Corporate Runs and Credit Reallocation*

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Abstract

We study how corporate clients react to bank distress on both sides of the bank's balance sheet, exploiting the 2017-failure of two regional banks in Italy. We find that deposit outflows from firms begin before households as soon as the banks' distress becomes public. Firms run simultaneously on the asset-side, applying for credit and establishing new lending relationships with larger and better capitalized banks. Low-risk firms with single-relationship are the first to leave, endogenously eroding the banks' loan portfolio in the period leading-up to widespread deposit runs and the banks' eventual collapse. These borrower runs trigger significant spillover effects on other banks in the region. High-risk borrowers, unable to leave the distressed banks, experience a decrease in credit availability and reduce investment.

JEL classification: G21, G28

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1 Introduction

Bank failures stemming from bank runs carry significant economic and social costs, eroding public trust in the banking system and triggering declines in credit and overall economic activity (see, e.g., Bernanke (1983); Calomiris and Mason (2003); Ashcraft (2005); Huber (2018); Peek and Rosengren (2000)). Complementing the extensive theoretical literature on bank runs (Diamond and Dybvig (1983); Goldstein and Pauzner (2005)), the empirical literature has focused predominantly on understanding which factors affect depositors' 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)).

While much is known about runs on the banks' liability-side, the asset-side dynamics during financial distress have received considerably less attention. Changes in the distressed banks' loan portfolios may interact and exacerbate depositor runs, intensifying the distress and leaving bank regulators with limited options beyond shutting down the bank. The endogenous nature of such changes in banks' loan portfolios can have significant consequences, impacting both the financial health of the distressed banks as well as other banks. A better understanding of the asset-side dynamics during episodes of bank distress is crucial for policymakers and regulators seeking effective interventions to mitigate the fallout from bank failures.

The events in the U.S. banking sector in the Spring of 2023 revived this discussion. Unlike previous banking 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 can impact bank stability for two key reasons. First, deposits from non-financial corporations are sizable and mostly uninsured, constituting a significant portion of banks' total private sector deposits.[1] This makes them highly responsive to news regarding their banks' financial health, particularly in this digital age (Cookson, Fox, Gil-Bazo, Imbet, and Schiller (2023); Koont, Santos, and Zingales (2023)). Second, since corporations are also borrowers, their deposit withdrawals imply a potential simultaneous relocation of their new "loan business" to other banks, further jeopardizing the distressed bank's future viability.[2]

[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 US, firm deposits are even more important.

[2] While fleeting corporate depositors may not necessarily terminate their lending relationships with the distressed banks or prepay their outstanding loans, they may direct new "loan business" to other banks.

In this paper, we focus on the period leading-up to the failure of two regional banking groups (consisting of 6 mutual banks, which we refer to as the "distressed banks") in Italy in 2017. Our aim is to shed light on the behaviour of the distressed banks' corporate clients on both sides of these banks' balance sheets during the unfolding distress, from the first public signals of distress until the final supervisory action declaring the banks as "likely to fail". We track their deposit flows and loan applications to other banks and study their impact on the distressed banks loan portfolios and associated spillover effects on other banks in the region.

We find that deposit outflows from firms begin as soon as the banks' distress becomes public. In addition, we find that firms run simultaneously on the asset-side of the banks' balance sheet, applying for loans and establishing new lending relationships with better capitalized banks, highlighting the synergies between firm deposits and credit (see, e.g., Kashyap, Rajan, and Stein (2002) and Mester, Nakamura, and Renault (2007)).[3] We find that low-risk firms with single-relationships are the first to leave, endogenously eroding the banks' loan portfolio quality in the period leading-up to widespread deposit runs and the banks' eventual collapse.[4] All else equal, incentives to secure new stable lending relationships are stronger for single relationship firms and low-risk firms for whom the opportunity costs of future refinancing disruptions are higher (Detragiache, Garella, and Guiso (2000)). As we show, low-risk firms tend to be more profitable and productive firms with a higher investment rate. These forces give rise to important spillover effects on other banks in the region. Faced with an improved borrower pool from the distressed banks, other banks reduce credit to their own riskier borrowers.

The failure of these Italian regional banks in 2017 provides an excellent setting for empirical investigation. First, the onset of their distress was largely idiosyncratic—revelation of accounting frauds inflating regulatory capital— providing a clear timing and enabling us to isolate its impact on their clients. Second, although not nationally significant, these banks were large enough at a regional level for their failure to have material spillover effects on other banks in the region. A quarter of firms in the region had an active lending relationship with them when distress began.

Our analysis relies on granular credit registry and loan application data from the Bank of Italy.

[3] Borrowers seeking to leave a failing bank are less adversely selected and thus have a higher chance of receiving credit from other banks (Darmouni (2020); Dell'Ariccia and Marquez (2004)).

[4] A similar mechanism has been described in the context of skilled workers ('worker runs') leaving distressed companies (Baghai, Silva, Thell, and Vig (2021); Hoffmann and Vladimirov (2023)).

We supplement this with deposit-volume data at the bank-province level and financial statements for banks and firms from bank supervisory reports and Cerved, respectively. The timeline of the banks' distress is characterized by two pivotal events. The first event unfolded in early 2015 when articles in the financial press exposed improper accounting practices at the two banking groups (in what follows we use the terms banking groups and banks interchangeably), aimed at inflating their regulatory capital. The articles, featuring interviews with former bank employees, garnered significant public attention and triggered deposit runs before formal supervisory intervention. After these initial outflows, deposits appear to stabilize until the end of 2015, when the ECB's Supervisory Review unveiled that the banks were not meeting the minimum capital requirements. This second event led to a second wave of larger deposit 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 became public in early 2015. In contrast, deposit withdrawals from households only start during the second distress event, and with less intensity. Over the entire study period, the distressed banks lost about 20% of their total deposits—amounting to over 40% of their firm deposits and 15% of their household deposits.

To understand which banks attract the fleeing deposits, we study the deposit inflows at other, non-distressed banks. These analyses rely on within-bank-time variation, leveraging the granularity of the deposit data at the bank-province level, and reveal 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, which underscore the importance of distinguishing between these two classes of depositors, are likely due not only to differences in incentives and ability to evaluate bank fundamentals, but also the nature of services that firms and households seek from their banks (Egan, Hortacsu, and Matvos (2017)). While households may be searching for a safe 'store of value' for their deposits, firms may be also trying to establish new stable lending relationships to ensure uninterrupted credit supply and operations (Detragiache et al. (2000)).

On the asset-side, we find that as soon as the banks' problems became public, low-risk firms with single-lending relationships and firms with more loans maturing within the year began applying for loans to 'outside' banks (i.e., banks with which the firms did not have existing lending relationships), setting in motion a process of endogenous deterioration of their loan portfolios. We find that low-risk firms are able to secure new lending relationships with larger and better capitalized banks (i.e., banks with lower credit capacity constraints).[5]

The inability of the distressed banks to retain their best corporate clients during this initial period eroded the quality of their loan portfolios. Our conservative estimates indicate that the 'lost business' to outside banks (i.e., the cumulative value of loans they obtained from outside banks) accounts for approximately 10% of the distressed banks' initial loan portfolio, with the majority occurring shortly after the first-distress event and driven by low-risk borrowers. These results highlight the critical role played by the simultaneous deterioration of the distressed banks' asset and liability positions, shedding light on the endogenous dynamics of distress.

Additional within-borrower analysis (Khwaja and Mian (2008)) shows that the reduction in credit volume to low-risk firms from the distressed banks following the first distress event is not accompanied by an increase in loan rates. On the contrary, during that period, the distressed banks were charging lower rates than other banks. This suggests that they were likely trying to retain their low-risk clients with cheaper loans. The distressed banks appear instead to reduce credit supply to riskier firms already during the first distress period. These findings are in line with prior research indicating that incentives to lend to riskier firms decrease when banks face stricter supervisory scrutiny (Bonfim, Cerqueiro, Degryse, and Ongena (2022)) and risk-based capital requirements (Peek and Rosengren (1997); Gropp, Mosk, Ongena, and Wix (2019)).

We also find that the influx of new, low-risk borrowers from the distressed banks had substantial spillover effects on other banks in the region. We find that banks receiving a greater number of loan applications from the distressed banks' borrowers reduced credit to their existing high-risk borrowers. This result is more pronounced for banks' facing greater capacity constraints (i.e., banks with ex-ante lower capital ratios). These results suggest that influx of

[5] Larger banks, with better access to capital markets and external liquidity, and banks with higher capital ratios are better able to accommodate the increased demand for credit.

low-risk borrowers from the distressed banks may have enabled other banks to "cleanse" their loan portfolios, crowding-out riskier borrowers, and improving their capital ratios.

We find that the transition of low-risk firms from the distressed banks to other banks is not accompanied by adverse effects on credit or other real outcomes. These firms do not lose access to credit during the sample period, with the exception of a temporary decline during the first distress event, which was not accompanied by adverse real effects. In contrast, high-risk firms, who are unable to leave the distressed banks, lose access to credit and have to reduce investment. Overall, our results indicate that absent widespread banking sector problems, the negative effects of bank distress are limited to the riskiest firms.

Our paper offers new valuable insights into the dynamics of deposit and borrower runs by corporate clients of banks in distress in the period leading-up to their failure, contributing to two strands of the literature. First, the paper contributes to the empirical literature on deposit 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 concerned about bank fundamentals, large uninsured depositors are more likely to run, seeking safety behind deposit insurance and implicit government guarantees (e.g., too-big-to fail, publicly-owned banks).[6] Our results reveal that low-risk firms run simultaneously on the asset-side in search of new lending relationships with more stable banks to ensure uninterrupted access to credit. This gives rise to a process of endogenous deterioration from corporate runs on both sides of the banks' balance sheet, which begins as soon as the banks' distress becomes publicly known, and long before formal supervisory intervention. This novel result has important policy implications on the timing and type of interventions by prudential authorities, especially as online banking and social media increase the speed and intensity of bank runs (see, e.g., Cookson et al. (2023); Rose (2023); Koont et al. (2023)).

The paper also contributes to the empirical literature on the impact of bank distress on credit supply and the real economy (e.g., Bernanke (1983); Calomiris and Mason (2003); Ashcraft (2005); Schnabl (2012); Huber (2018); Darmouni (2020); Beck, Da-Rocha-Lopes, Samuel, and Silva (2021); Gropp, Mosk, Ongena, and Wix (2022)). Unlike these studies, which focus primarily

[6]Others have studied 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)).

on periods when problems in the banking sector are widespread, we find that adverse effects on the distressed banks' borrowers are fairly small and limited to the riskiest firms. When bank distress is idiosyncratic, the borrowers of the distressed banks are more easily accepted by other banks as adverse selection and "winner's curse" problems are lower. In contrast to studies focusing on crises periods (e.g., Ivashina and Schrfstein (2010); Ippolito, Peydrò, Polo, and Sette (2016); Chodorow-Reich, Darmouni, Luck, and Plosser (2022)), we do not observe abnormal credit line draw-downs at the distressed banks. When the banks' problems are largely idiosyncratic, firms appear more inclined to secure new lending relationships with stable banks instead of drawing-down their existing credit lines with the distressed banks.[7] Finally, as we show, the borrower runs we document, carry important positive spillover effects on other banks in the region.

The remainder of the paper is organized as follows. Section 2 offers an overview of the distressed banks and a timeline events that let to their failure. Section 3 describes the data. Section 4 reports and discusses our findings, and Section 5 concludes.

2 Timeline of Distress

In this section, we provide an overview of the distressed banks under examination and a chronological account of the events which ultimately led to their eventual collapse. Comprising of six banks within two banking groups, the distressed banks were prominent regional lenders in Northern Italy. Operating as mutual savings institutions, these banks were predominantly owned by the local elite, including local entrepreneurs. Despite their relatively modest size on a national scale (ranked 10^{th} and 11^{th} by total assets in 2013), these banks were significant regional lenders in one of Italy's wealthiest and most economically powerful areas. About a quarter of the region's firms had an active lending relationship with the distressed banks.

The problems, which led to their eventual downfall, began in 2012. Following the European sovereign debt crisis, many Italian banks needed to raise fresh equity to address growing losses on non-performing loans. Lacking access to capital markets and with the local private market depressed from the sovereign debt crisis, unlisted mutual banks found it challenging to attract

[7] Drawing-down their credit lines with the distressed lenders may not be desirable as high credit line usage is often associated with poor credit quality (Chodorow-Reich et al. (2022)), which in turn reduces the likelihood of establishing new lending relationships. CR stores and shares this information with other banks. Outside banks can see how much credit prospective borrowers have at other banks when they apply for credit.

fresh capital. As a result, the distressed banks resorted to "loan-for-share" schemes, whereby loan applicants were asked to use a portion of the loan proceeds to acquire shares of the bank.[8] While not illegal, equity raised through such schemes must receive approval from an extraordinary shareholders' meeting and, crucially, must be excluded from regulatory capital.

The first signs of trouble emerged in November 2014 when the ECB-SSM Comprehensive Assessment revealed a minor capital shortfall in both institutions. Initially, it appeared that both banks could address the shortfall adequately. However, about two and a half months later, in mid-February 2015, an article published 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 further revealed that the banks' managers were under investigation by local judicial authorities for obstructing bank supervisory functions, following a 2013 on-site inspection, which uncovered the loan-for-share scheme and other deficient governance practices. The publication of this article marked the first public disclosure of the banks' impending distress, triggering a significant increase in public attention, as evidenced by the sharp increase in Google searches for the banks' names (first spike in Figure 1), and initiating a period of heightened 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 the board. Shortly after these revelations, the stock prices of the distressed banks were 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 that the only chance for the banks' survival was to raise 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 response to the growing crisis, the distressed banks proposed a recapitalization plan in early

[8] The Franco-Belgian bank Dexia, which failed in 2012, was using similar loan-for-share schemes to inflate its regulatory capital.

2016, aiming to raise the necessary €2.5 billion by listing on the Italian stock exchange. This step was also necessary following the approval of a law in 2015, mandating all mutual savings banks in Italy with assets exceeding €8 billion to transition into publicly listed companies by 2016. However, plagued by disappointing results in 2015 and a lack of confidence in their 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. Hence, 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 their 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.[10]

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, draw-downs on 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' real outcomes such as investment, sales, wage expenses, and likelihood of default based on a proprietary z-score, akin to the Altman Z-score, computed by Cerved, and ii) annual data on individual and consolidated bank balance sheets from the Italian Supervisory Reports of the Bank of Italy.

With regard to credit volumes, the credit registry tracks the amount of credit granted from each bank to each borrower on a quarterly basis, differentiating between loan types such as credit lines and term loans, and distinguishing between short-term and long-term term loans. For identification purposes, we focus our credit analysis on borrowers located in the areas where the distressed banks concentrate their lending activities the most.[11] This includes 10 provinces in Northern Italy, where the two distressed banks allocate 60% of their total loan portfolios, and yields a sample of 56,505 unique borrowers and 155,000 bank-firm relationships (i.e., on average each firm in the sample maintains 2.8 bank lending relationships). At the time, the distressed banks were providing loans to about 26% of the firms in the region.

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.

[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] Data by account size are only available with less granularity (i.e., at the bank-level and annual frequency).

[11] While with the advent of online banking geographical distance may matter less for deposit and other credit products to households, it remains important for the provision of credit to firms (see, e.g., Degryse and Ongena (2005); Agarwal and Hauswald (2010); Nguyen (2019)).

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 available by type of loan (Sette and Gobbi (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 comprises of 480 banks, with an average total asset size of approximately €6 billion and an average capital ratio of 12.5%.[12] Deposits from both households and non-financial firms collectively represent 42% of total assets, with firms contributing around 25% of total deposits. The share of private sector deposits is considerably lower than in the US, where core deposits typically constitute about 60% of total assets. This difference is due to funding from bank bonds, which in Italy accounts for about 22.5% of total assets (Carletti, De Marco, Ioannidou, and Sette (2021)).

Panel B of Table 1 offers an overview of key firm characteristics. On average, firms in the sample have total assets and sales of about €4 million, with an average age of 17.3 years and an EBITDA to assets ratio of 7.2%. The Cerved Z-score, which ranges from 1 to 9 with higher values indicating higher credit risk, averages at 4.9 for the sample firms. About 27.9% of firms are classified as "High-Risk" with Z-scores ≥ 7 (Rodano, Serrano-Velrde, and Tarantino (2018)). Additionally, 42.8% of the firms have loans from only one bank, 26.6% of firms have loans from the distressed banks, with an average loan share from the distressed banks of 44%.

Further in Panel C of Table 1, we provide summary statistics on bank credit at the bank-firm-quarter level. The average probability of applying for a loan to an 'outside bank', *ApplOut*, during the sample period is 4.3% and it is notably higher for borrowers of the distress banks at 5.8% compared to only 3.9% for borrowers of non-distressed banks. Conditional on applying, the average probability of establishing a new relationship is approximately 27%. The borrowers of the distressed banks' exhibit a notably higher probability of starting a new lending relationship than borrowers of other banks (29.3% vs. 26.2%). All else equal, other banks may be more inclined to accept borrowers from distressed banks, due to lower concerns about winner's curse problems associated with switching borrowers, and fleeting borrowers may be more likely to accept their

[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.

offers (see, among others, Darmouni (2020) and Bonfim, Nogueira, and Ongena (2021)).

Finally, in Panel D of Table 1, we report summary statistics on changes in total bank credit and various real outcomes (such as 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 eventually collapsed. These analyses are organized in three sub-sections: i) deposit runs and deposit re-allocation, ii) borrower runs and credit re-allocation, and iii) spillover effects on other banks in the region.

4.1 Depositor Runs and Deposit Re-allocation

In this section, we study the timing and intensity of deposit outflows from the distressed banks' corporate clients and their choice of new banks.

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 the 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. As observed in Figure 2, the deposits of the distressed banks, which had been increasing at the same rate as other banks, began to decline and diverge significantly from other banks at the start of 2015, when their problems became publicly known. After these initial outflows, it appeared that their deposits were stabilizing. 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 delineated by the vertical lines in Figure 2. 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 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.[13]

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 Post 1 decrease is mainly driven by firms. During that period, the firm deposits of 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 significantly decrease

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

during Post 2, but again with less 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 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.[14]

Deposit Re-allocation Next, we study the characteristics of banks that take 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):

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

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. $HS_{p,2013}$ is a dummy equal to 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 bank-month and province fixed effects, $\alpha_{b,t}$ and α_p, respectively. The latter are important insofar as different time-varying shocks or spillover effects could 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.

[14]Figure A1 in the Online Appendix shows how the level of firm and household deposits of the distressed banks varied over time and paints a similar picture. As in Figure 2 all values are normalized to 1 as of January 2014. At the beginning of the Post 1 period, firm deposits drop sharply by about 10% (€1.3 billion), while household deposits remain fairly stable. Household deposits do not being declining until the start of Post 2. Also during Post 2, the decline in firm deposits is larger than households' (€2.8 billion vs. €1.2 billion).

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

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 further allow for 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 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 11% and 22%, respectively. The smaller coefficient for Post 1 is consistent with the 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 a capital ratio above the median, and equals 0 otherwise. Similarly, $LargeBank_{b,2013}$ is a variable that equals 1 for banks with assets exceeding €100 billion in 2013 (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 findings show that household and firm deposits exhibit distinct behavior 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 less intensity, and towards large, systemically important banks, regardless of their capital. These differences are likely due to differences in incentives and ability to evaluate bank fundamentals as well as the nature of services that firms and households seek from their 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 safety in large, systemically important banks, firms may also be trying to establish new stable lending relationships to ensure uninterrupted credit supply and operations.[16]

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

4.2 Borrower Runs and Credit Re-allocation

In what follows, we study the evolution of the distressed banks' loan portfolios during the event window to determine whether these forces also cause an endogenous deterioration in the distressed banks' loan portfolio in the period leading-up to their ultimate failure. For these analyses, we utilize credit registry data at the bank-firm-quarter level, which allow us to trace loan applications to other banks and study how these vary across firms (e.g., high-risk or low-risk firms, firms with single or multiple lending relationships, firms with upcoming liquidity needs), shedding light on the dynamics of their loan portfolio during this crucial period leading up to their failure.

The balance test on firm characteristics, reported in Table 4, shows that at the start of the event window firms borrowing from the distressed and non-distressed banks 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)). For example, the sample is well-balanced with respect to factors such as 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 analysis below, we control for this small difference in borrower composition.

4.2.1 Borrower Runs

In this sub-section, we examine whether borrowers with higher credit dependence on the distressed banks were more likely to seek credit from outside banks and whether the distressed

[16]There are important synergies between deposits and the provision of 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 empirical support in Cao, Garcia-Appendini, and Huylebroek (2024)).

[17]Figure A2 in the Online Appendix further shows that until 2015 the distressed banks NPLs were growing at a similar pace to the national average.

banks experienced 'credit-line runs' as their problem became publicly known.

Loan Applications to Outside Banks To study loan applications to outside banks, we estimate the following linear probability model:

$$ApplOut_{f,t} = \beta_1\, SD_{f,2013}\times\text{Post 1}+\beta_2\, SD_{f,2013}\times\text{Post 2}+\gamma' X_{f,t-4}+\alpha_{k,p,s,t}+\lambda_{j,t}+\mu_f+\epsilon_{f,t}, \quad (3)$$

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., 2013). $SD_{f,2013}$ 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 distressed banks and 1 indicates that all of the firm's credit was from the distressed banks. 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. Eqn. (3) thus allows us to study how loan applications to outside banks by borrowers of the distressed banks changed over time relative to borrowers of other banks.

To ensure comparability between the two groups of firms, we use entropy balancing regression weights (Hainmueller (2012)) on firm size when estimating Eqn. (3), as Table 4 shows small differences in firm size between the two groups.[18] In addition, 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) among the control variables in $X_{f,t-4}$. To further account for local business cycle conditions that may vary across firms of different sizes, industries, or creditworthiness, we incorporate industry×province×size×quarter fixed effects, $\alpha_{k,p,s,t}$, and Z-score×quarter fixed effects, $\lambda_{j,t}$.[19] We also include firm-fixed effects, μ_f. These absorb the level effect of $SD_{f,2013}$, but allow us to obtain estimates for β_1 and β_2 and thus assess whether borrowers with higher credit dependence on the distressed banks (i.e, with higher $SD_{f,2013}$ values) are more likely to apply for credit to outside banks during the two distress periods, using only within firm-variation across time. For completeness, we also estimate Eqn. (3) without firm-fixed

[18] Robustness tests without entropy balancing on firm size yield qualitatively and quantitatively similar results.
[19] Size denotes firms' asset quintiles at the end of 2013.

effects to verify that the distressed banks' borrowers are not more likely to apply for credit at outside banks also in the 'pre-period'.

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 statistically insignificant and close to zero, 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. The coefficients of Post 1 and Post 2 are both positive and statistically significant, indicating that during this period firms with higher credit dependence on the distressed banks (i.e., higher $SD_{f,2013}$) were more likely to apply for loans to outside banks. The coefficients are economically large and remain stable as we add firm-fixed effects in column (2). In Post 1, a 1-standard deviation increase in $SD_{f,2013}$ (by 0.26) is associated with a 0.26 pps higher likelihood of applying to an outside bank. Evaluated at the mean (4.9%), this represents a 5.3% increase. For a firm fully dependent on distressed banks (i.e., with $SD_{f,2013} = 1$), this effect represents a 25% increase relative to the mean. The coefficient of Post 2 indicates an even larger increase of 9.1%.

In Figure 4 we report the estimated DiD coefficients and confidence intervals from a dynamic DiD specification of Eqn. (3), where we fully interact $SD_{f,2013}$ with a set of dummy variables for each quarter. The results show that the estimated coefficients turn positive and statistically significant in 2015Q1, precisely when the distressed banks' problems became public, and deposit runs from firms began. Furthermore, we observe a continuous increase in loan applications to outside banks over time, peaking in Post 2 when widespread runs began by both households and firms. These findings provide compelling evidence of the changing behaviour of the distressed banks' corporate borrowers in seeking credit from outside banks during this critical period.

In columns (3)-(6) of Table 5, we distinguish between low-risk and high-risk firms with single or multiple relationship firms. This analysis reveals that the increase in loan applications to outside banks during Post 1 is primarily driven by low-risk firms with single-lending relationships, in line with predictions in Detragiache et al. (2000). As (local) 'outside funding' is arguably in limited capacity, low-risk firms, which tend to have higher investment opportunities, and those borrowing exclusively from the distressed banks have stronger incentives to try and secure a new stable lending relationship as soon as their banks' distress becomes public.[20] As shown in Figure 5, low-risk firms tend to be more profitable and productive with a higher investment rate.

Low-risk firms with with multiple lending relationships do not show a higher probability of applying for credit to outside banks until Post 2. The coefficient for Post 1 in column (4), though positive, is not statistically significant. As they have existing relationships with other banks, these firms have lower incentives to turn to new lenders, at least initially. On the other hand, for high-risk firms we find that β_1 and β_2 are statistically insignificant and economically very close to zero, indicating that during both distressed periods these firms were not more likely to seek credit at outside banks relative to high-risk firms of other banks.

The patterns of loan applications above show that as soon as the distressed banks' problems surfaced and the distressed banks began experiencing outflows on firms deposits, their best corporate clients also began applying to other banks, setting in motion a process of endogenous deterioration of their loan portfolios.[21] Fearing credit supply disruptions, these firms may have began turning to other banks to establish new stable lending relationships. Consistent with this interpretation, in columns (7)-(8) of Table 5, we also find that the likelihood of applying to outside banks is higher for firms with higher upcoming credit needs (i.e., firms that the start of 2015 had more that 50% of their total credit maturing within the year).

'Credit-line Runs' In a second set of tests, we examine whether the distressed banks experienced 'credit-line runs' as their problems became publicly known. Prior studies find that firms tend to draw on their credit lines from banks facing funding liquidity shocks in anticipation of future credit supply restrictions (see, e.g., Ivashina and Schrfstein (2010), Ippolito et al. (2016), and Chodorow-Reich et al. (2022)). To investigate whether the distressed banks faced similar 'runs' on their credit lines, we estimate similar DiD specifications at the bank-firm-quarter level:

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

where $ShareDrawn_{b,f,t}$ denotes the share of drawn credit lines over total credit lines granted

[20]Local capacity constraints are relatively more important for smaller firms that tend to borrow from smaller local banks that have a comparative advantage in the use of "soft information" (see, e.g., Stein (2002); Berger, Stein, Miller, Petersen, and Rajan (2005); Degryse and Ongena (2005); Agarwal and Hauswald (2010)).

[21]Due to lower loan losses and higher information rents (Dell'Ariccia and Marquez (2004); Ioannidou and Ongena (2010)) low-risk firms with single relationships are among banks' more desirable customers.

from bank b to firm f in quarter 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 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 also include firm×time fixed effects, $\mu_{f,t}$ (Khwaja and Mian, 2008).

The results are reported in Table A2 in the Online Appendix. We find no evidence of 'credit line runs' on the distressed banks as the estimated DiD coefficients are mostly zero and not statistically significant. A critical difference between our paper and previous studies, which may explain the different results, lies in the nature of the shock examined. While the literature typically focuses on a systemic shock during a financial crisis, our study deals with an idiosyncratic bank shock.[22] Firms' behaviour under these scenarios may differ significantly. In the case of widespread liquidity shocks, firms may drawdown credit lines from troubled banks due to limited alternative sources of funding. In contrast, when the bank's liquidity problems are largely idiosyncratic, firms may be more inclined to establish new relationships with stable banks instead of rushing to drawdown their credit lines. Moreover, when firms are trying to establish new relationships, running up their credit lines with their existing lenders may be undesirable as high credit line usage is often associated with poor credit quality (Chodorow-Reich et al., 2022).

4.2.2 Credit Re-allocation

Next, we study whether attempts to establish new relationships are successful. We study which firms are more likely to secure new lending relationships, with which types of banks, and their impact on the distressed banks' loan portfolios. In a second set of tests, we further study how firms' outstanding credit and loan interest rates from the distressed banks change during the event window relative to non-distressed banks for firms with multiple lending relationships.

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:

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

[22] Ivashina and Schrfstein (2010) examine the period after the failure of Lehman Brothers in the summer of 2008 and Ippolito et al. (2016) focus on the interbank market freeze in the summer of 2007.

where $NewRel_{f,t}$ is a dummy variable that 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 lending relationships and with which types of banks, we also 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 on 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, albeit 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.[23]

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. This could be due to several reasons. For example, firms seeking new stable lending relationships may have a preference of better capitalized banks. In addition, larger banks with better access to capital markets and banks with higher capital ratios may also have more capacity to accommodate the increased demand for credit from the distress banks' borrowers, also considering the influx of deposits towards these banks. Comparing Post 1 and Post 2, we observe in fact that bank capital appears to be relatively more important during the first wave of runs, when deposit outflows from the distressed banks from firms were mainly flowing towards better capitalized banks. Conversely, bank size appears relatively more important during the second wave of runs, when household deposits were flowing towards larger systemically important banks.

The "lost business" to outside banks is quite 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 the cumulative value of loans that these firms received from outside banks during the event window and scale it their total loans from the distressed banks at the start of the event window. We compute the corresponding figure for other banks. As shown in

[23]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.

Figure 6, until the distressed banks problems became public in 2015Q1 the share of lost business to outside banks was similar between distressed and non-distressed banks. This changes sharply in 2015Q1, when the distressed banks' problems became publicly known, and began losing new loan business to outside banks at a substantially faster rate. The gap between the two figures indicates that by the end of the event window the lost business to outside banks was 10 pps larger for the distressed banks, with the majority of this loss already occurring before Post 2, as the distressed banks' single-relationship low-risk firms began applying to outside banks.[24] As further illustrated in Figure 7, nearly all of the distressed banks' lost business during Post 1 is driven by low-risk firms (Panel A).

Credit Relative to Existing Lenders Further in Table 7, we examine how firms' outstanding credit and loan interest rates from the distressed banks change during the event window relative to non-distressed banks for firms with multiple lending relationships. As for the credit lines analysis, we employ DiD specifications at the bank-firm-quarter level:

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

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, 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 with multiple relationships and reflect the changes in outstanding credit and loan interest rates to the *same firm* at the *same time* (Khwaja and Mian, 2008).[25] Figure 8 reports the estimated coefficients and associated 95% confidence intervals for corresponding dynamic DiD specifications.

This analysis yields two key insights. First, in line with the notion that low-risk firms seek to establish new lending relationships once the problems of their banks become known (Detragiache

[24]Note that the figures for both sets of banks have positive slopes as over time their customers will naturally obtain loans from outside banks for a variety of reasons. We compute these figures only for firms with single-relationships, as for multiple-relationship firms it is more challenging to attribute the lost business to any one of the firms' existing lenders. Since multiple-relationship firms are typically larger with larger loans, the estimates in Figure 6 represent a lower bound of the distressed banks' lost business to outside banks.

[25]For completeness, we also report results of less conservative specifications for all firms, replacing $\mu_{f,t}$ with industry×province×size×quarter fixed effects (Degryse, De Jonghe, Jakovljević, Mulier, and Schepens (2019)).

et al., 2000), we find that the reduction in credit from the distressed banks during Post 1 is not accompanied by an increase in loan interest rates for these firms. The latter scenario would have been expected if there was a decrease in credit supply from the distressed banks (i.e, a drop in volume and an increase in price). Instead, as depicted in Panel A of Figure 8, during Post 1, the distressed banks charge lower interest rates to low-risk firms compared to other banks, indicating that, if anything, they were trying to retain their low-risk customers.

Second, as problems emerged and deposit outflows began in Post 1, the distressed banks reduce credit supply to high-risk firms. While credit volume does not significantly decrease until Post 2, loan interest rates to riskier firms begin increasing already in Post 1 (see also Panel B of Figure 8). These findings are in line with prior research indicating that incentives to lend to riskier firms or engage in "zombie lending" to avoid recognition of nonperforming loans and maintain regulatory capital requirements (Caballero, Hoshi, and Kashyap (2008)), decrease when banks face stricter supervisory and public scrutiny (Bonfim et al. (2022)). In addition, as can be observed in Panel B of Figure (8), in the 'pre-period', the distressed banks were not charging lower interest rates to high-risk firms relative to other banks. This suggests that if they were involved in zombie lending during the pre-period, it was not to a greater extent than other banks as zombie lending is typically associated with "unusually cheap" (Caballero et al. (2008)).

Overall, our credit analysis suggests that as soon as the distressed banks' problems became public and they begin experiencing outflows on firm deposits, they also began losing their best corporate clients on the asset-side. We find that low-risk firms with single relationships and firms with more loans maturing within one year begin applying for loans to outside banks. As we show, low-risk firms are able to establish new relationships with larger and better capitalized banks. Despite distressed banks attempting to retain their low-risk clients by offering cheaper loans, credit extended by distressed banks to low-risk firms decreases compared to non-distressed banks. Faced with greater regulatory and public scrutiny, the distressed banks instead appear to reduce credit supply to high-risk firms as soon as their problems become public. These results 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.

4.3 Firm Outcomes: Total Credit & Real Effects

In this section, we study how total credit and real outcomes for firms with greater initial credit dependence on the distressed banks fare over time relative to other firms. Evidence provided earlier shows in fact 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 study how these firms' total credit and real outcomes varied over the event window compared 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 real outcomes (e.g., investment, sales, wage expenses) of firm f in quarter t, and equals 0 otherwise. $SD_{f,2013}$ is a dummy variable that equals 1 if firm was borrowing from the distressed banks in 2013, and equals 0 otherwise. All other variables are defined as before.

The results are reported in Table 8. Panel A reports results for total credit growth and Panel B for investment.[26] The first three columns begin with a baseline specification which compares the growth rate of total credit and investment of firms with higher $SD_{f,2013}$ over the entire event window (i.e., without distinguishing across the different sub-periods). Column (1) reports results for all firms, while columns (2) and (3) distinguish between high-risk and low-risk firms. The next three columns (columns (4)-(6)), report results of corresponding specifications breaking-down the event window into the three sub-periods, as outlined in Eqn. (5).

Overall, we find that adverse credit and real effects are limited and confined to high-risk firms. In particular, starting in column (1) of Panel A, we find that over the entire event window firms with higher $SD_{f,2013}$ do not have systematically lower credit growth. Distinguishing by firm risk in columns (2)-(3), we find that while low-risk firms do not see any decline in total credit, high-risk firms do. The coefficient of $SD_{f,2013}$ is negative and statistically significant at the 10% level, indicating that the total credit of high-risk firms fully dependent on distressed banks ($SD_{f,2013} = 1$) grew by 2 pps less than other high-risk firms.[27] The corresponding coefficient for

[26]Corresponding results for sales and wage growth are reported in Table A3 in the Appendix.

[27]Comparisons within high-risk firms are important as these firms may have lower demand for credit than low-risk firms, which as shown earlier tend to be more profitable and have higher investment rates (Figure 5).

low-risk firms is very close to zero and statistically insignificant (0.007).

Distinguishing between the three sub-periods, reveals that the decline in credit growth for high-risk firms is concentrated in Post 1. The interaction coefficient with Post 1 in column (5) is negative and statistically significant at the 1% level, indicating that the total credit of high-risk firms with $SD_{f,2013} = 1$ grew by 6.1 pps less than other high-risk firms. High-risk firms continue to have lower access to credit also during Post 2 (i.e., the interaction coefficient with Post 2 in column (5) is negative, though not statistically significant). Results for low-risk firms in column (6), show that also low-risk firms saw a decline in credit growth during in Post 1 (-1.9* pps), which turn out be temporary as credit growth recovers in Post 2 (2.6** pps).

Corresponding specifications for investment rate in Panel B Table 8 show that adverse effects are generally small and confined to high-risk firms. In particular, the interaction coefficient with Post 1 in column (5) shows a slow-down in the investment rate of high-risk firms (-0.355* pps), which does not reverse in Post 2. Corresponding results for low-risk firms in column (6) do not show any significant decline in the investment rate. Although the interaction coefficients with Post 1 and Post 2 are negative, they are not statistically significant. Additional results in Appendix Table A3 for sales or wage growth paint a similar picture. We find no economically or statistically significant decline with respect to either firm sales or wages.

Overall, our results indicate that firms with higher initial credit dependence on the distressed banks are able to adequately substitute credit from other banks, especially low-risk firms. Adverse credit or real adverse effects are limited to high-risk firms.

4.4 Spillover Effects on Other Banks' Loan Portfolios

In this section, we explore the potential spillover effects on borrowers of other banks. We aim to understand whether the reallocation of credit towards the distressed banks' borrowers had any adverse effects on the existing borrowers of other banks in the region. Faced with credit capacity constraints (e.g., due to binding capital constraints), the influx of new low-risk borrowers from the distressed banks may crowd out their own high-risk borrowers.

To investigate the potential spillover effects of the larger and better borrower pool on the other banks' borrowers, we calculate the share of loan applications that each bank receives from distressed banks' borrowers as a fraction of the total applications they received in a given period:

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

where $DistBorrAppl_{b,t}$ indicates the number of loan applications to bank b in period t from the distressed banks' borrowers, where bank b includes any other bank in the region, except for the distressed banks. The variable $TotalAppl_{b,t}$ indicates the total number of loan applications to bank b in period t from new customers.[28] 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 period 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 absorb unobserved heterogeneity, we include both industry×province×quarter and bank×quarter fixed-effects, $\alpha_{k,p,t}$ and $\alpha_{b,t}$, respectively.

Results are reported in Table 9. In column (1), we estimate Eqn. (9) without bank×quarter fixed-effects, allowing for the inclusion of $Exp_{b,t}$. 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 distinguishing 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 remains robust to the inclusion of bank×quarter fixed effects in column (3).

To 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.[29] 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 ratios. This result is consistent

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

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

with the idea that the influx of new low-risk borrowers may have allowed these banks to improve their loan portfolios, crowding out their riskier customers and improving their capital ratios. These results provide valuable insights into the dynamics of credit reallocation during periods of bank distress and the consequences for different types of borrowers and banks.

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.

Focusing on the period leading-up to the failure of two regional banking groups in Italy in 2017, we investigate the behavior of the distressed banks' corporate clients on both sides of the banks' balance sheet during the unfolding distress. Our analysis utilizes granular credit registry and loan application data from the Bank of Italy, supplemented by deposit volume data and financial statements. The timeline of the banks' distress is characterized by two critical events: the revelation of accounting frauds in early 2015, which triggered an initial wave of deposit outflows from firms, and the ECB's SREP report, revealing larger capital deficiencies in late 2015, causing a second, much larger wave of deposit outflows from both firms and households.

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 better-capitalized 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.

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, indicating minimal negative credit and real effects, 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. When the bank problems are largely idiosyncratic, high-quality borrowers are able to secure new lending relationships with healthy banks without suffering significant adverse credit or real effects.[30] While these forces may be destabilizing for the distressed banks, they are beneficial to the overall stability of the banking system by facilitating a more efficient credit allocation.

[30] 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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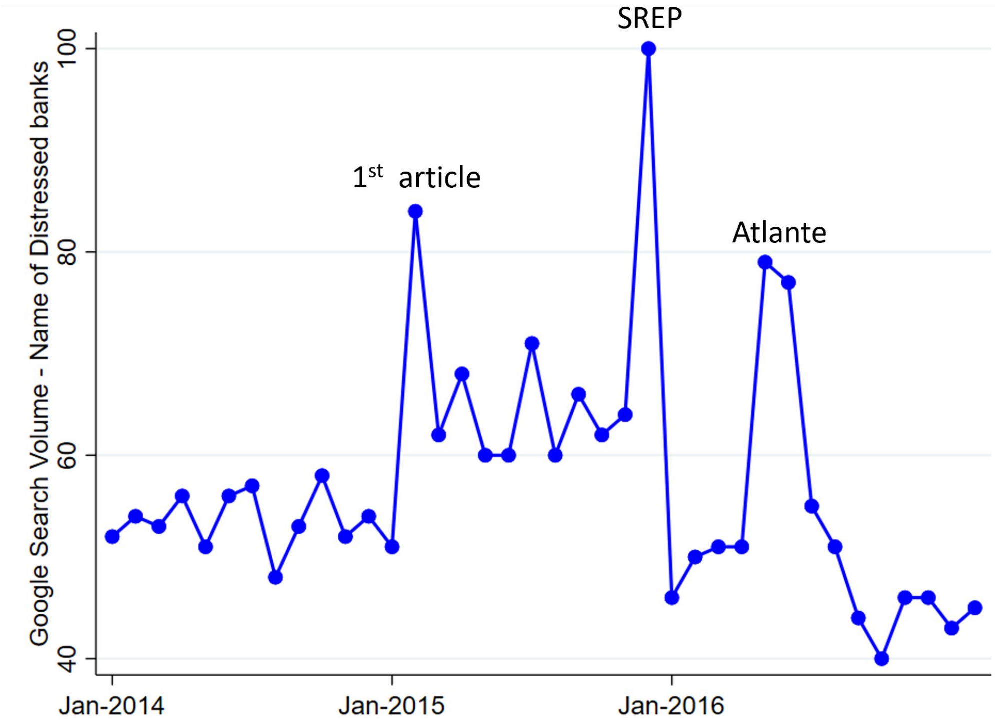
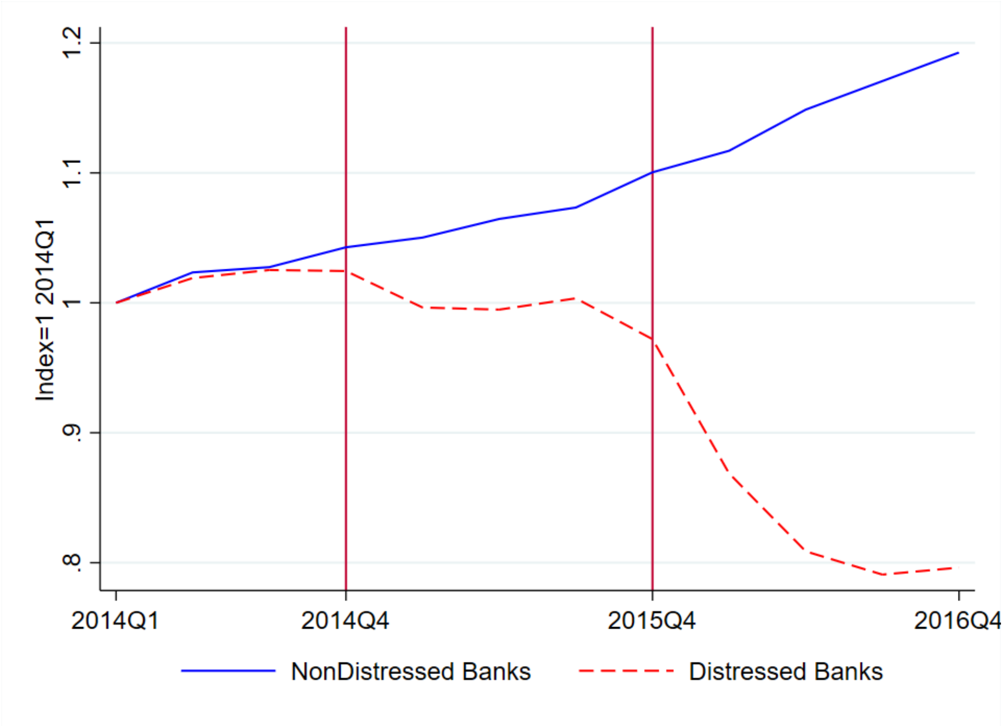
Figure 1: Google Trends



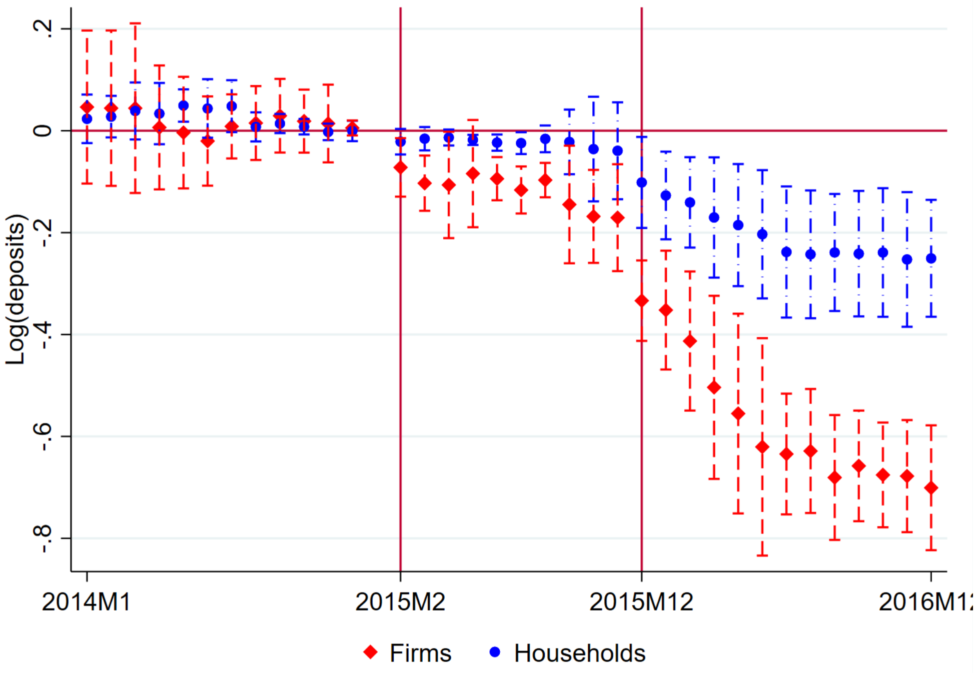
This figure shows the Google searches for the name of the distressed banks between January 2014 and February 2017. Numbers represent search interest relative to a time period, with 100 indicating the peak number of searches during the event period. "1^{st} article" refers to the February 2015 article published in the Italian financial press containing interview with former bank employees about loans-for-share schemes; "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" 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 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 (February 2015) and Post 2 (2015Q4) periods.

Figure 3: Dynamic DiD: Firm vs. Household Deposits

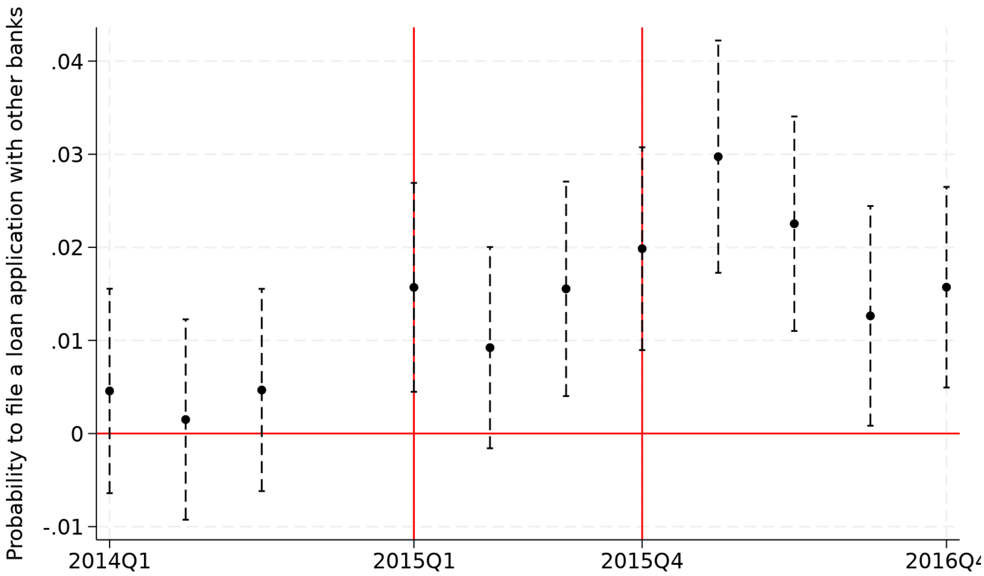


This figure plots the β_t coefficients and 95% confidence intervals from the following dynamic DiD specifications at the bank-month:

$$\text{Log(Dep)}_{b,t} = \sum_{t=2014M2}^{2016M12} \beta_t I(t) \times D_b + \alpha_b + \alpha_t + \epsilon_{b,t},$$

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



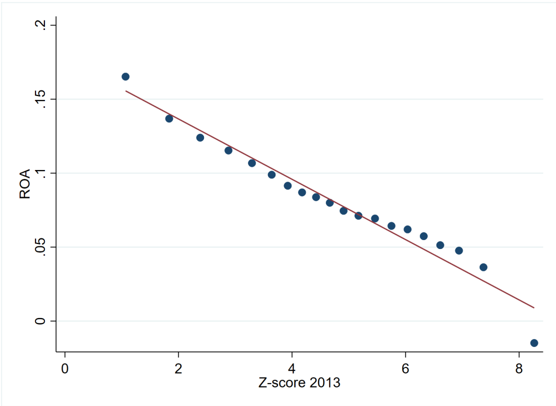
This figure plots the β_t coefficients and associated 95% confidence interval for the following equation:

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

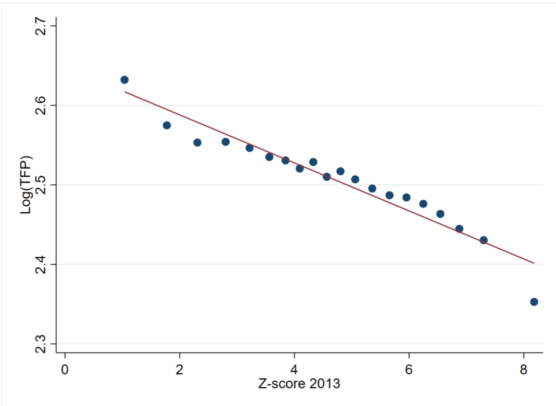
where $\text{ApplOut}_{f,t}$ is a dummy equal to one if firm f applies to an 'outside banks' with which the firm has no previous relationship (i.e., first-time borrowers). $SD_{f,2013}$ is the share of credit of firm f from distressed banks in 2013 and it is equal to zero if the firm was not borrowing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

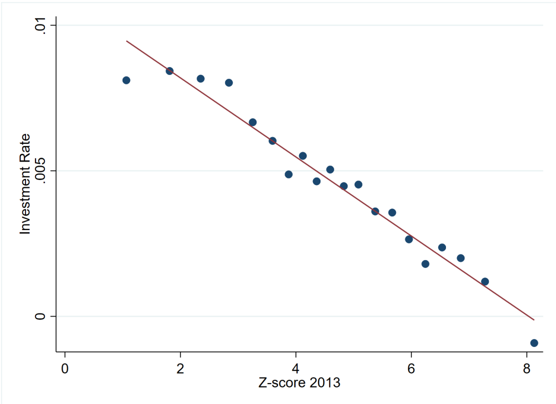
A. Firm Profitability & Credit-Risk



B. Total Factor Productivity & Credit-Risk

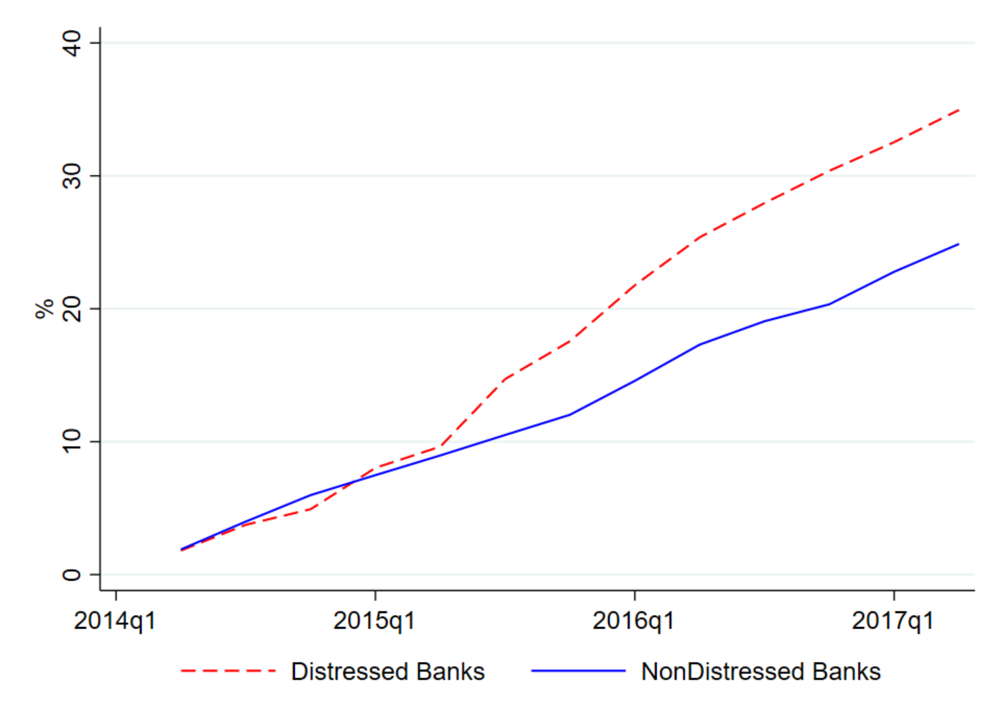


C. Investment Rate & Credit-Risk



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.

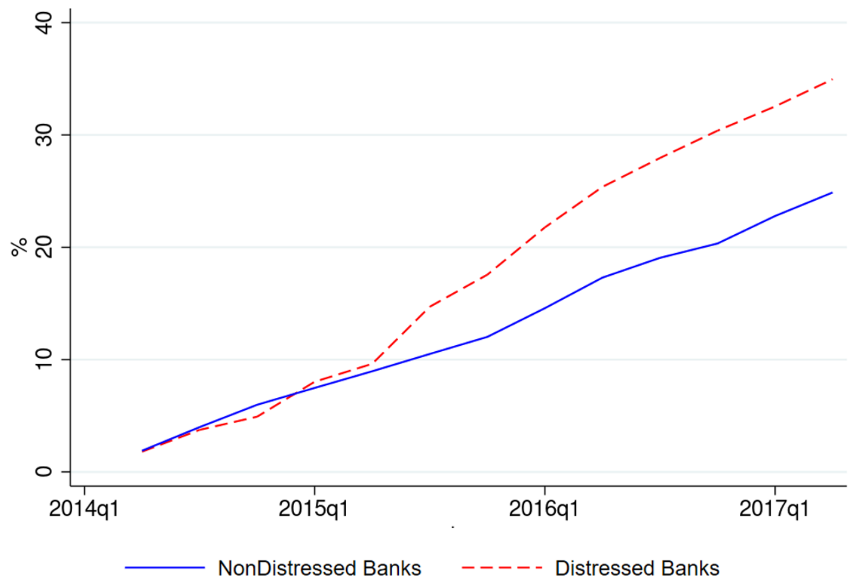
Figure 6: Lost 'Loan Business' to Outside Banks



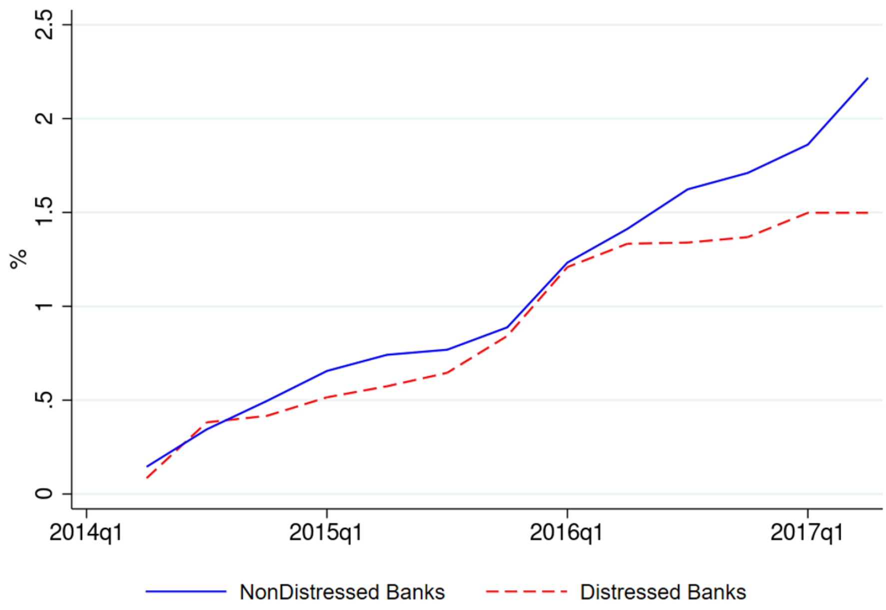
This figure plots the cumulative values of loans that single-relationship firms of the distressed (non-distressed) banks received from outside banks during the event window (2014Q1-2016Q4) as a fraction of their total loans from the distressed (non-distressed) banks at the start of the event window.

Figure 7: Lost 'Loan Business' to Outside Banks

A. Low-Risk Firms



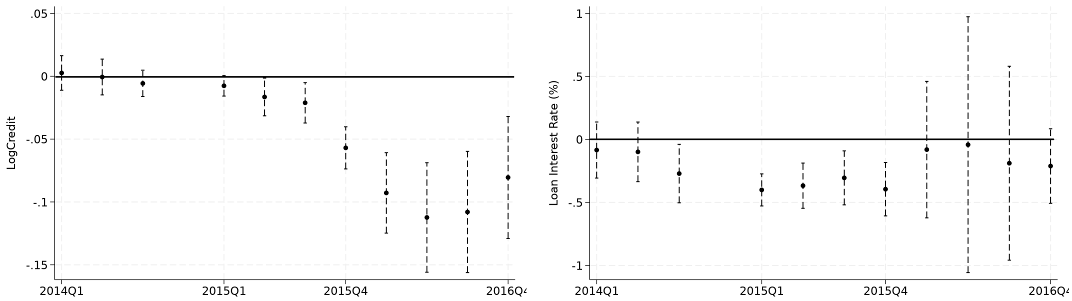
B. High-Risk Firms



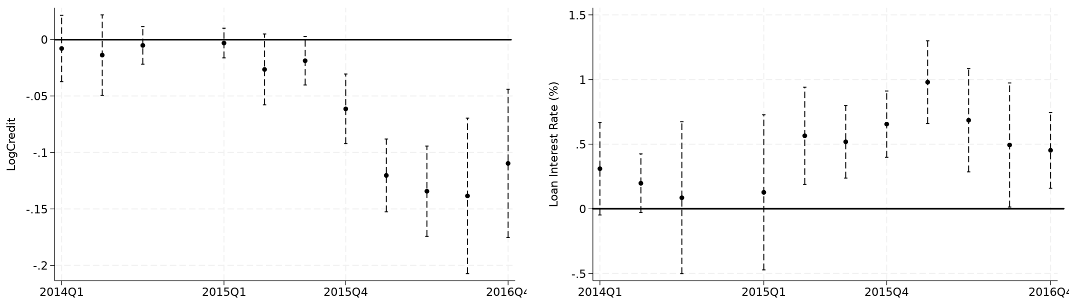
This figure plots the cumulative value of loans that single-relationship firms of the distressed (non-distressed) banks received from outside banks during the event window (2014Q1-2016Q4) as a fraction of their total loans from the distressed (non-distressed) banks at the start of the event window. Panels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

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

A. Low-Risk Firms



B. High-Risk Firms



This figure plots the estimated coefficients and associate 95% confidence intervals of corresponding dynamic specifications of Eqn. (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

	Panel A. Bank characteristics as of 2013Q4					
	Obs.	Mean	St. Dev.	Median	5th pct.	95th pct.
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
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
Rel. with DBs=1	160,425	0.061	0.239	0	0	1
Rel. with DBs=0	473,435	0.041	0.197	0	0	1
New Relationship	25,436	0.273	0.445	0	0	1
Rel. with DBs=1	8,478	0.293	0.455	0	0	1
Rel. with DBs=0	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 (1)	Firms (2)	Households (3)
$D_b \times$Post 1	-0.068**	-0.132***	-0.045
	(0.030)	(0.041)	(0.029)
$D_b \times$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	0.999	0.994	0.997
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	0.116**						
	(2.39)						
$\text{HS}_{p,2013}$ × Post 2	0.219***						
	(2.87)						
$\text{HS}_{p,2013}$ × Post 1 × $\text{HighCapital}_{b,2013}$		0.318***		0.323***	-0.153		-0.077
		2.99)		(2.99)	(-1.64)		(-0.85)
$\text{HS}_{p,2013}$ × Post 2 × $\text{HighCapital}_{b,2013}$		0.257		0.243	-0.181		-0.113
		(1.63)		(1.51)	(-1.45)		(-0.91)
$\text{HS}_{p,2013}$ × Post 1 × $\text{LargeBank}_{b,2013}$			-0.104*	0.027		0.359***	0.431***
			(-1.97)	(0.60)		(2.69)	(3.58)
$\text{HS}_{p,2013}$ × Post 2 × $\text{LargeBank}_{b,2013}$			-0.197**	-0.084		0.311**	0.376***
			(-2.32)	(-0.98)		(2.47)	(3.14)
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	195,010	195,010	195,010	195,010	172,453	172,453	172,453
R-squared	0.475	0.480	0.480	0.480	0.438	0.438	0.438

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: Firm Characteristics Balance

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

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

Table 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)							
$SD_{f,2013}$ × 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)
$SD_{f,2013}$ × 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 × Province × Size × Year-Quarter	Yes		Yes	Yes	Yes	Yes	Yes	Yes
CreditScore × Year-Quarter	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. (3). The unit of observation is at the firm-quarter level, and the sample period is 2014Q1-2016Q4. The dependent variable is $ApplOut_{f,t}$, a dummy = 1 if firm f applies to an outside bank in quarter t, and =0 otherwise. $SD_{f,2013}$ is the share of firm's f total credit from the distressed banks in 2013 (this variable = 0 if the firm was not borrowing from distressed banks in 2013). Post 1 is a dummy equal to one between 2015Q1 and 2015Q3, Post 2 is a dummy equal to one between 2015Q4 and 2016Q4. Lagged firm-controls include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. Credit score dummies, which range from 1 (safest) to 9 (riskiest), are interacted with the year-quarter indicator. Firms with a credit score <7 are classified as "Low-Risk". Conversely, firms with a credit score $\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
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. (4). 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. (4) for all firms. Columns (2) and (3) report results for "Low-Risk" (z-score < 7) and "High-Risk" (z-score ≥ 7) firms separately. columns (4) and (5) distinguish banks with respect to bank capital $\text{HighCapital}_{b,2013}$, a dummy variable that = 1 if the bank had an above the median capital ratio in 2013, and = 0 otherwise. Columns (6) and (7) distinguish banks with respect to bank capital using $\text{LargeBank}_{b,2013}$ is a dummy variable that = 1 if the bank had total assets above €100 billion in 2013 (i.e., if it was one of the top five banks in the country), and = 0 otherwise. Standard errors are clustered at the firm level.

Table 7: Credit volume and Loan Interest Rates

			Low-Risk		High-Risk	
	All (1)	Only multiple (2)	All (3)	Only multiple (4)	All (5)	Only multiple (6)
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)
Fixed Effects						
Bank	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Province×Size×Time	Yes	No	Yes	No	Yes	No
Firm×Time	No	Yes	No	Yes	No	Yes
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
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×Province×Size×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. (5). 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 reports results on the effects of bank distress on on total credit and investment. 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.

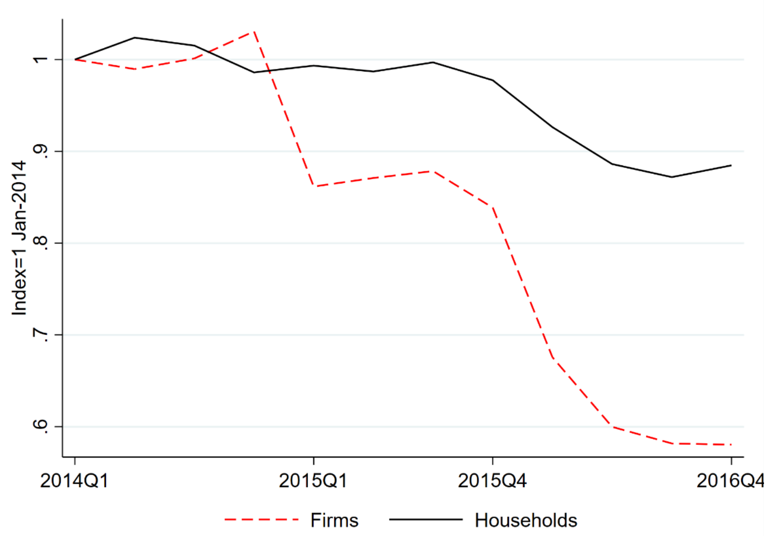
Table 9: Credit Spillovers Effects on Other Banks in the Region

	(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. (5). 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.

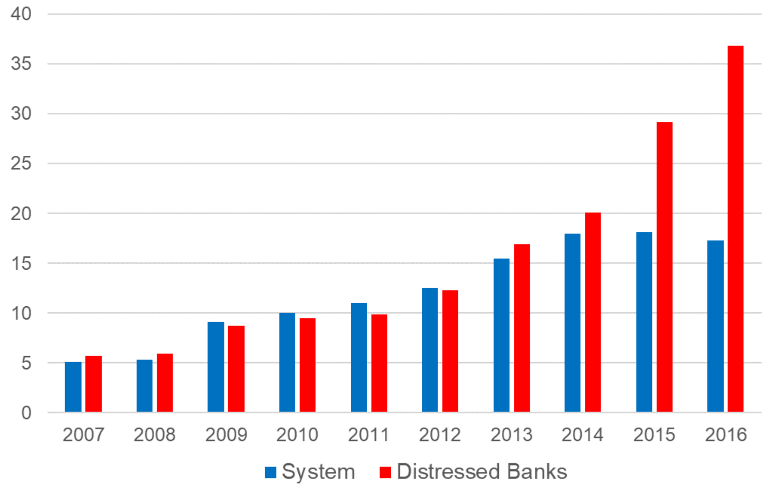
Appendix

Figure A1: Distressed Banks: Firm vs. Household Deposits



This figure shows the evolution of firm and household deposits of the distressed banks between 2014Q1 and 2016Q4. All series are normalized to 1 as of 2014Q1.

Figure A2: NPL over Loans ratio: Distressed Banks vs. System



This figure shows the evolution of the NPL to total loans ratio of the distressed banks vs. all Italian banks between 2009 and 2016.

Table A1: 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.

Table A2: Credit Line Drawdowns

	Share of Credit Lines Drawn					
	All Borrowers		Low-Risk		High-Risk	
	All	Only multiple	All	Only multiple	All	Only multiple
	(1)	(2)	(3)	(4)	(5)	(6)
D_b×Post 1	-0.003	-0.001	-0.004	-0.002*	0.006	0.003
	(0.003)	(0.001)	(0.003)	(0.001)	(0.004)	(0.004)
D_b×Post 2	-0.009**	-0.001	-0.004	0.001	-0.001	0.001
	(0.004)	(0.004)	(0.003)	(0.003)	(0.009)	(0.011)
Fixed Effects						
Bank	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Province×Size×Time	Yes	No	Yes	No	Yes	No
Firm×Time	No	Yes	No	Yes	No	Yes
Observations	1,184,318	969,992	926,316	765,639	257,458	204,353
R-squared	0.0776	0.0855	0.0873	0.0810	0.0874	0.0896

This table provides the estimates for Eqn. (4). 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 A3: Firm outcomes: Firm Sales & Wage Growth

	A. Sales Growth					
	All	High-Risk	Low-Risk	All	High-Risk	Low-Risk
	(1)	(2)	(3)	(4)	(5)	(6)
$SD_{f,2013}$	0.003	0.005	0.001			
	(0.95)	(0.56)	(0.23)			
$SD_{f,2013}$ × Pre				0.002	0.004	-0.002
				(0.33)	(0.29)	(-0.35)
$SD_{f,2013}$ × Post 1				0.002	0.009	-0.001
				(0.34)	(0.62)	(-0.20)
$SD_{f,2013}$ × Post 2				0.007	0.001	0.007
				(1.08)	(0.04)	(1.11)
Fixed-effects						
Province×Industry×Year	Yes	Yes	Yes	Yes	Yes	Yes
I(CreditScore)×Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135,212	31,603	103,325	135,212	31,603	103,325
R-square	0.079	0.149	0.070	0.079	0.149	0.070

	B. Wage Growth					
	All	High-Risk	Low-Risk	All	High-Risk	Low-Risk
	(1)	(2)	(3)	(4)	(5)	(6)
$SD_{f,2013}$	0.004	-0.002	0.005			
	(1.13)	(-0.21)	(1.19)			
$SD_{f,2013}$ × Pre				0.002	-0.014	0.008
				(0.34)	(-0.89)	(1.21)
$SD_{f,2013}$ × Post 1				0.004	0.007	0.001
				(0.73)	(0.46)	(0.21)
$SD_{f,2013}$ × Post 2				0.007	0.006	0.005
				(1.13)	(0.40)	(0.75)
Fixed-effects						
Province×Industry×Year	Yes	Yes	Yes	Yes	Yes	Yes
I(CreditScore)×Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	123,300	27,623	95,371	123,300	27,623	95,371
R-square	0.07	0.123	0.062	0.07	0.123	0.062

This table reports results on the effects of bank distress on firm sales and wage growth. 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 firm sales, while and in Panel B it is the annual growth rate of wages. $SD_{f,2013}$ 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.