit, in line with the national average and other European periphery countries. The average investment rate (i.e., the percentage change in fixed assets over total assets) was 0.6%, while average sales and wage growth were 0.4% and 1.8%, respectively.

4 Empirical Methodology and Results

In what follows, we use difference-in-difference (DiD) analyses at different levels of aggregation to track the behavior of the distressed banks' corporate clients as distress intensified, studying their impact on the distressed banks and other banks in the region. Our event window begins in January 2014, about a year before the public disclosure of their problems, marked as the 'pre-distress' period, and ends in December 2016, when the banks collapsed. These analyses are organized in four sections on: i) deposits, ii) credit, iii) real outcomes, and iv) spillover effects.

4.1 Deposits

In this section, we study the timing and intensity of deposit outflows from the distressed banks' corporate clients (depositor runs) and their choice of new banks (deposits re-allocation).

Depositor Runs The revelations of accounting frauds and capital shortfalls and the negative media coverage eroded confidence in the distressed banks' viability, leading to depositor runs. In Figure 2 we provide a visual illustration of how total deposits of the distressed banks evolved during this period relative to all other banks, which we label as 'non-distressed banks'. To facilitate comparison, all values are normalized to 1 as of January 2014. The total deposits of the distressed banks, which had been increasing at the same rate as other banks, began to decline and diverge significantly from other banks at the start of 2015, when their problems became publicly known. After these initial outflows, their deposits seem to stabilized. However, a second wave of larger outflows began at the end of 2015, when the SREP report exposed the greater extent of their capital shortfalls. Over the entire period, the distressed banks lost about 20% (€5.1 billion) of their total deposits. Other banks instead saw a notable increase 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. In addition, we study how outflows on firm deposits varied during the event window and how they compare to outflows on household deposits. For these analyses, we estimate the following baseline specification:

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

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 starts in February 2015 (i.e., when the distressed banks' problems first became public) and ends in November 2015 (i.e., when the final SREP results are released). The second sub-period starts in December 2015 (i.e., right after the SREP report) and ends in December 2016. The omitted period is 2014 (i.e., the year before their problems became public).

The DiD coefficients, β_1 and β_2, indicate how the deposits of the distressed banks change relative to non-distressed banks in Post 1 and Post 2 compared to the omitted period. To control for possible confounding factors, Eqn. (1) includes both bank and time-fixed effects, α_b and α_t, respectively. The model is estimated with OLS. Observations are weighted by total assets, giving more weight to larger banks, and standard errors are clustered at the bank-level.[14]

The results are reported in Table 2. During Post 1 and Post 2, the deposits of the distressed banks decrease relative to non-distressed banks by 6.8% and 34.4%, respectively. Distinguishing between household and firm deposits in columns (2) and (3), we find that the decrease in Post 1 is mainly driven by firms. During that period, the firm deposits of the distressed banks record a 13.2% decline relative to other banks. Decreases in household deposits during Post 1 are much smaller and statistically insignificant. Household deposits only begin to decrease significantly during Post 2, but again with much lower intensity than firm deposits (22.4% vs. 58.8%).

To inspect the full dynamics of deposits, we also estimate corresponding dynamic DiD specifications for firm and household deposits separately by replacing Post 1 and Post 2 in Eqn. (1) with monthly dummy variables. The estimated coefficients and 95% confidence intervals are reported in Figure 3 (January 2015 is the omitted period). This analysis confirms that firms run as soon as the distressed banks' problems become public in February 2015 (i.e., at the start of Post 1). Significant outflows on households deposits do not begin until almost a year later in

[14]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).

December 2015 (i.e., at the start of Post 2), when the distressed banks faced the second wave of runs. Even during this period, firms run with greater intensity than households. Importantly, we also observe that prior to February 2015 (i.e., during the 'pre-period'), the deposits of the distressed banks move in parallel to other banks, supporting the 'parallel trends' assumption.

Deposits Re-allocation Next, we study the characteristics of banks that attract their deposits. For this analysis, we exploit the bank-province heterogeneity in the data by estimating the following baseline DiD specification at the bank-province-month level for 'non-distressed banks' (i.e., for all other banks in Italy, excluding the distressed banks under study):

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

where $\log(Dep)_{b,p,t}$ indicates the log of (firm or household) deposits of non-distressed banks 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.[15] Eqn. (2) 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. Hence, 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 in the province. All else equal, we expect that as depositors begin to run on the distressed banks, a non-distressed bank will see a larger increase in its deposits in the provinces where the distressed banks had a larger initial share of the local deposit market. To investigate how inflows varied across banks, we augment Eqn. (2) allowing interactions between Post 1 and Post 2 and key bank characteristics.

The results are presented in Table 3. Column (1) indicates 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 coefficient for Post 1 is consistent with our earlier finding that deposit runs on the distressed banks were less severe during this period. Further in columns (2)-(4), we introduce interaction terms with bank capital and bank size. $HighCapital_{b,2013}$ is a variable that equals 1 if in 2013 the bank had an above-median capital ratio, and equals 0 otherwise. Similarly, $LargeBank_{b,2013}$ is a variable that equals 1 for banks with assets exceeding €100 billion in 2013

[15] In robustness tests, we confirm that results are similar using the continuous share of deposits.

(i.e., one of the top 5 banks in Italy), and equals 0 otherwise. These specifications additionally include province-month fixed effects, which absorb the coefficients of the double-interaction terms, β_1 and β_2. We find that increases in firm deposits during Post 1 are larger for banks with stronger capital positions. Corresponding specifications for household deposits in columns (5)-(7), show that households behave quite differently from firms. Contrary to firms, households do not appear to prioritize bank soundness: they run towards large, systemically important banks, regardless of their capital. The results of household deposits are in line with results for total deposits from Iyer et al. (2019), Acharya et al. (2023), and Caglio et al. (2024).

Overall, our deposits analysis shows that household and firm depositors exhibit distinct behaviors in their timing, intensity and choice of new banks. Firms run first and with greater intensity towards better capitalized banks, regardless of their size. Households instead run almost a year later, with lower intensity, and towards large, systemically important banks, regardless of their capital. These differences likely stem from differences in incentives, ability to evaluate bank fundamentals, and the nature of services sought from banks (Egan et al. (2017)). Contrary to household deposits, firm deposits are predominately uninsured and firms are on average more financially sophisticated than households. In addition, while households may be seeking a safe 'store of value' in systemically important banks, firms may also be trying to establish new lending relationships with stronger banks to ensure uninterrupted credit supply and operations.[16]

In what follows, we study how the distress banks' corporate clients behaved on the asset-side and the impact they had on the distressed banks' loan portfolios and other banks.

4.2 Credit

Utilizing credit registry data at the bank-firm-quarter level, we analyze draw-downs on existing credit lines and loan applications to other banks and study how these vary across different groups of firms (e.g., high-risk vs. low-risk firms, firms with single vs. multiple lending relationships, and firms with upcoming liquidity needs). These analyses allow us to shed light on the dynamics of the distressed banks' loan portfolios during the critical period leading-up to their failure.

The balance test on firm characteristics, reported in Table A1 in the Online Appendix, shows that at the start of the event window firms borrowing from distressed and non-distressed banks

[16] The are also important synergies between deposits and credit products. For example, savings on costly liquidity create a synergies in the provision of deposits and credit-lines to firms (Kashyap et al. (2002)). In addition, information from firms' deposit activities can enhance banks' credit screening and monitoring (Mester et al. (2007); Norden (2010)) and can help firms switch to new lenders by reducing asymmetric information (see recent empirical support in Cao et al. (2024)).

were similar in terms of observable characteristics.[17] The normalized differences between the two groups, reported in parentheses, are smaller in absolute value than 0.25, the commonly used threshold for determining balance (Imbens and Wooldridge (2018)). The sample is balanced with respect to firm age, credit risk, profitability, and industry composition. The only exception is firm size, measured by total assets or revenues, where the normalized differences are around 0.25. As the distressed banks were prominent lenders in the region, some of the region's larger firms were among their clients. In our empirical analyses below, we control for this small difference in borrowers' composition.

4.2.1 'Credit Line Runs' and Loan Applications to Outside Banks

In this subsection, we report results on 'credit-line runs' and loan applications to outside banks.

'Credit-line Run' In a first set of tests, we examine whether the distressed banks experienced a 'credit-line run' as their problems became publicly known. Prior studies find that firms tend to draw on their credit lines from banks facing funding liquidity shocks, either in anticipation of future credit supply restrictions or out of fear that their lines may be recalled (Ivashina and Schrfstein (2010); Ippolito et al. (2016); Chodorow-Reich et al. (2022); Greenwald et al. (2023)). To investigate whether the distressed banks faced a similar 'credit-line run' as their problems became publicly known, we estimate similar DiD specifications at the bank-firm-quarter level:

$$ShareDrawn_{b,f,t} = \beta_1 \; D_b \times \text{Post } 1 + \beta_2 \; D_b \times \text{Post } 2 + \alpha_b + \mu_{f,t} + \epsilon_{b,f,t}, \tag{3}$$

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. As in Greenwald et al. (2023), we exclude bank-firm relationships that have reached the credit line limit, as these borrowers cannot freely adjust their draw-downs. 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 is equal to 1 between 2015Q1 and 2015Q3, and equals 0 otherwise, while Post 2 is equal to 1 between 2015Q4 and 2016Q4, and equals 0 otherwise. The 'pre-period' is between 2014Q1 and 2014Q4. In addition to bank-fixed effects, α_b, which control for time-invariant differences between banks, in our most conservative specifications we use firm×time fixed effects, $\mu_{f,t}$, as shown in Eqn. (3), to provide an even more stringent control for time-varying firm-specific factors (Khwaja and Mian (2008)). This allows us to determine

[17] Figure A1 in the Online Appendix further shows that until 2015 the distressed banks' NPLs were growing at a similar pace to the national average.

if the same firm, at the same point in time, draws more on credit lines from the distressed banks than from non-distressed banks. We also a report a less conservative specification with industry×province×size×quarter fixed effects (Degryse, De Jonghe, Jakovljević, Mulier, and Schepens (2019)); firm size is determined using quintiles of total assets at the end of 2013.

The results are reported in Table 4 and provide evidence of 'credit-line runs' on the distressed banks, driven primarily by high-risk firms with single lending relationships.[18] We find that these firms draw more on their credit lines from the distressed banks already in Post 1 (column (5)). During this early period, low-risk firms and high-risk firms with multiple lending relationships do not draw more from the distressed banks (columns (3), (4) and (6)), likely because these firms have other options, such as tapping credit from other existing lenders or establishing new relationships (Detragiache et al. (2000)). Instead, establishing new relationships may be much more difficult for high-risk firms. In addition, firms trying to establish new lending relationships may want to avoid running up their credit lines as high credit line usage is often associated with poor credit quality (Chodorow-Reich et al. (2022)).[19] During Post 2, also multiple relationships firms, both high and low-risk, draw-down more from the distressed banks, but with lower intensity, particularly low-risk firms.

Loan Applications to Outside Banks Next, we examine whether borrowers with a higher credit dependence on the distressed banks were more likely to seek new lending relationships when the banks' problems became public by estimating the following linear probability model:

$$ApplOut_{f,t} = \beta_1\, SD_{f,2013}\times\text{Post }1+\beta_2\, SD_{f,2013}\times\text{Post }2+\gamma' X_{f,t-4}+\alpha_{k,p,s,t}+\lambda_{j,t}+\mu_f+\epsilon_{f,t}, \quad (4)$$

where $ApplOut_{f,t}$ is a dummy variable that equals 1 if firm f applied for a loan to an 'outside bank' in quarter t, and equals 0 otherwise. A bank is defined as an 'outside bank' to firm f if the firm did not have any loans from that bank in the year prior to the start of the event window (i.e., in 2013). The variable $SD_{f,2013}$ denotes the share of firm's f credit from the distressed banks in 2013 and takes values from 0 to 1, where 0 indicates that the firm did not borrow from the distressed banks and 1 indicates that all of the firm's credit was from the distressed banks.[20]

[18] As detailed in Section 3, the Italian Credit Register has a reporting threshold at 30,000 euros. This means that some firms that we classify as single relationships may actually have multiple lending relationships below the reporting threshold. At best, this should create a bias against finding results, as it adds noise in the measure of single versus multiple relationship borrowers.

[19] Credit line usage is observable through the credit registry and high usage may adversely affect a firm's Z-score.

[20] To ensure comparability between the two groups of firms, we use entropy balancing regression weights (Hainmueller (2012)) on firm size when estimating Eqn. (4), since Table A1 shows small differences in firm size between the two groups. Robustness tests without entropy balancing yield qualitatively and quantitatively similar results.

The dummy variables Post 1 and Post 2 are defined as in Eqn. (3).

Among the control variables in $X_{f,t-4}$, we include several time-varying firm characteristics, such as lagged firm size (log of total assets), profitability (EBITDA to total assets), and probability of default (Z-score). To further account for time-varying firm-specific factors, we include industry×province×size×quarter fixed effects, $\alpha_{k,p,s,t}$, and Z-score×quarter fixed effects, $\lambda_{j,t}$. Eqn. (4) also includes firm fixed effects, μ_f. These absorb the level effect of $SD_{f,2013}$, along with other firm characteristics such as the strength of a firm's relationship with the distressed banks at the start of the event window. This allows us to obtain estimates for β_1 and β_2 using only *within* firm variation across time. For completeness, we also estimate specifications without the firm fixed effects, μ_f, to verify that the distressed banks' borrowers are not more likely to apply for credit at outside banks during the 'pre-period' (parallel-trends).

The results are reported in Table 5. In column (1), where we do not include firm-fixed effects, we find that the coefficient of $SD_{f,2013}$ is very close to zero and statistically insignificant, confirming that in 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 they began experiencing deposit runs. In particular, the coefficients on the interaction of $SD_{f,2013}$ with Post 1 and Post 2 are both positive and statistically significant, indicating that during these periods, firms with higher credit dependence on the distressed banks (i.e., higher $SD_{f,2013}$) are more likely to apply for outside loans. The estimated coefficients remain similar as we add firm fixed effects in column (2) and point to economically meaningful effects. For a firm fully dependent on the distressed banks (i.e., with $SD_{f,2013} = 1$), the effect represents a 24% increase relative to the mean (0.011/0.046). The coefficient on the interaction with Post 2 indicates an even larger increase of 37% (0.017/0.046).[21]

In columns (3)-(6) of Table 5, we distinguish between low-risk and high-risk firms with single or multiple lending relationships. The results reveal that the increase in loan applications to outside banks during Post 1 is primarily driven by low-risk firms with single lending relationships. Anticipating potential liquidity problems, these firms may be proactively trying to diversify their credit sources (Detragiache et al. (2000)). As local 'outside funding' is arguably limited, these firms, which tend to have higher investment opportunities and are attractive to other banks, may have stronger incentives to try to secure new lending relationships quickly.[22] As shown in

[21]The results of corresponding dynamic DiD specifications, reported in Figure 4, paint a very similar picture and confirm that applications to outside banks began increasing precisely when the distressed banks' problems became public in 2015Q1 (i.e., at the start of Post 1).

[22]Local capacity constraints may be more important for single relationship firms which tend to be smaller firms borrowing from smaller local banks with comparative advantage in the use of "soft information" (Stein (2002);

Figure A2 in the Online Appendix, low-risk firms are more profitable and productive, with higher investment rates (i.e, they are firms with high continuation values that are attractive borrowers to other banks).

In contrast, low-risk firms with multiple relationships do not need to increase their applications to outside banks as urgently. They already have diversified credit sources and can rely on existing relationships for additional funding. This could explain why we do not see a significant increase in loan applications to outside banks from this group until Post 2.

High-risk firms, regardless of whether they have single or multiple relationships, do not increase their applications for outside loans during either distressed period. The β_1 and β_2 coefficients for these firms are close to zero and statistically insignificant (columns (5) and (6)). Facing difficulties in securing new relationships, high-risk firms instead "run" on the distressed banks. As shown in Table 4, high-risk firms draw-down more on their credit lines from the distressed banks, with single relationships starting earlier (already in Post 1).

Overall, the observed patterns of credit line draw-downs and loan applications highlight a simultaneous process of endogenous deterioration of the distressed banks' loan portfolios which begins as soon as the distressed banks problems become public. Fearing credit supply disruptions, their riskier corporate customers begin drawing on their credit lines with the distressed banks, while their more creditworthy clients begin trying to establish new lending relationships. Consistent with this interpretation, additional results in columns (7)-(8) of Table 5 show that firms with higher upcoming credit needs at the start of 2015 (i.e., those with more than 50% of their total credit maturing within the year) are more likely to apply to outside banks.

In further tests, reported in Online Appendix Table A2, we examine whether the likelihood of applying for outside loans varies with the length and breadth of a firm's relationship with the distressed banks. In column (1), we interact Post 1 and Post 2 with LongRel, a dummy variable equal to 1 for firms with an above-median relationship length with the distressed banks and 0 otherwise. We find that the coefficients of the new interaction terms with LongRel are not statistically significant. Importantly, the coefficients of interest, β_1 and β_2, remain consistent with those reported in Table 5. Additionally, in column (2), we interact Post 1 and Post 2 with Shareholder, a dummy variable equal to 1 if the borrower was also a shareholder of the distressed banks, and 0 otherwise.[23] We find that firms with shareholder ties are less likely to apply to

Berger, Miller, Petersen, Rajan, and Stein (2005); Degryse and Ongena (2005); Agarwal and Hauswald (2010)).

[23]Ownership data for these banks are only available as of 2016. Since the distressed banks were not listed and their shares were devalued during that period, we believe the 2016 data reasonably approximates which firms were holding shares in the distressed banks during the event window.

outside banks, indicating that broader relationships can help banks retain clients during periods of distress. Crucially, the main coefficients of interest, β_1 and β_2, remain unchanged.

4.2.2 Credit Re-allocation

In this sub-section, we investigate whether attempts to establish new relationships are successful. We examine which firms are more likely to secure new lending relationships, with which types of banks, and estimate the aggregate volume of new "loan business" lost to outside banks. For firms with multiple relationships, we conduct additional tests to examine how their outstanding credit and loan interest rates from the distressed banks changed compared to non-distressed banks.

New Lending Relationships Using the sub-sample of firms that applied for an outside loan, we begin by estimating the following linear probability model at the firm-year level:

$$\begin{aligned} NewRel_{f,t} =& \beta_0 \; SD_{f,2013} + \beta_1 \; SD_{f,2013} \times \text{Post } 1 + \beta_2 \; SD_{f,2013} \times \text{Post } 2 \\ & + \gamma' X_{f,t-4} + \alpha_{k,p,s,t} + \lambda_{j,t} + \epsilon_{f,t}, \end{aligned} \tag{5}$$

where $NewRel_{f,t}$ equals 1 if a new bank-firm relationship with an outside bank is created following a loan application from firm f in year t, and equals 0 otherwise. All other variables are defined as before. To further examine which firms are more likely to secure new relationships and with which types of banks, we estimate Eqn.(5) for different sub-samples of firms and banks.

The results are reported in Table 6. In column (1), the coefficient of $SD_{f,2013}\times$Post 1 is positive and statistically significant at the 5% level, indicating that during Post 1 firms with higher credit dependency from the distressed banks are more likely to initiate new lending relationships. Distinguishing between high and low-risk firms in columns (2) and (3) shows that this result is driven by low-risk firms. Low-risk firms are also more likely to begin new lending relationships during Post 2, but to a lesser degree than during Post 1. In sharp contrast, the coefficients for high-risk firms are smaller and statistically insignificant during both Post 1 and Post 2.[24]

Further results in columns (4)-(7) of Table 6 show that the distressed banks' borrowers are more likely to establish new relationships with larger and better capitalized banks. Firms seeking new lending relationships may have a preference for these banks as larger and better capitalized banks have better access to capital markets and more capacity to accommodate the increased demand for credit from the borrowers of the distressed banks, also considering the higher influx

[24] In all cases, the coefficient of $SD_{f,2013}$ is statistically insignificant indicating that borrowers of distressed banks do not have a different probability of establishing new lending relationships during the 'pre-period'. This result confirms the absence of significant pre-trends in new relationships, supporting the 'parallel trends' assumption.

of deposits towards these banks. Comparing the interaction coefficients, we observe in fact that bank capital appears to be relatively more important during the first wave of runs, when firm deposits from the distressed banks were mainly flowing towards better capitalized banks. Instead, bank size appears relatively more important during the second wave of runs, when household deposits were flowing towards larger systemically important banks.

The overall "lost business" to outside banks is substantial. Using the set of firms that were only borrowing from the distressed banks at the start of the event window (i.e., their existing single-relationship customers), we compute and report the cumulative value of loans that these firms received from outside banks over the event window, scaled by total loans from the distressed banks at the start of the event window.[25] As can be observed in Figure 5, until the distressed banks' problems became public in 2015Q1, the share of new loan business lost to outside banks was similar for both distressed and non-distressed banks.[26] However, this changed sharply in 2015Q1, when the distressed banks' problems became public, and they began losing loan business to outside banks at a substantially faster rate. By the end of the event window, the lost business to outside banks was 10% larger for the distressed banks. Importantly, most of this gap formed before Post 2, when low-risk firms with single relationships began applying to outside banks.

As shown in Figure A3 in the Online Appendix, nearly all of the distressed banks' lost business to outside banks is in fact driven by low-risk firms. Additional results, reported in Figure A4 in the Online Appendix, confirm that these results are robust to computing the volume of lost business using the outstanding amount of drawn credit rather than the granted amount.[27] This indicates that credit lines with new lenders are actively used.

Terms of Credit: Distressed vs. Non-distressed Banks For firms with multiple relationships, we examine how firms' outstanding credit and loan interest rates from the distressed banks change during the event window relative to non-distressed banks. Similar to the credit lines analysis, we estimate the following DiD model at the bank-firm-quarter level:

$$Y_{b,f,t} = \beta_1 \; D_b \times \text{Post } 1 + \beta_2 \; D_b \times \text{Post } 2 + \alpha_b + \mu_{f,t} + \epsilon_{b,f,t}, \tag{6}$$

[25]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 with larger loans, these estimates provide a lower bound of the distressed banks' lost business.

[26]Both figures trend upwards (have positive slopes) because over time a fraction of banks' existing customers switch to outside banks for reasons other than bank distress.

[27]Approximately 69% of the new relationships include a credit line, and 60% include a term loan. However, term loans are much larger on average and thus represent a higher share of total new credit compared to credit lines (37% vs. 13%; the remaining 50% is credit backed by receivables and invoices).

where $Y_{b,f,t}$ denotes the log of total outstanding credit or 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 equals 0 otherwise. Post 1 and Post 2 are defined as in Eqn. (3). In addition to bank-fixed effects, α_b, which control for time-invariant differences between banks, in our most conservative specifications we include firm×time fixed effects, $\mu_{f,t}$. The coefficients of interest, β_1 and β_2, are identified using within firm-time variation for firms and reflect the changes in outstanding credit and loan interest rates to the *same firm* at the *same time* (Khwaja and Mian (2008)). The results are reported in Table 7.[28] In Figure 6 we also report the estimated coefficients of dynamic DiD specifications.

These analyses yield three key insights. First, in line with the idea that low-risk firms were trying to diversify their credit sources and establish new stable lending relationships, we find that the decline in credit from the distressed banks to low-risk firms, is not accompanied by higher interest rates. The latter scenario would have been expected if the distressed banks were contracting credit supply to these firms (i.e, a drop in volume paired with a rise in price). Instead, as shown in Panel A of Figure 6, during Post 1 the distressed banks were charging lower interest rates to these firms relative to other banks, indicating that, if anything, during this period they were trying to retain these firms with cheaper loans. Accounting for expected credit losses, low-risk firms are among the banks' more profitable customers (Figure A5).

Second, as problems emerged and deposit outflows began in Post 1, the distressed banks appear instead to reduce credit supply to high-risk firms. While credit volumes do not significantly decrease until Post 2, loan interest rates to riskier firms begin increasing already in Post 1 (Panel B of Figure 6). This result is in line with prior research showing that incentive to lend to risky firms or engage in "zombie" lending (e.g., to avoid recognizing of nonperforming loans and maintain regulatory capital requirements (Caballero et al. (2008)), tend to decrease when banks face stricter supervisory and public scrutiny (Bonfim et al. (2022)).

Finally, as can be observed in Panel B of Figure (6), during the 'pre-period' the distressed banks were not charging lower interest rates to high-risk firms compared to other banks. Since zombie lending is typically associated with "unusually cheap" credit (Caballero et al. (2008)), this result indicates that if the distressed banks were engaging in zombie lending during the pre-period, this was not to a greater extent than other (non-distressed) banks.

Summary Our results show that a process of endogenous, gradual deterioration of the distressed banks' loan portfolios began as soon as their problems became public and began facing

[28]For completeness, we also report results of a baseline specification for all firms using industry×province×size×quarter fixed effects instead of the firm×time fixed effects.

runs from their corporate clients. Anticipating future credit supply disruptions and facing difficulties in securing new relationships, their high-risk clients with single relationships began drawing on their existing credit lines from the distressed banks to a greater extend as soon as the banks' problems became publicly known. Instead, their low-risk clients with single relationships began applying to outside banks and were able to establish new relationships with stronger banks. Although initially the distressed banks appear to be trying to retain their low-risk firms with cheaper loans, credit from the distressed banks to these firms declines relatively more over time. Our estimates show that the overall lost business to outside banks, was substantial and driven primarily by the banks' best corporate clients.[29] These findings underscore the critical role played by the simultaneous deterioration of the distressed banks' asset and liability positions, shedding light on the endogenous dynamics of distress in the period leading-up to their failure.

4.3 Firm Outcomes: Total Credit and Investment

In this section, we study the total credit and real outcomes of firms with greater initial credit dependence on the distressed banks during the event window. Evidence provided earlier shows that firms with greater initial credit dependence on the distressed banks are more likely to apply and receive credit from other banks, especially when they are low-risk. Hence, to examine how these firms' total bank credit and investment fared over the event window relative to other firms, we estimate the following model at the firm-year level:

$$Y_{f,t} = \beta_0 \; SD_{f,2013} + \beta_1 \; SD_{f,2013} \times \text{Post 1} + \beta_2 \; SD_{f,2013} \times \text{Post 2} + \alpha_{k,p,t} + \lambda_{j,t} + \epsilon_{f,t}, \quad (7)$$

where $Y_{f,t}$ indicates the growth of total credit or investment rate of firm f in quarter t, and equals 0 otherwise. $SD_{f,2013}$ denotes the share of firm's f credit from the distressed banks in 2013, while $\alpha_{k,p,t}$ and $\lambda_{j,t}$ denote industry×province×quarter and Z-score×quarter fixed effects.[30]

The results are reported in Table 8. Panel A reports results for total credit and Panel B for investment. The first three columns (columns (1)-(3)), report results of a baseline specification, which studies the relationship between $Y_{f,t}$ and $SD_{f,2013}$ without distinguishing across the different sub-periods. Column (1) reports results for all firms and columns (2) and (3) distinguish between high-risk and low-risk firms. The next three columns (columns (4)-(6)), report results

[29]The accelerated deterioration in the distressed banks' loan portfolios is also visible at the bank-level. Figure A1 in the Online Appendix shows a visible and exponential decline in the quality of distressed banks' nonperforming loans to total loans ratio, beginning more than two years before their ultimate failure. This pattern is remarkably similar to the findings of Correia et al. (2023), as illustrated in their Figure 2 and Figure 3.a.

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

of corresponding specifications distinguishing the three sub-periods as shown in Eqn. (7).

Starting from column (1), we find that over the entire event window and across all firms, the coefficients of $SD_{f,2013}$ in Panels A and B 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 rate decline to a greater extent than 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 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 (i.e., a 40% decline relative to the average investment rate).[31]

Distinguishing across the three sub-periods reveals that low-risk firms also experienced declines in credit growth during Post 1. However, this decline was 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. High-risk firms, which were unable to adequately substitute, 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, our results indicate that low-risk firms were able to adequately substitute credit from other banks without facing significant declines in their investment rate. In contrast, high-risk firms, which were unable to adequately access credit from other banks, saw significant declines in their total credit growth and investment rate, particularly during Post 1.

4.4 Spillover Effects on Other Banks' Loan Portfolios

In this section, we explore potential spillover effects on borrowers of other banks operating in the same local market. We aim to understand whether the influx of new low-risk borrowers from the distressed banks, had adverse effects on the existing borrowers of other banks in the region (e.g., a crowding out). To examine the potential spillover effects on the borrowers of other banks, we first compute the share of loan applications that each bank received from the borrowers of the

[31] Comparisons within high-risk firms are important as high-risk and low-risk firms may have systematically different demand for credit and investment needs (see, e.g., Figure A2 in the Online Appendix).

distressed banks as a fraction of the total loan applications each bank received in a given quarter:

$$Exp_{b,t} = \frac{DistBorrAppl_{b,t}}{TotalAppl_{b,t}}, \tag{8}$$

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.[32] Using this measure, we estimate:

$$\Delta \log(Credit)_{b,f,t} = \beta_1 \; Exp_{b,t} \times HighRisk_{f,2013} + \gamma' X_{f,t-1} + \alpha_{k,p,t} + \alpha_{b,t} + \epsilon_{b,f,t}, \tag{9}$$

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 the firm 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 reported in Table 9. In column (1), we find that the coefficient of $Exp_{b,t}$ is statistically insignificant, indicating that, on average, there are no significant spillover effects on the customers of other banks. However, when we distinguish between high-risk and low-risk borrowers in column (2), by allowing for an interaction term between $Exp_{b,t}$ and $HighRisk_{f,2013}$, a different picture emerges. We find that high-risk firms in banks that received a larger number of applications from the distressed banks' borrowers saw larger reductions of their credit from these banks. This result is robust to the inclusion of bank×quarter fixed effects in column (3).

To further examine whether these spillover effects vary with bank balance sheet constraints, in column (4) we allow for interaction terms between $Exp_{b,t} \times HighRisk_{f,2013}$ and key bank characteristics such as bank capital (Tier 1 capital ratio), size, and inter-bank borrowing.[33] We find that the interaction with bank capital is positive and statistically significant, indicating that the decrease in credit to high-risk firms is stronger for banks with lower capital ratio. The larger and better borrower pool may thus have enabled these banks with to "cleanse" their loan portfolios and improve their capital ratios by reallocating credit away from their riskier customers

[32] In robustness tests, we also compute $Exp_{b,t}$ using instead of loans applications the amount of credit to new customers from the distressed as a fraction of the total credit to new customers from any bank.

[33] Among the controls, we include double interactions between $HighRisk_{f,2013}$ and bank characteristics.

towards more profitable and productive firms. Overall, the results provide valuable insights into the dynamics of credit re-allocation during periods of bank distress and the consequences these have on different types of borrowers, banks, and credit allocation.

5 Conclusions

Unlike previous crises, the collapse of mid-sized regional banks in the United States in 2023 witnessed large and rapid withdrawals of deposits from non-financial corporations. Corporations, being both depositors and borrowers, can play a critical role in bank stability. The withdrawal of corporate deposits not only undermines the banks' liability-side, but it also implies a potential relocation of their loan business to other banks, further destabilizing distressed banks. While the existing empirical literature offers many valuable insights into depositors' behavior during episodes of bank distress, much less is known about their behavior on banks' asset-side.

We find that firms begin withdrawing deposits before households as soon as the banks' distress becomes public and concurrently seek loans and establish new lending relationships with stronger banks, setting off an endogenous deterioration of the distressed banks' loan portfolios. Low-risk firms with single relationships are the first to leave, eroding the banks' loan portfolio on the asset-side, long before formal supervisory action and widespread depositor runs. High-risk firms, unable to leave the distressed banks, draw down more on their existing credit lines, further increasing credit risk on the remaining pool of borrowers.

Our analysis also reveals significant spillover effects on other banks in the region. Banks receiving a greater number of loan applications from distressed banks' borrowers reduce credit to their existing high-risk borrowers, particularly banks facing greater capacity constraints with weaker regulatory capital ratios. Importantly, as we show, the transition of low-risk firms from distressed banks to other banks does not adversely affect their credit availability or other real outcomes. Negative credit and real effects remain confined to the riskiest borrowers.

Our results provide valuable insights for bank supervisors and resolution authorities seeking effective interventions and ways to mitigate the fallout from bank failures. A common approach in bank resolution is to separate a distressed bank's assets in two categories: a 'good' and a 'bad' bank, where all non-performing assets are consolidated in a public 'bad' bank. Our results show that, well before any formal regulatory intervention, market forces begin a process of credit reallocation that separates the 'good' from the 'bad' bank as soon as the impending distress of the bank becomes publicly known. Absent a widespread banking crisis, high-quality borrowers are able to secure new lending relationships with healthy banks without suffering significant adverse credit or real effects.[34] While destabilizing for the distressed banks, these forces maybe beneficial to the overall stability of the banking system, facilitating a more efficient credit allocation.

[34] The results may not generalize to all types of bank distress. For example, during a financial crisis or the failure of a systemically important bank, it may be harder for borrowers to switch to alternative lenders.

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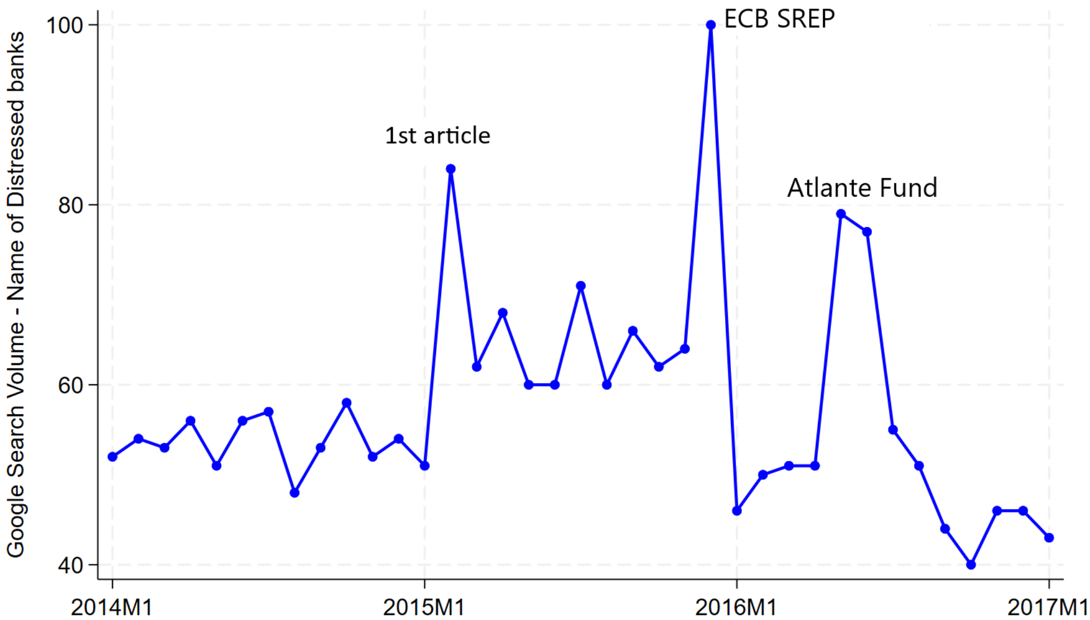
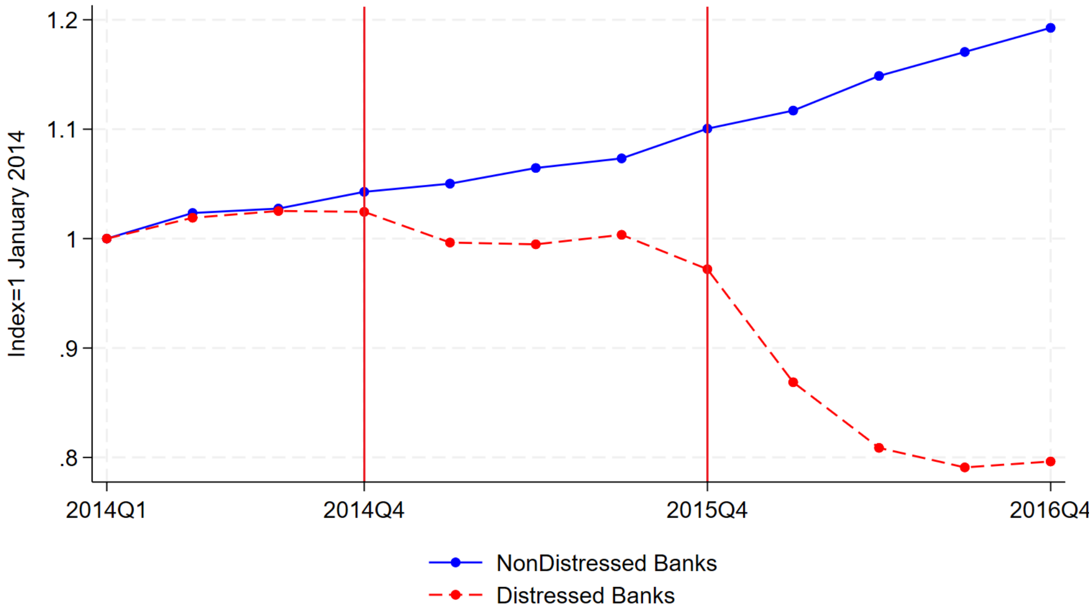
Figure 1: Google Trends



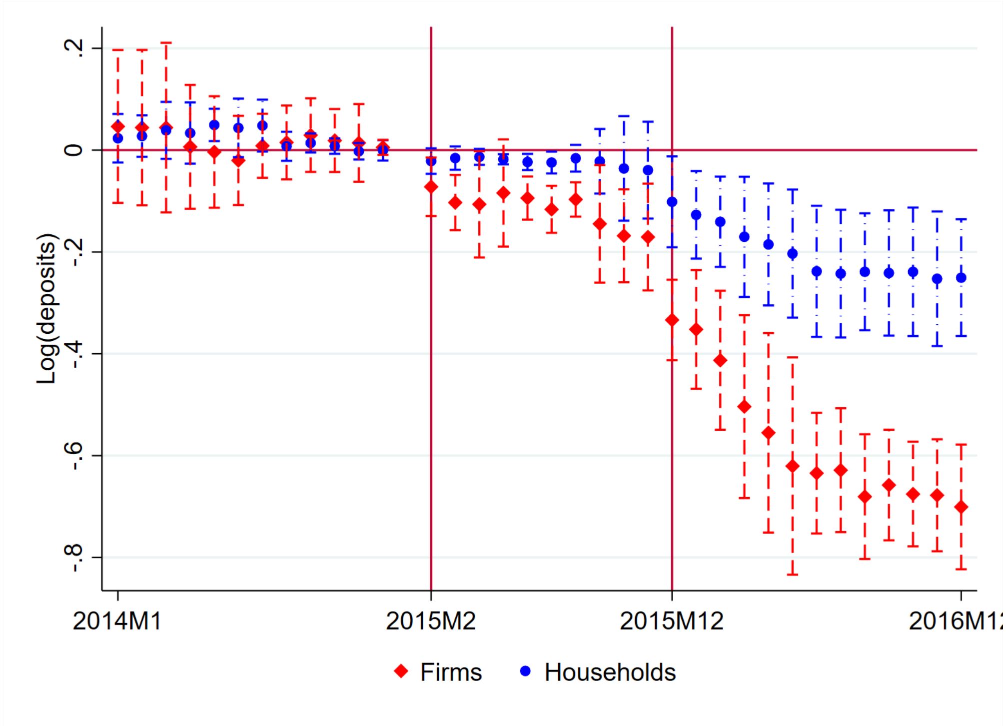
This figure shows the Google searches for the name of the distressed banks between January 2014 and January 2017. Numbers represent search interest relative to a time period, with 100 indicating the peak number of searches during the event period. "1^{st} article" refers to the February 2015 article published in the Italian financial press containing interview with former bank employees about loans-for-share schemes; "ECB SREP" refers to the release of the ECB Supervisory Review (SREP) final results on November 30, 2015 announcing that the banks 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 2014Q1 to 2016Q4. All series are normalized to 1 as of 2014Q1. The vertical lines indicate the beginning of Post 1 (January 2015) and Post 2 (December 2015) periods.

Figure 3: Dynamic DiD: Firm vs. Household Deposits

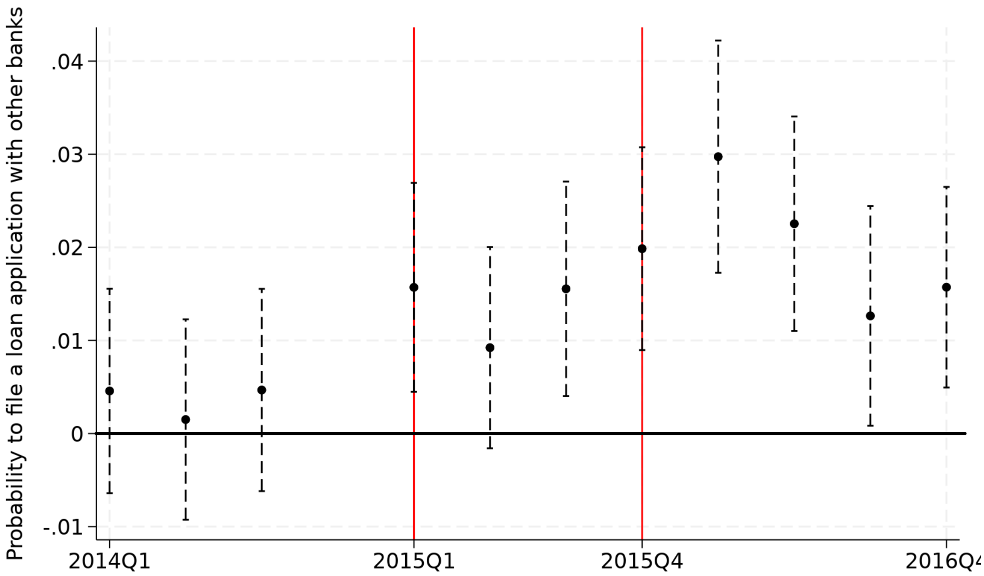


This figure plots the β_t coefficients and 95% confidence intervals from the following dynamic DiD specifications at the bank-month:

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

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 time fixed-effects, α_b and α_t, respectively. The red vertical lines indicate the start of the two distress periods, Post 1 (Feb. 2015 - Nov. 2015) and Post 2 (Dec. 2015 - Dec. 2016). Standard errors are clustered at the bank-level.

Figure 4: Dynamic DiD: Loan Applications to Outside Banks

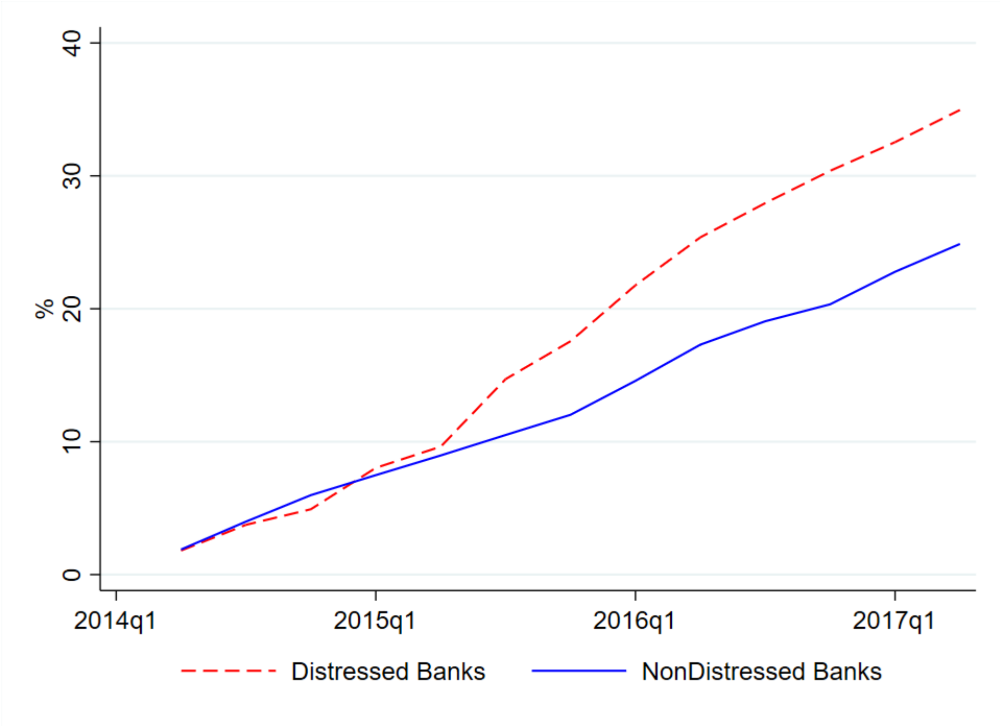


This figure plots the β_t coefficients and associated 95% confidence interval for the following equation:

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

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. Standard errors are clustered at the firm-level.

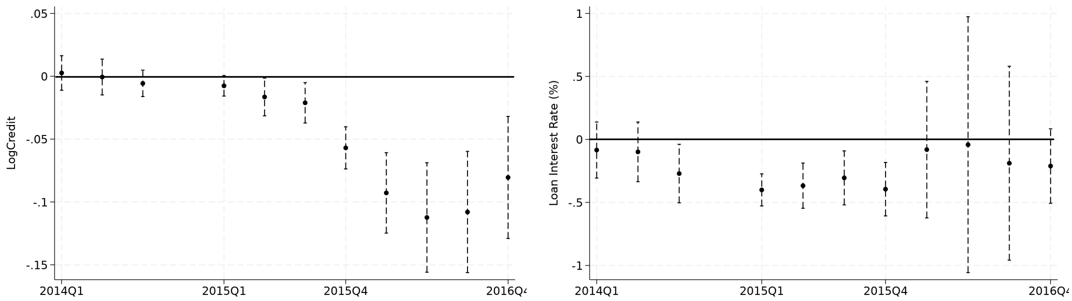
Figure 5: Lost 'Loan Business' to Outside Banks



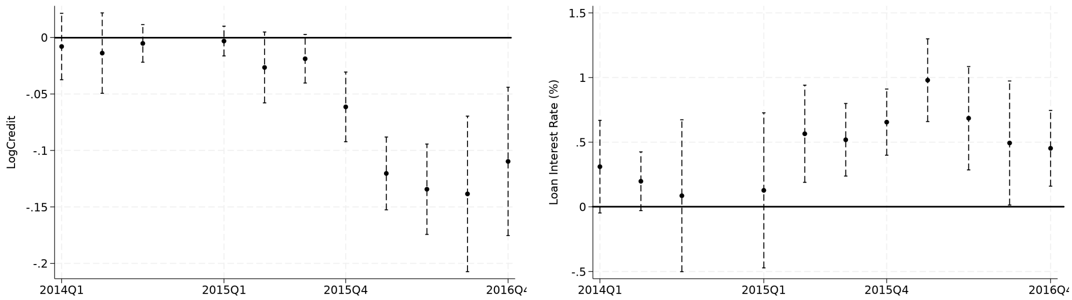
This figure plots the cumulative values of loans that single-relationship firms of the distressed (non-distressed) banks received from outside banks during the event window (2014Q1-2016Q4) as a fraction of their total loans from the distressed (non-distressed) banks at the start of the event window.

Figure 6: 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. (5) 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. Panels A and B distinguish between Low-Risk (z-score < 7) and High-Risk (z-score ≥ 7) firms.

Table 1: Summary statistics

	Obs.	Mean	St. Dev.	Median	5th pct.	95th pct.
	Panel A. Bank characteristics as of 2013Q4					
Total Assets (€mil.)	480	5988	48444	503	76	8987
Capital Ratio (%)	480	12.461	3.994	12.045	6.700	19.679
Deposits/Assets (%)	480	42.018	12.515	41.957	20.322	61.431
Firm Deposit Share (%)	480	24.785	14.900	22.372	7.954	51.621
	Panel B. Firm characteristics as of 2013Q4					
	Obs.	Mean	St. Dev.	Median	5th pct.	95th pct.
Total Assets (€mil.)	565,05	4.001	9.687	1.061	0.063	70.668
Sales (€mil.)	56,505	4.007	9.874	1.025	0.019	70.917
Age (years)	56,505	17.334	11.816	14	2	54
EBITDA/Assets	56,505	0.072	0.129	0.069	-0.504	0.467
Altman Z-score	56,505	4.921	2.067	5	1	9
High-Risk	56,505	0.279	0.0448	0	0	1
Number of bank relationships	56,505	2.397	1.935	2	1	6
Single Relationship Firm	56,505	0.428	0.494	0	0	1
Rel. with Distressed Banks (DBs)	56,505	0.266	0.442	0	0	1
Share Credit Distressed ($SD_{f,2013}$)	56,505	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. Bank Credit (bank-firm-quarter level)					
	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	25,436	0.273	0.445	0	0	1
Distressed bank borrowers	8,478	0.293	0.455	0	0	1
Non-Distressed bank borrowers	16,957	0.262	0.439	0	0	1
	Panel D. Firm-year panel, 2014-2016					
	Obs.	Mean	St. Dev.	Median	5th pct.	95th pct.
Δlog(Credit)*100	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
Δlog(Sales)	135,212	-0.331	32.203	1.952	-50.376	42.3504
Δlog(Wages)	123,318	-1.493	28.221	-2.450	-39.641	40.439

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

Table 2: Deposit Runs at the Distressed Banks

	All	Firms	Households
	(1)	(2)	(3)
D_b×Post 1	-0.068**	-0.132***	-0.045
	(0.030)	(0.041)	(0.029)
D_b×Post 2	-0.344***	-0.588***	-0.224***
	(0.076)	(0.102)	(0.074)
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-level.

Table 3: Deposit Re-allocation

	Firms				Households		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{HS}_{p,2013}$ × Post 1	0.128**						
	(2.34)						
$\text{HS}_{p,2013}$ × Post 2	0.208**						
	(2.56)						
$\text{HS}_{p,2013}$ × Post 1 × $\text{HighCapital}_{b,2013}$		0.223**		0.222**	-0.184**		-0.070
		(2.16)		(2.10)	(-1.99)		(-0.77)
$\text{HS}_{p,2013}$ × Post 2 × $\text{HighCapital}_{b,2013}$		0.271*		0.265*	-0.209		-0.093
		(1.78)		(1.69)	(-1.62)		(-0.72)
$\text{HS}_{p,2013}$ × Post 1 × $\text{LargeBank}_{b,2013}$			-0.107*	-0.002		0.369**	0.501***
			(-1.74)	(-0.03)		(2.57)	(3.95)
$\text{HS}_{p,2013}$ × Post 2 × $\text{LargeBank}_{b,2013}$			-0.158*	-0.024		0.386***	0.515***
			(-1.70)	(-0.28)		(2.74)	(4.14)
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. (2). 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 province-level.

Table 4: 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	0.018***	0.011***	-0.004	0.009***	0.029*	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. (3). 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 5: Loan Applications to Outside Banks

	All Firms		Low-Risk		High-Risk		Maturing with 1-Year	
			Single	Multiple	Single	Multiple	$\geq$50%	$<$ 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SD$_{f,2013}$	0.001							
	(0.08)							
SD$_{f,2013}$ $\times$ Post 1	0.010***	0.011***	0.014***	0.010	0.008	0.001	0.013***	0.008
	(2.82)	(3.01)	(2.77)	(1.42)	(0.89)	(0.01)	(3.17)	(1.05)
SD$_{f,2013}$ $\times$ Post 2	0.017***	0.017***	0.015***	0.030***	0.007	0.006	0.024***	0.005
	(5.34)	(5.34)	(3.11)	(4.71)	(0.83)	(0.56)	(6.32)	(0.73)
Fixed Effects								
Firm	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Province $\times$ Size $\times$ Year-Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CreditScore $\times$ 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	0.082	0.211	0.304	0.221	0.420	0.336	0.178	0.223

This table reports estimation results for Eqn. (4). 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 $\geq$7.

Table 6: 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)
$SD_{f,2013}$	0.00335	0.00391	-0.00194	-0.0374	0.0320	0.0203	-0.0540
	(0.12)	(0.11)	(-0.03)	(-0.89)	(0.78)	(0.56)	(-1.12)
$\text{SD}_{f,2013} \times$ Post 1	0.102**	0.124**	0.0247	0.0810	0.169***	0.0975*	0.168**
	(2.52)	(2.45)	(0.27)	(1.35)	(2.89)	(1.76)	(2.52)
$\text{SD}_{f,2013} \times$ Post 2	0.0621	0.0905*	-0.0649	0.0933	0.0362	0.0553	0.119*
	(1.46)	(1.77)	(-0.68)	(1.46)	(0.61)	(0.94)	(1.79)
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. (3). 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. (3) for all firms. Columns (2) and (3) report results for "Low-Risk" (z-score < 7) and "High-Risk" (z-score $\geq$7) firms separately. columns (4) and (5) distinguish banks with respect to bank capital $\text{HighCapital}_{b,2013}$, a dummy variable that = 1 if the bank had an above the median capital ratio in 2013, and = 0 otherwise. Columns (6) and (7) distinguish banks with respect to bank capital using $\text{LargeBank}_{b,2013}$ is a dummy variable that = 1 if the bank had total assets above €100 billion in 2013 (i.e., if it was one of the top five banks in the country), and = 0 otherwise. Standard errors are clustered at the firm level.

Table 7: 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
	(0.0077)	(0.00621)	(0.007)	(0.007)	(0.008)	(0.011)
$D_b\times$ Post 2	-0.099***	-0.094***	-0.098***	-0.089***	-0.101***	-0.104***
	(0.021)	(0.019)	(0.019)	(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	0.25**	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	1,053,092	916,727	951,079	828,892	96,120	87,835
R-squared	0.214	0.615	0.214	0.608	0.387	0.566

This table provides the estimates for Eqn. (6). 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 8: 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			
	(-0.24)	(-1.76)	(1.12)			
$SD_{f,2013} \times$Pre				1.199	0.568	1.489
				(1.31)	(0.31)	(1.41)
$SD_{f,2013} \times$Post 1				-3.184***	-6.084***	-1.947*
				(-3.13)	(-2.88)	(-1.68)
$SD_{f,2013} \times$Post 2				1.573	-1.251	2.649**
				(1.51)	(-0.57)	(2.21)
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-square	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			
	(-1.64)	(-1.78)	(-1.05)			
$SD_{f,2013} \times$Pre				-0.011	-0.165	0.067
				(-0.10)	(-0.80)	(0.50)
$SD_{f,2013} \times$Post 1				-0.214*	-0.355*	-0.174
				(-1.79)	(-1.66)	(-1.21)
$SD_{f,2013} \times$Post 2				-0.170	-0.275	-0.201
				(-1.29)	(-1.02)	(-1.34)
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-square	0.035	0.069	0.040	0.035	0.069	0.040

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

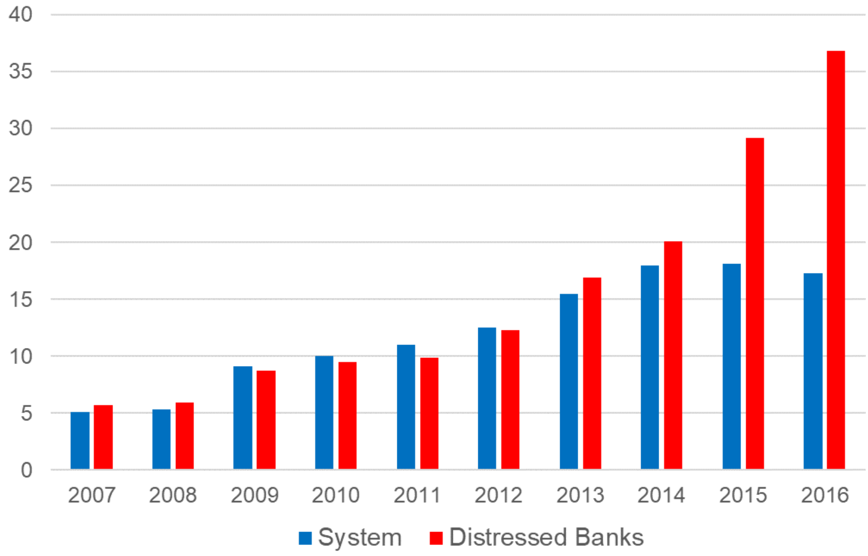
Table 9: Credit Spillovers Effects on Other Banks in the Region

	(1)	(2)	(3)	(4)
$\text{Exp}_{b,t}$	-0.0062	-0.001		
	(-0.52)	(-0.13)		
$\text{Exp}_{b,t} \times \text{HighRisk}_{f,2013}$		-0.019***	-0.019***	-0.079***
		(-5.54)	(-5.34)	(-2.14)
$\text{Exp}_{b,t} \times \text{HighRisk}_{f,2013} \times \text{CapitalRatio}_b$				0.010***
				(2.24)
$\text{Exp}_{b,t} \times \text{HighRisk}_{f,2013} \times \text{Log(Ass)}_b$				-0.023
				(-0.57)
$\text{Exp}_{b,t} \times \text{HighRisk}_{f,2013} \times \text{Interbank}_b$				-0.095
				(-1.05)
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. (9). 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. T-statistics are reported in parentheses.

Online Appendix

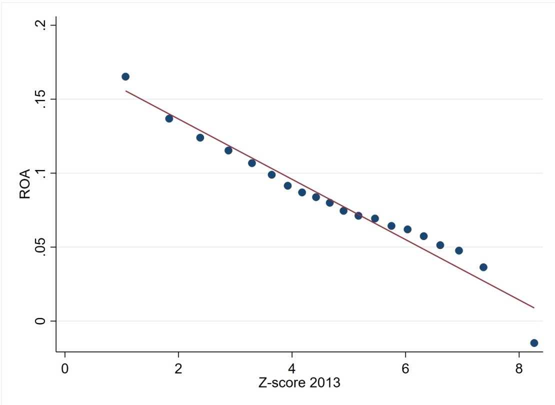
Figure A1: NPL over Loans ratio: Distressed Banks vs. System



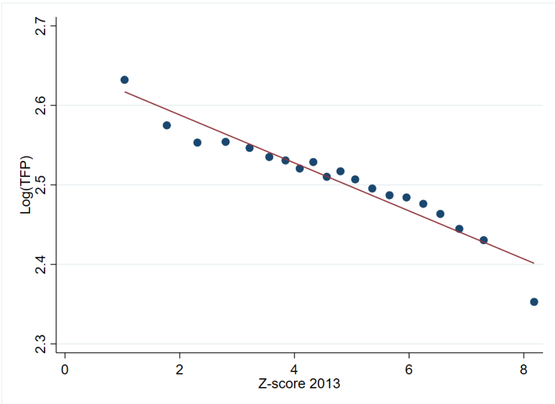
This figure shows the evolution of the Non-Performing Loans (NPL) to total loans ratio of the distressed banks vs. all Italian banks between 2007 and 2016.

Figure A2: Firm Credit-Risk and Other Firm Characteristics

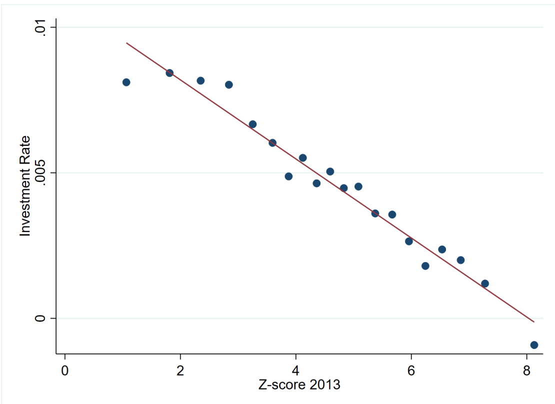
A. Firm Profitability & Credit-Risk



B. Total Factor Productivity & Credit-Risk



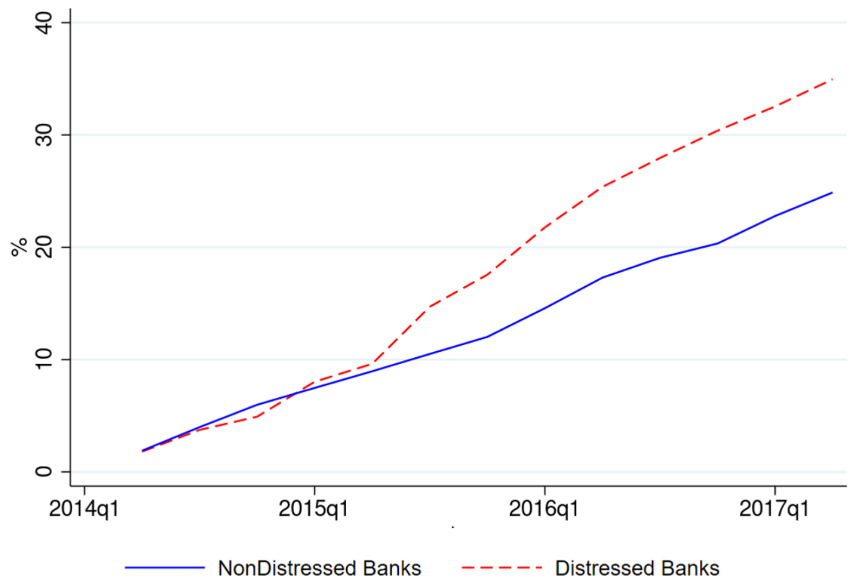
C. Investment Rate & Credit-Risk



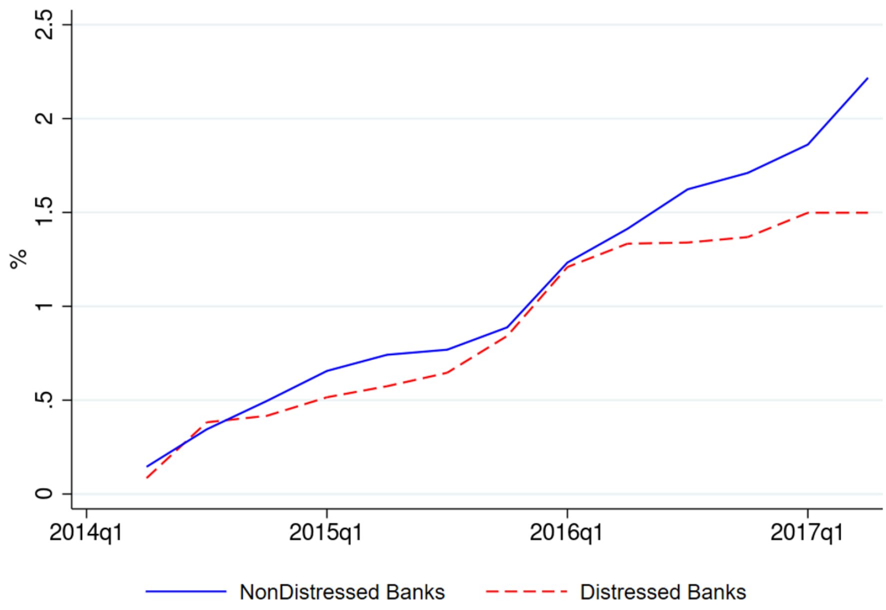
This figure shows the relationship between firms' Cerved Z-score and: profitability (EBITDA over total assets), productivity (TFP), and investment rate (change in total fixed assets over lagged total assets) in 2013 using a binscatter plot controling for $X_{f,t-4}$ (the log of total assets, the log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

A. Low-Risk Firms



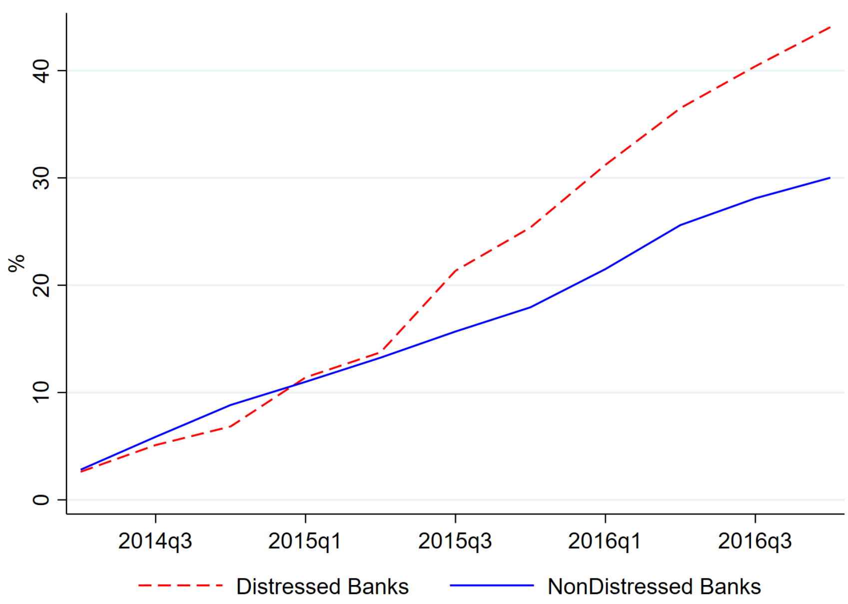
B. High-Risk Firms



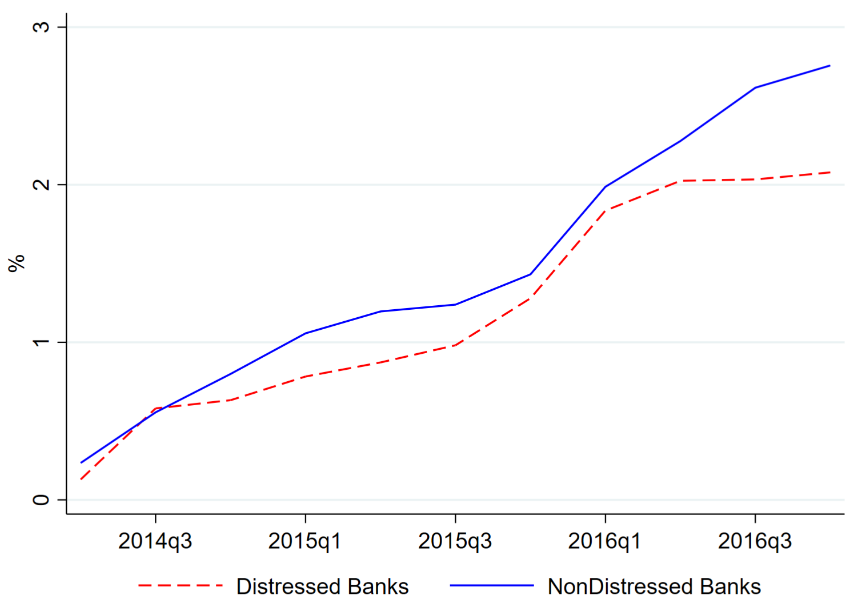
This figure plots the cumulative value of loans that single-relationship firms of the distressed (non-distressed) banks received from outside banks during the event window (2014Q1-2016Q4) as a fraction of their total loans from the distressed (non-distressed) banks at the start of the event window. Panels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

Figure A4: Lost 'Loan Business' to Outside Banks: Outstanding Drawn Credit

A. Low-Risk Firms

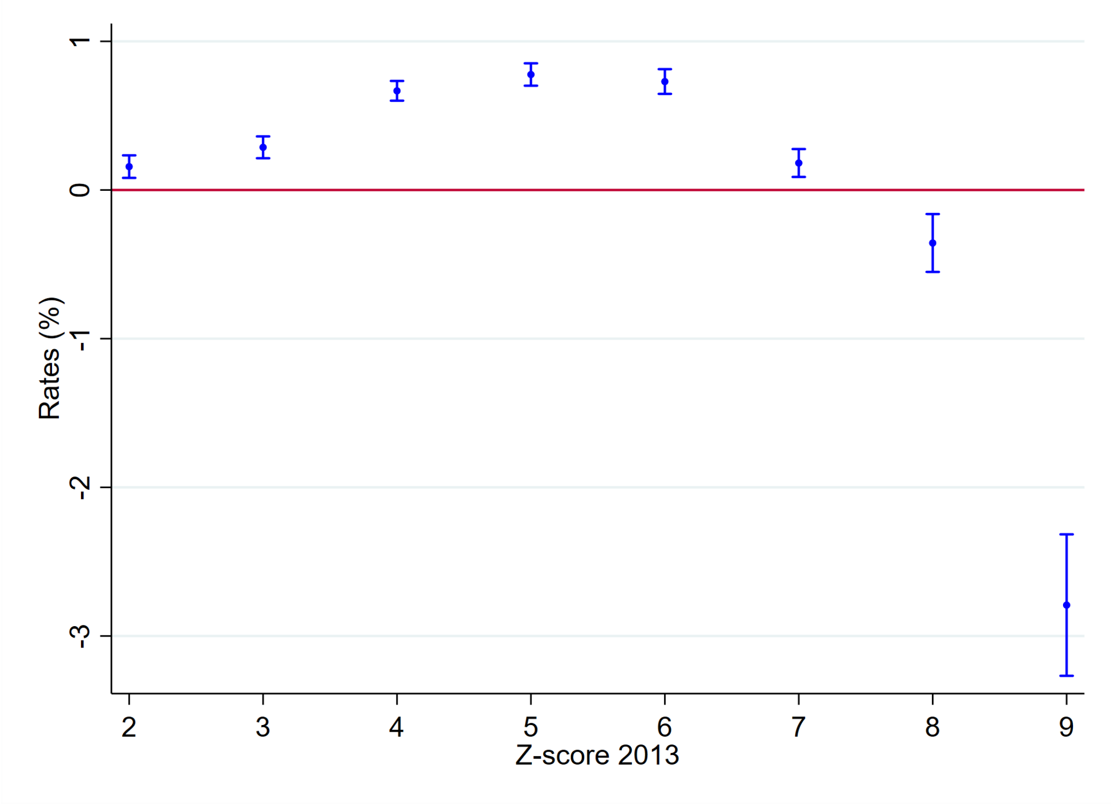


B. High-Risk Firms



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.

Figure A5: 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 coefficients we obtain 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 average interest rate paid by firm f on its loans at time t. $\text{BadLoan}_{f,t}$ is a dummy equal to one if at least one of the loans of firm f becomes a bad loan in year t. $ZScore(i)$ 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.

Table A1: Firm Characteristics Balance

	Existing Borrowers	
	Distressed banks	Non-distressed banks
	(1)	(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 A2: Loan Applications to Outside Banks: Relationship Length and Breadth

	All Firms	
	(1)	(2)
$SD_{f,2013}$ × Post 1	0.010***	0.013***
	(2.79)	(3.42)
$SD_{f,2013}$ × Post 2	0.017***	0.019***
	(5.27)	(5.65)
LongRel × Post 1	-0.001	
	(-0.06)	
LongRel × Post 2	0.001	
	(0.54)	
Shareholder × Post 1		-0.018***
		(-3.37)
Shareholder × Post 2		-0.013***
		(-2.63)
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. (4). 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. T-stat clustered at the firm level are reported in parenthesis

Table A3: Granted Credit Lines

	Log(Credit Lines Granted)					
	All Firms		Low-Risk		High-Risk	
			Single	Multiple	Single	Multiple
	(1)	(2)	(3)	(4)	(5)	(6)
D_b×Post 1	0.00274	0.00717*	-0.00361	0.00642	-0.00409	0.0112
	(0.00420)	(0.00385)	(0.0182)	(0.00457)	(0.0300)	(0.00695)
D_b×Post 2	-0.00803	0.000835	0.00416	0.000269	0.0123	0.000524
	(0.00934)	(0.0110)	(0.0230)	(0.0125)	(0.0409)	(0.0147)
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	0.403	0.744	0.745	0.745	0.734	0.734

This table provides the estimates for Eqn. (3). The dependent variable is the log of total credit lines granted from bank b to firm f in quarter 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 A4: Are Single Relationship Borrowers Less Risky?

	I(Single relationship borrower)			
	(1)	(2)	(3)	(4)
High-Risk	0.00501	-0.0550***	-0.0689***	-0.0902***
	(1.16)	(-13.52)	(-16.23)	(-21.07)
Log(Assets)		-0.143***	-0.132***	-0.129***
		(-129.11)	(-104.43)	(-93.78)
EBITDA/Total Assets			-0.0341**	-0.0290**
			(-2.55)	(-2.09)
Log(Age)			-0.0537***	-0.0458***
			(-18.81)	(-16.07)
Fixed-effects				
Province×Industry	No	No	No	Yes
Observations	61,493	58,197	57,485	57,437
R-square	0.276	0.293	0.263	0.272

This table studies the characteristics of single relationship borrowers. The unit of observation is at the firm-level and the sample includes all firms in 2013Q4 (the last quarter before start of the event window). The dependent variable is a dummy variable = 1 if a firm had only one lending relationship in 2013Q4, and = 0 otherwise. High-Risk is a dummy variable = 1 if the firms had an Z-score ≥ 7. Standard errors are robust. T-statistics are reported in parentheses.