Corporate Runs and Credit Reallocation

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Abstract

Focusing on the period before the failure of two regional banks in Italy in 2017, we study the behavior of their corporate clients on both sides of the bank balance sheet - deposits and loans. We find that deposit outflows from firms begin as soon as banks' distress becomes public and before households. Firms run simultaneously on the asset-side, applying for credit and establishing new lending relationships with larger and better capitalized banks. Low-risk firms are the first to go, endogenously eroding the banks' loan portfolio in the period leading up to widespread deposit runs and their eventual collapse. Importantly, in the absence of a systemic crisis, the negative effects on the distressed banks' borrowers are limited, with runs carrying significant positive spillover effects on other banks in the region.

Keywords: bank runs; bank failures; loan applications; cleansing effect of crises
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1. Introduction

Bank failures resulting from bank runs can have far-reaching economic and social costs, eroding public trust in the banking system and triggering declines in credit supply and overall economic activity (Bernanke, 1983; Calomiris and Mason, 2003). Complementing the extensive theoretical literature on this subject, the empirical literature has explored when and how runs occur, which factors affect depositors' incentives to run and how contagion spreads to other banks (see, among others, Iyer and Puri, 2012; Martin, Puri and Ufier, 2022; Iyer, Puri and Ryan, 2016).

While much is known about runs on the liability side, the dynamics of the asset side during financial distress have received considerably less attention. Changes in the composition of distressed banks' loan portfolios may interact and exacerbate depositor runs, further intensifying the distress and leaving regulators with limited options beyond shutting down the bank. The endogenous nature of such changes in banks' loan portfolio can have significant consequences, impacting both the financial health of the distressed banks and 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 have reignited this discussion. Unlike previous banking crises, the failure of midsized regional banks in the U.S. saw large and rapid runs from non-financial corporations. Corporations can significantly impact bank stability for two primary reasons. First, corporate deposits are substantial, accounting for 25% of total deposits in Europe. Since these deposits are larger and largely uninsured, they are also likely to be more responsive to news about their banks' health. Due to digitalization and the growing influence of social media, their runs can occur more rapidly than in the past (Cookson et al., 2023; Rose, 2023). Second, since corporations are also borrowers, their withdrawal of deposits implies a potential simultaneous relocation of their business loans, jeopardizing the banks' viability.[1]

In this paper, we zoom into the period leading up to the failure of two regional banking groups (consisting of 6 individual banks) in Italy in 2017. Our aim is to shed light on the behaviour of their corporate clients on both sides of these banks' balance sheets during the unfolding bank distress. We analyze their actions from the first public signals of financial distress until the final supervisory action declaring the banks as "likely to fail". We track their movements on both sides

[1] Applying and receiving credit from other banks does not necessarily imply that they terminate their relationships with distressed banks by repaying loans in advance but rather that they secure alternative sources of credit and new lending relationships should funding from distressed banks dry-up in the future.

of the balance sheet (i.e., deposit flows and loan applications to other banks) and study their impact on the distressed banks' loan portfolios and spillover effects on other banks in the region.

We find that deposit outflows from firms begin before households as soon as banks' distress becomes public. Firms run simultaneously on the asset-side of the balance-sheet, applying for loans and establishing new lending relationships with larger and better capitalized banks. Low-risk firms (and single-relationship firms) are the first to "go", endogenously eroding the banks' loan portfolio in the period leading up to widespread deposit runs and the banks' collapse.[2] These firms have stronger incentives to secure new stable lending relationships, given the higher likelihood and costs of future credit disruptions (Detragiache, Garella, and Guiso, 2000).[3] As we show, these forces also generate important positive spillover effects on other banks.

The 2017 failure of these Italian regional banks provides an ideal setting for empirical investigation. First, the origin of distress was idiosyncratic, unrelated to a broader systemic financial crisis, enabling us to isolate its impact on borrowers' behaviour. 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 and the local economy. Approximately, one-quarter of firms in the region had an active lending relationship with them when the distress began.

Our analysis relies on granular credit registry and loan application data from the Bank of Italy, supplemented by deposit volume data at the bank-province level, firms' financial statements from Cerved, and bank balance sheet data from supervisory reports. The timeline of the banks' distress is characterized by two pivotal events. The first event unfolded in early 2015 when articles in the Italian financial press, featuring interviews with former bank employees, exposed improper accounting practices at the two banking groups (we use banking groups and banks interchangeably in what follows), aimed at inflating their regulatory capital. This event garnered significant public attention and triggered deposit runs before formal supervisory intervention. The second event, occurring at the end of 2015, involved the ECB's Single Supervisory Mechanism (SSM) declaring the banks undercapitalized and unable to raise the required capital, leading to larger 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 firm deposits started declining as soon as information about the banks' impending distress became public in early 2015. In contrast, households only responded

[2] 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, 2022).

[3] This is also consistent with the idea that borrowers seeking to leave a failing bank are less adversely selected and thus have a higher chance of receiving credit at other banks (Dell'Ariccia and Marquez, 2004; Darmouni, 2020).

during the second distress event and with less intensity. Over the entire period, the banks lost about 20% of their deposits, over 40% of their firm deposits, and 15% of their household deposits.

We then explore the deposit *inflows* at other, non-distressed banks. In regions where the distressed banks held a larger share of firm deposits, other banks experienced more significant increases in firm deposits. These analyses rely within-bank-time variation, leveraging the granularity of the deposit data at the bank-province level. Notably, firms and households exhibit distinct behaviors, not only in terms of the timing and intensity of their withdrawals, but also in their choice of new banks. Firms turn to better capitalized banks, even if they are relatively small. In contrast, households do not seem to prioritize bank soundness; instead, they seek safety in large, systemically important banks, in line with results from Iyer et al. (2019) and Acharya et al. (2022).

On the credit side, shortly after the first distress event, low-risk firms in single lending relationships began applying for loans to 'outside' banks, primarily establishing new lending relationships with larger and better capitalized banks. 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. The distressed banks' inability to retain their best corporate customers on both sides of their balance sheet during the first stress period adversely impacted their viability by deteriorating their loan portfolio. Based on our estimates, the "lost loan business" to outside banks accounted for approximately 10% of the banks' initial loan portfolio, with the majority of which occurring shortly after the first stress event.

Overall, our findings suggest that as news about the banks' impending distress surfaced, low-risk firms with single lending relationships may have started seeking new stable lending relationships to ensure uninterrupted credit supply and operations, in line with predictions from Detragiache, Garella, and Guiso (2000). This interpretation is supported by additional within-borrower analysis (Khwaja and Mian, 2008), which indicates that the initial decrease in credit from the distressed banks is not accompanied by increases in loan interest rates, which would have been more indicative of a decrease in credit supply from the distressed banks.

The influx of new low-risk borrowers from the distressed banks had significant positive spillover effects on other banks. Banks receiving a greater number of loan applications from the distressed banks' borrowers reduced credit to their existing high-risk borrowers. This result was more pronounced for banks' facing greater capacity constraints (i.e., banks with ex-ante lower capital ratios). The influx of low-risk borrowers from the distressed banks allowed these banks to "cleanse" their loan portfolios, crowding-out riskier borrowers, and improving their capital ratios.

In a final set of tests, we find that the transition of firms from the distressed banks to other lenders was not accompanied by adverse effects on credit or other real outcomes. While total credit

from the distressed banks decreased by about 30% between 2014 and 2016, their total credit from other banks increased, leaving their total credit unchanged. Micro-level estimates confirmed that, overall, borrowers of distressed banks did not lose access to credit, with the exception of a temporary decline in 2015, primarily affecting high-risk firms. Given the limited impact on credit, we also observed minimal to no effects on real outcomes, such as investment, sales and wage growth, which remained similar to other borrowers. Overall, our results indicate that absent a systemic banking crisis, the negative effects on the distressed banks' borrowers are fairly limited.

Our paper offers valuable new 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 (e.g., Iyer and Puri, 2012, Iyer et al., 2016, Martin, Puri and Ufier, 2022, Artavanis et al., 2019, Blickle et al., 2022, Acharya et al., 2022). This body of work finds that in the face of uncertainty 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 or publicly-owned banks).[4]

Our results further reveal that firms run ahead of households and do so simultaneously on the asset-side, establishing new lending relationships with larger and better capitalized banks. Low-risk firms in single-lending relationships are the first to go, endogenously deteriorating the banks' loan portfolio in the critical period leading up to larger widespread runs and the banks' collapse.[5] Our results show that this process of endogenous deterioration from firm runs on both sides of the banks' balance sheet begins as soon as the banks' distress becomes known, long before formal supervisory intervention. This novel result has important policy implications on the timing and type of interventions by prudential authorities, especially in light of the impact of digitalization and social media on the speed and intensity of runs (Cookson et al., 2023; Rose, 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 et al., 2021; Gropp et al. 2022; Goncharenko et al., 2022). Unlike these studies, which focus primarily on crisis periods, when problems in the banking sector are widespread, we find that adverse effects on the distressed banks' borrowers are small and limited to risky firms. Similarly, we do not observe abnormal credit line drawdowns at the distressed banks, in contrast to studies focusing on crisis periods (e.g., Ivashina

[4] 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, 2022).

[5] This mirrors findings in corporate finance literature where high-skilled workers leave firms experiencing financial distress (Baghai et al., 2021; Hoffmann and Vladimirov, 2023).

and Scharfstein, 2010; Ippolito et al., 2016; Chodorow-Reich et al., 2022). When the banks' liquidity problems are idiosyncratic, firms may be more inclined to establish new relationships with stable banks instead of running up their credit lines with the distressed banks.[6] As we show, the runs we document, tigger important positive spillover effects in other banks in the region.

The remainder of the paper is organized as follows. Section 2 offers an overview and timeline of the bank distress events. Section 3 describes the data. Section 4 reports and discusses our findings, and Section 5 concludes.

2. Timeline of bank distress

The distressed banks under examination in this paper, while small-to-medium in size on a national scale, were important regional players in Northern Italy. Their distress stemmed from idiosyncratic factors, primarily linked to governance issues, occurring during a period when the local economy was outperforming the national average. For example, throughout the sample period, the growth rate of the region's GDP was 1.7%, nearly double the 1% GDP growth rate at the national level.

In this section, we provide a chronological account of the events that ultimately led to their failure. The first indications of distress in the banks became apparent in November 2014 when the ECB-SSM Comprehensive Assessment revealed a minor capital shortfall in both institutions. At the time, it seemed that the banks could address the shortfall adequately. However, around two and a half months later, in mid-February 2015, an article surfaced in the Italian financial press, unveiling that the distressed banks had been involved in "loan-for-share" schemes since 2012. Under these schemes, clients seeking loans were asked to purchase bank shares.

Although this practice is not illegal, the shares acquired through this process had to be excluded from regulatory capital calculations due to inadequate loss-absorption capacity. This article marked the first public disclosure of their impending distress, leading to a significant surge in public attention, as evidenced by the sharp increase in Google searches for the banks' names (Figure 1). The article raised concerns about the two banks' financial stability and signalled the beginning of a period of heightened scrutiny and uncertainty surrounding their viability.

(Insert Figure 1 about here)

Over the following two months, the situation escalated further with the release of two additional articles in the press. These articles shed light on the distressed banks' practices of

[6] In such cases, running up their credit lines with their existing distressed lenders may not be desirable as high credit line usage is often associated with poor credit quality (Chodorow-Reich et al., 2022).

extending loans to "close" customers without conducting proper creditworthiness screenings since 2012. In addition, the articles further revealed that the banks had capital shortfalls relative to the minimum required levels. Shortly after their publication, the stock price of the distressed banks, which were not listed, was devaluated by about 23% by their respective boards.

Between August and September 2015, a series of new articles in the press, along with the preliminary findings from the ECB's Supervisory Review (SREP), brought to light further distressing news. It was discovered that the loan-for-share practice, which had been more widespread than initially believed, had resulted in 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 evident that banks' only chance of survival was to raise fresh capital. Google searches of the banks' names surged again markedly in this period (see second spike in Figure 1).

In response to the escalating crisis, the distressed banks proposed a recapitalization plan to raise the required capital (€2.5 billion) through a listing on the Italian stock exchange in early 2016. However, due to their disappointing results in 2015 and lack of confidence in their credibility, investors did not to participate in the capital increase. Left with no other option, in the first half of 2017, the ECB declared the banks as "failing" or "likely to fail". Subsequently, the banks underwent liquidation and were eventually acquired by another bank.

Overall, the distress faced by the banks in our study can be attributed to a combination of lax lending standards and flawed governance practices. These factors resulted in loss of confidence in their viability, ultimately leading to their downfall. In our empirical analysis, we zoom into the period leading up to their eventual failure to understand the behaviour of the banks' corporate clients as bank distress unfolded.

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 supervisory reports. The second dataset includes detailed bank-firm credit data from the Italian Credit Register ("Centrale dei Rischi"). 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 they were declared non-viable by the ECB.

The data on deposits are reported on a monthly frequency and are available by type of counterparty (households or firms) and province of residence. This data is available for

approximately 500 banking groups across 106 Italian provinces.[7] For our empirical analysis, we exclude from the sample bank-province pairs with less than €1 million in total deposits.[8]

The Italian credit register contains credit information for borrowers with total outstanding loans with a single intermediary in excess of €30,000. It includes data on credit volumes, credit line drawdowns, interest rates, and loan applications at the bank-firm level. For additional information, we merge the credit registry data with: i) annual balance sheet data on non-financial firms from Cerved, which provides insights into firms' investment, wage expenses, sales, and probability of default based on the Altman z-score; and ii) annual data on individual and consolidated bank balance sheets from the Italian Supervisory Reports of the Bank of Italy.

In regard to credit volumes, the registry tracks the amount of credit granted from each bank to each borrower on a monthly basis, differentiating between loan types such as credit lines and term loans, distinguishing between short-term and long-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. 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). The distressed banks, though small-to-medium size on a national scale, were regionally important, providing loans to about 26% of the firms in the region.

The subsection "Richiesta di credito" in the credit registry contains data on information requests made by banks following loan applications from new 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.

The subsection "Taxia" of the credit registry includes quarterly data on loan interest rates for a subgroup of approximately 90 banks, accounting for over 80% of aggregate credit. These interest rates are calculated as the ratio of interest payments to the average outstanding loan amount and are available by type of loan (see Gobbi and Sette, 2015; Crawford et al., 2018).

In Table 1, we present descriptive statistics for our sample. Panel A provides an overview of bank characteristics at the start of the sample period. The sample comprises 480 banks, with an average total asset size of approximately €6 billion and an average capital ratio of 12.5%. Deposits

[7] 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).
[8] Data by account size are only available with less granularity (i.e., at the bank-level and annual frequency).

from both households and firms collectively represent 42% of total assets, with non-financial firms contributing around 25% of total deposits. The share of deposits is considerably smaller than in the US, where core deposits typically constitute about 80% of total assets. This difference is due to bank bonds, which in Italy, represent about 22.5% of total assets (see Carletti et al., 2021).

(Insert Table 1 about here)

Panel B offers an overview of key firm characteristics at the end of 2013. On average, firms in the sample have total assets and sales of nearly €4 million, with an average age of 17 years and an EBITDA to asset ratio of 7%. The Altman Z-score, which ranges from 1 to 9 with higher values indicating higher credit risk, averages at almost 5 for the sample firms. About 27.9% of firms are classified as "high risk" with Altman Z-scores greater than 7 (Rodano et al., 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 of approximately 44%.

Panel C provides summary statistics on bank credit at the bank-firm-quarter level. The average probability of applying for a loan to an 'outside bank' over 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 for credit, the average probability that a new relationship is formed is approximately 27%, with distressed banks' borrowers exhibiting a higher switching rate at 29.3%, relative to 26.2% for borrowers of non-distressed banks.

Finally, Panel D reports summary statistics for changes in total firm credit and other real outcomes at the firm-level over the event window (i.e., between 2014Q1 and 2016Q4). We observe that firms experienced a 2.2% decline in total bank credit, in line with the national average and trends in European periphery countries (see also Figure A1 in the Internet Appendix). Additionally, we observe an increase in the firm investment rate, sales, and wage expenses of 5.1%, 1.2%, and 2.5%, respectively. All variables exhibit substantial time-series and cross-sectional variation.

4. Results

4.1. Depositor runs and deposit reallocation

The combination of adverse media coverage, revelations of lenient lending practices, and capital shortfalls generated uncertainty and eroded confidence, leading to depositor runs.

Figure 2 provides a visual illustration of how deposits at the distressed banks evolved during this period. Panel A compares the deposits of distressed banks to non-distressed banks in the region.

Panel B distinguishes between household and firm deposits at the distressed banks. To facilitate comparison, all values are normalized to 1 as of 2014Q1, the beginning of the event window.

(Insert Figure 2 about here)

Panel A of Figure 2 shows that the total deposits of the distressed banks, which had been increasing at the same rate as other banks until the end of 2014, began to diverge in 2015Q1, when their financial distress first became public information. Distinguishing between firm and household deposits in Panel B reveals that the decline in deposits in 2015Q1 was primarily driven by firms, who between 2015Q1 and 2015Q4 withdrew approximately 15% of their deposits.

After the initial outflows in 2015Q1, it appeared that deposits were stabilizing. However, a new wave of widespread deposit outflows began in 2015Q4, after news articles and the SREP report exposed the greater extent of their capital shortfalls. During this period, deposit outflows by both firms and households began accelerating. Over the entire period, the distressed banks lost about 20% of their total deposits, more than 40% of their deposits from firms, and 15% of their deposits from households. Non-distressed banks in the region saw instead a notable increase in their deposits, especially during the second wave of widespread runs at the distressed banks.

Overall, Figure 2 indicates that firms began running on deposits before households, as soon as the banks' financial distress became public in February 2015. Larger runs by both households and firms followed nearly a year later. In what follows, we confirm these insights from Figure 2 using regression analysis controlling for bank and time-fixed effects and study the characteristics of the banks that were able to captured these deposits. For these analyses, we distinguish the "distress period" into two broad sub-periods delineated by the vertical lines in Figures 1 and 2. In particular, we begin by estimating the following baseline specification at the bank-month level:

$$Log(Deposits)_{b,t} = \beta_1 D_b \times Post\ 1_t + \beta_2 D_b \times Post\ 2_t + \alpha_t + \alpha_b + \varepsilon_{b,t}, \qquad (1)$$

where $Log(Deposits)_{b,t}$ denotes the log of total deposits at bank b in month t. The variable D_b takes the value of one if bank b is one of the distressed banks, and 0 otherwise. The two dummy variables, $Post\ 1_t$ and $Post\ 2_t$, split the 'distress period' in two sub-periods.[9] The first sub-period starts in February 2015 (i.e., when the banks' problems first became public) and ends in November 2015. 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 first became public information). The coefficients, β_1 and β_2, indicate how the deposits of the distressed banks' change differently from the non-distressed banks in $Post\ 1_t$ and $Post\ 2_t$ compared to the omitted

[9] In robustness tests, we confirm the timing of the two sub-periods using corresponding dynamic DiD specifications.

period. To control for possible confounding factors, Eqn. (1) includes both bank and time-fixed effects, α_b and α_t. 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.

The results are reported in Panel A of Table 2. During $Post\ 1_t$ and $Post\ 2_t$, the distressed banks began experiencing larger deposits outflows than other non-distressed banks in the region by 6.1% and 34.1%, respectively. When we distinguish between households and firms, we find that deposit outflows in $Post\ 1_t$ are driven primarily by firms, leading to an 11.9% decline in firm deposits. The decrease in household deposits is smaller and statistically insignificant. In $Post\ 2_t$, households also begin to run, but again less intensively than firms (22.7% vs. 58.2%).

In robustness tests, we also estimate corresponding dynamic DiD specifications by replacing $Post\ 1_t$ and $Post\ 2_t$ with monthly dummy variables to inspect the full dynamics of deposits during the event window. The estimated coefficients and their associated 95% confidence intervals are reported in Internet Appendix Figure A2. This analysis shows that until February 2015, the deposits of the distressed banks move in parallel with other banks and confirms the timing of the two distinct periods of instability, captured by $Post_1$ and $Post_2$, respectively.

Next, we study where depositors move their funds (i.e., which types of banks attract these deposits). For this analysis, we exploit the bank-province dimension of the data by estimating the following specification for non-distressed banks in the region:

$$Log(Deposits)_{b,\mathrm{p},t} = \beta_1 HighShare_{p,2013} \times Post\ 1_t + \beta_2 HighShare_{p,2013} \times Post\ 2_t + \alpha_{b,t} + \alpha_p + \varepsilon_{b,t}, \quad (2)$$

where $Log(Deposits)_{b,\mathrm{p},t}$ indicates the log of firm or household deposits of non-distressed banks b, in province p in month t. $HighShare_{p,2013}$ 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.[10] The coefficients of the interactions terms, β_1 and β_2 allows us to examine whether non-distressed banks with branches in areas where the distressed banks had a larger presence experienced larger increases in deposits during the two distress periods.

Eqn. (2) includes both province and bank-month fixed effects, α_p and $\alpha_{b,t}$. Identification is thus 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

[10] In robustness tests, reported in the Internet Appendix Table A1, we confirm our results using estimate corresponding specifications with the continuous share of deposits instead of a dummy variable based on the median value.

province. The bank-time fixed effects are important insofar as different time-varying shocks or spillover effects could hit banks in the same provinces differently.

The results are reported in Panel B of Table 2. In column (1) we find that in areas where the distressed banks had an above median presence in the local deposit market, other banks saw an 11% and 22% larger increase in firm deposits in $Post\ 1_t$ and $Post\ 2_t$, respectively. The larger coefficient for $Post\ 2_t$ is consistent with our earlier findings that deposit runs on the distressed banks were less intense in $Post\ 1_t$. These results also indicate that firms reallocate their deposits within the same geographic areas. But to which types of banks do they move their funds?

To investigate this in columns (2)-(4), we introduce interaction terms with two key bank characteristics such as bank capital and size. $HighCap_b$ is a dummy variable equal to 1 if the bank has an above than median capital ratio in 2013, and equal 0 otherwise. Similarly, $LargeB_b$ is a dummy variable equal to 1 for banks that are likely systemically important with assets above €100 billion in 2013 (i.e., one of the top 5 banks in Italy) and equals 0 otherwise. These specifications include province-month fixed effects, absorbing the coefficients of the double-interaction terms, β_1 and β_2. We find that firms running in $Post\ 1_t$ turn primarily to better capitalized banks, even if these are relatively small. Interestingly, corresponding specifications for household deposits in columns (5)-(7) show that households behave quite differently to firms. Contrary to firms, households do not appear to prioritize bank soundness. They seem instead to seek safety in large systemically important banks, in line with results from Iyer et al. (2019) and Acharya et al. (2022).

Overall, our findings underscore that households and firms exhibit distinct behaviours, and that their behaviours may be driven by different motives. Contrary to household deposits, firm deposits are predominately uninsured. 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. In the remaining part of the paper, we study how the distress banks' corporate clients behave on the asset side and the impact they have on the distressed banks' loan portfolio and other banks in the region.

4.2. Borrower runs and credit (re)allocation

In this section, we investigate the evolution of the distressed banks' loan portfolio during the event window to determine whether these forces may have also caused an endogenous deterioration in the distressed banks' loan portfolio in the period leading up to the banks' ultimate failure. For these analyses, we utilize granular credit registry and loan application data at the bank-firm level. These

allow us to trace loan applications to other banks and in the distressed banks' loan portfolio as soon as information about the banks' problems became public. We also study how these changes varied across different types of firms (e.g., high or low risk firms, firms with single or multiple lending relations), shedding light on the dynamics of their loan portfolio during this crucial period.

We first examine whether firms that had a higher level of credit dependence on the distressed banks were more inclined to apply for loans from outside banks as the problems of the distressed banks became publicly known by estimating the following linear probability model:

$$ApplOutside_{f,t} = \beta_1 SD_{f,2013} + \beta_2 SD_{f,2013} \times Post\ 1_t + \beta_3 SD_{f,2013} \times Post\ 2_t + \gamma X_{f,t-4} + \alpha_{k,p,s,t} + \varepsilon_{f,t}, \quad (3)$$

where $ApplOutside_{f,t}$ is dummy variable that takes the value of 1 if firm f applies for a loan to an outside bank in quarter t. 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). The variable $SD_{f,2013}$ indicates the share of the firm's f loans from the distressed banks in 2013 (i.e., the year prior to the start of the event window). This variable takes values from 0 to 1, where 0 indicates that in 2013 the firm did not borrow from distressed banks, and 1 indicates that all of the firm's credit was from the distressed banks. The variables $Post\ 1_t$ and $Post\ 2_t$ are defined as in Eqn. (1). This specification allows us to examine how the distressed banks borrowers' loan applications to outside banks changed over time in comparison to borrowers of non-distressed banks.

The balance covariance test, reported in Appendix Table A2, shows that firms borrowing from the distressed banks (i.e., firms with $SD_{f,2013} > 0$) are similar to those of other banks in the region (i.e., with $SD_{f,2013} = 0$). The normalized differences between the two groups, reported in parentheses, are mostly smaller in absolute terms than the threshold of 0.25 commonly used for assessing balance (Imbens and Wooldridge, 2009). 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 either at or very close the commonly used threshold (at 0.25 and 0.23, respectively).

To ensure comparability between the two groups of firms, when estimating Eqn. (3), we match the sample based on firm size using entropy balancing regression weights. Additionally, 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 (Altman z-score), among the control variables in vector $X_{f,t-4}$. Furthermore, we include industry×province×size×time fixed-effects, $\alpha_{k,p,s,t}$, to account for local business cycle conditions that may vary across different-sized

firms in different industries.[11] The coefficient β_1 indicates whether firms with higher credit dependence on the distressed banks were more or less likely to apply for loans to outside banks in the 'pre-period' i.e., before their problems became public. The coefficients β_2 and β_3 indicate how this likelihood changed in the two distress periods, $Post\ 1$ and $Post\ 2$, respectively.

The results are reported in Table 3. In column (1), we find that the coefficient of $SD_{f,2013}$ is statistically insignificant and close to zero, indicating that, in the pre-period, loan applications to outside banks were similar regardless of firms' reliance on the distressed banks. However, this changed sharply as information about the distressed banks' problems became public, and they began facing deposit runs. The coefficients of $Post\ 1_t$ and $Post\ 2_t$ are both positive and statistically significant, indicating that during that period firms with higher credit dependence on the distressed banks (i.e., with higher $SD_{f,2013}$) were more likely to apply for loans to outside banks. The estimated coefficients are economically large. In $Post\ 1_t$, a 1-standard deviation increase in $SD_{f,2013}$ (equivalent to 0.26) is associated with a 0.3 pp higher likelihood of applying to an outside bank. At the mean, this represents a 7.3% increase in the probability of applying for an outside loan.[12] The coefficient of $Post\ 2_t$ indicates a larger increase of 13.9%.[13]

(Insert Table 3 about here)

In Figure 3 we report the estimated DiD coefficients and confidence intervals from a dynamic DiD specification of Eqn. (2), where we fully interact $SD_{f,2013}$ with a set of dummies 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 $Post\ 2_t$ when widespread runs began by both households and firms. These findings provide compelling evidence of the changing behaviour of distressed banks' borrowers in seeking credit from outside sources during this critical period.

(Insert Figure 3 about here)

In columns (3) to (6) of Table 3 we also distinguish between low-risk and high-risk firms, as well as single and multiple relationship firms. The results reveal that the increase in loan applications to outside banks during the first stress period, $Post\ 1_t$, is primarily driven by low-risk firm. This is true for firms with single or multiple lending relationships. For high-risk firms, the coefficients of $Post\ 1_t$ are statistically insignificant and economically very close to zero for both

[11] For firm size we use the decile of firms' total assets.
[12] The average likelihood of applying to an outside bank is 4.3%.
[13] Results without matching are qualitatively and quantitatively very similar.

firms with single or multiple lending relationships. In $Post\ 2_t$, when widespread runs began, we do find that high-risk firms with single relationship were also more likely to apply to outside banks. This result is fairly weak and statistically significant only at the 10% percent level.

Moving forward, we explore whether these attempts to establish new lending relationships are successful. We study which firms are more likely to initiate new relationships and with which types of banks. Using the sample of firms that applied for an outside loan during the event window, we begin by estimating the following liner probability model:

$$NewRelation_{f,b,t} = \beta_1 \cdot SD_{f,2013} + \gamma \cdot X_{f,t-4} + \alpha_{k,p,s,t} + \varepsilon_{f,t}, \qquad (4)$$

where $NewRelation_{f,b,t}$ takes the value of 1 if firm f begins borrowing from outside bank b in the quarter after applying to bank b, and 0 otherwise. All other variables are defined as in Eqn. (3).

Results are reported in Table 4. In column (1), we find that $\hat{\beta}_1$ is positive and significant at the 5% level, indicating that firms with higher credit dependence from the distressed banks are more likely to establish new lending relationships with outside banks. Further in columns (2)-(5), we find that it is the low-risk firms that are able to secure new lending relationships. The estimated coefficients for all other groups are positive, but not statistically significant. As shown in Figure 4, by the end of the event window the "lost business" to outside banks accounted for about 35% of the value of their initial loan portfolio, 10 percentage points (pp) more than non-distressed banks.[14]

(Insert Table 4 and Figure 4 about here)

In Table 5, we further study how this transition to outside banks varied over the event window and the characteristics of their new banks. In column (1), we report again our baseline line result from column (1) of Table 4 (to ease comparison) and in columns (2)-(4) we open it up by year, by estimating the same specification for each year of the event window. In columns (5)-(8), we repeat this analysis allowing for interactions with key bank characteristics.

We find that the increase in the probability to establish a new lending relationship is highest in 2015 when the distressed banks' low-risk firms first began applying to outside banks. Importantly, borrowers of distressed banks do not have a different probability of establishing a new relationship with other banks in 2014, before bank distress was publicly revealed. This confirms

[14] Using the set of firms that borrowing from the distressed banks at the start of the event window (i.e., their existing customers), we compute the total cumulative value of loans that these firms received from outside banks over time and scale it by the value of the distressed banks' loan portfolio at start of the event window. We compute the same figure for non-distressed banks. As can be observed in Figure 4, both figures have positive slopes as over time some of the banks' existing customers will naturally switch to other lenders for a variety of reasons. Importantly, however, the two figures, which until 2015Q1 move together, they begin to diverge. The growing distance between the two figures indicates that the distressed banks started losing more business than the distressed banks.

the absence of significant pre-trends, supporting the 'parallel trends' assumption. Interactions with bank characteristics in columns (5)-(8) reveal that the distressed banks' borrowers were more likely to establish new banking relationships with larger and better capitalized banks.

(Insert Table 5 about here)

Overall, these results indicate that as soon as the distressed banks' problems surfaced and the banks began experiencing deposit outflows from firms, they also began losing their best corporate borrowers. Low-risk and single relationships firms began applying for loans to outside banks to either replace the distressed banks or add new stable lending relationships. We find that low-risk firms were able to establish new lending relationships, primarily with larger and better capitalized banks. These results underscore the critical role played by the simultaneous deterioration of the distressed banks' asset and liability positions. They shed light on the endogenous dynamics of distress, indicating that the distressed banks' inability to retain their best corporate customers on both sides of their balance sheet have significantly impacted their viability.

Additional results

In additional analyses, we also explore how firms' borrowing from the distressed banks evolved during the event widow. Firstly, we investigate how firms' outstanding credit and loan interest rates changed during the event window in comparison to non-distressed banks. Distressed banks could decreasing credit supply, faced with higher losses and deposits outflows. In a second set of tests, we examine firms' drawdowns on committed credit lines during the period when the distressed banks' problems became public. Previous studies indicate that firms tend to draw down their credit lines from banks facing funding liquidity shocks, as they anticipate credit supply restrictions (see, e.g., Ivashina and Scharfstein, 2010; Ippolito, Peydro, Polo, and Sette, 2016; Chodorow-Reich, Darmouni, Luck and Plosser, 2022). We thus investigate whether the distressed banks experienced similar 'runs' on their credit lines as their problems became public. For both analyses, we control for differences in firm composition using a restrictive set of control variables and fixed effects, in line with the approaches of De Jonghe et al. (2019) and Khwaja and Mian (2008).

In particular, to study how **outstanding credit** and **loan interest rates** from the distressed banks changed during the event window relative to non-distressed banks, we estimate the following specification using bank-firm level data from the credit registry:

$$Log(Credit)_{b,f,t} = \beta_1 D_b \times Post\ 1_t + \beta_2 D_b \times Post\ 2_t + \alpha_b + \alpha_{k,p,s,t} + \varepsilon_{b,p,t}, \quad (5)$$

where $Log(Credit)_{f,b,t}$ indicates the log of total outstanding loans from bank *b* to firm *f* at time *t*. We estimate similar specifications using loan interest rates as the dependent variable. The variable

D_b takes the value of one if bank b is among the distressed banks, and 0 otherwise. The two dummy variables, $Post\ 1_t$ and $Post\ 2_t$, divide the 'distress period' into the two sub-periods.[15] The coefficients, β_1 and β_2, indicate how credit or loan interest rates from distressed banks change relative to the non-distressed banks in $Post\ 1_t$ and $Post\ 2_t$ compared to the omitted period (2014).

To control for potential confounding factors, we use a comprehensive set of fixed-effects. In addition to bank-fixed effects, α_b, which account for time-invariant differences across banks, we also include industry×province×size×time fixed effects, $\alpha_{k,p,s,t}$, to control for business cycle conditions that may vary across provinces, industries, and different sized-firms. This s allows us to estimate the model for both single and multiple relationship firms (De Jonghe et al., 2019). In robustness tests, we also estimate even more conservative specifications with firm×time fixed effects, $\alpha_{f,t}$, instead of $\alpha_{k,p,s,t}$. These are only possible for multiple relationship firms (Khwaja and Mian, 2008). In this case, the coefficients, β_1 and β_2, reflect the changes in outstanding credit or loan interest rates to the same firm at the same time. In all cases, the model is estimated with OLS and the standard errors are corrected for heteroskedasticity and clustered at the bank-level.

The results are reported in Table 6. Panel A reports results for outstanding credit and Panel B for loan interest rates. Column (1) reports results with $\alpha_{k,p,s,t}$ for both single and multiple relationship firms. Column (2) reports the results of the more restrictive specification with $\alpha_{f,t}$ for the multiple relationship firms. Columns (3)-(6) report results of corresponding specifications for sub-samples of low-risk and high-risk firms. Consistent with earlier findings, we find that credit from the distressed banks decreases relatively to other banks both in $Post\ 1_t$ and $Post\ 2_t$, with a larger decrease in $Post\ 2_t$. Nevertheless, a statistically and economically significant decline driven primarily by low-risk firms begins already in $Post\ 1_t$.[16] The reduced magnitude and statistical significance of $\hat{\beta}_1$ as we move from column (3) to column (4) suggests that this decline is primarily concentrated in low-risk single relationship firms. Consistent with the idea that these firms may be actively trying to establish new stable lending relationships (i.e., a decrease in demand for credit from the distressed banks), in Panel B we find that the decrease in credit from the distressed banks is not accompanied by increases in loan interest rates, which would have been more consistent with a decrease in credit supply from the distressed banks.[17]

(Insert Table 6 about here)

[15] In robustness tests, we also estimate corresponding dynamic DiD specifications by replacing $Post\ 1_t$ and $Post\ 2_t$ with quarterly dummy variables to inspect the full dynamics of credit provision over the event window.
[16] This is also evident from corresponding dynamic DiD specifications reported in Appendix Figure A3.
[17] In further tests, we confirm that controlling for other firm characteristics, single relationship firms tend to be less risky firms on average, based on the Altman z-score (Appendix Table A3).

In a second test, we also investigate firms' **drawdowns on committed credit lines** during the period when the distressed banks' problems became public. To examine this type of "credit runs" in Table 7 we estimate Eqn. (5) with the ratio of the drawn amount over the granted credit for each credit line as the dependent variable. Our specifications include firm×time fixed effects, $\alpha_{f,t}$, and are similar to Ippolito, Peydro, Polo, and Sette (2016) testing whether a firm with credit lines from multiple banks draws more on its credit lines from the distressed banks than from its other lenders after the distressed banks began facing a liquidity shock.

(Insert Table 7 about here)

Our results show no evidence of "credit line runs" on the distressed banks. The estimated DiD coefficients are mostly statistically insignificant, and when significant, they are negative, suggesting smaller drawdowns at the distressed banks. A critical difference between our study and previous research, which may explain the different results, lies in the nature of the shock examined. While both Ivashina and Scharfstein (2010) and Ippolito, Peydro, Polo, and Sette (2016) focus on a systemic shock, our study deals with entirely idiosyncratic shock.[18] Firms' behaviour under these scenarios may differ significantly. In cases of widespread liquidity shocks, firms may drawdown credit lines from troubled banks due to limited alternatives. In contrast, when the bank's liquidity problems are idiosyncratic, firms may be more inclined to establish new relationships with stable banks instead of rushing to drawdown their credit lines with the distressed banks. 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). This key distinction in the nature of the shock could explain the divergent results and offers new valuable insights into firms' response to idiosyncratic liquidity shocks.

4.3. Spillover effects: "Cleansing" of other banks' loan portfolios

In this section, we explore the potential spillover effects on the 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. For example, if other banks were facing capacity constraints, the influx of new high-quality customers from distressed banks might have allowed other banks to improve their loan portfolios.

[18] Ivashina and Scharfstein (2010) focuses on the period after the failure of Lehman Brothers in the summer of 2008. Ippolito, Peydro, Polo, and Sette (2016) focuses in the summer of 2007 when the European market froze and Chodorow-Reich, Darmouni, Luck and Plosser (2022) on Covid-19.

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:

$$Exp_{b,t} = \frac{DistrBorrAppl_{b,t}}{TotAppl_{b,t}}, \quad (6)$$

where $DistrBorrAppl_{b,t}$ 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 $TotAppl_{b,t}$ indicates the total number of loan applications to bank b in period t from new customers.[19] Using this measure, we estimate the following specification:

$$\Delta logCredit_{b,f,t} = \beta_1 Exp_{b,t} \times Risky_f + \gamma X_{f,t-1} + \alpha_{k,p,t} + \gamma_{b,t} + \epsilon_{b,f,t}, \quad (7)$$

where $\Delta logCredit_{b,f,t}$ represents the quarterly growth rate of credit from bank b to firm f in period t. The dummy variable $Risky_f$ equals 1 if the firm is high-risk (i.e., has an Altman Z-score above 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 $\gamma_{b,t}$, respectively.

(Insert Table 8 about here)

Table 8 presents our findings. In column (1), we estimate Eqn. (7) without bank×time fixed-effects, allowing for the inclusion of $Exp_{b,f}$. The coefficient of $Exp_{b,f}$ is statistically insignificant, indicating that, on average, there are no significant spillover effects on the existing customers of other banks. However, when distinguishing between high-risk and low-risk borrowers in column (2) by allowing for an interaction term between $Exp_{b,f}$ and $Risky_f$, we observe a different picture. We find significant adverse effects on high-risk borrowers: high-risk firms in banks that received a larger number of applications from the distressed banks' borrowers saw larger reductions of their credit from those banks. This result remains robust to the inclusion of bank×quarter fixed effects.

To examine whether these spillover effects vary with bank balance sheet constraints, in column (4) we allow for interaction terms between $Exp_{bt} \times Risky_f$ and bank characteristics such as bank capital (Tier 1 capital ratio), size, and interbank borrowing.[20] We find that the interaction with bank capital is positive and statistically significant, indicating that the decrease in credit to high-risk firms is more pronounced for banks with lower capital ratios. This is consistent with the

[19] 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.
[20] Among the control variables, we also include double interaction terms between $Risky_f$ and bank characteristics.

idea that the influx of new low-risk borrowers at these banks may have allowed them 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.

4.4. Total credit and real effects: Direct and indirect impact of bank distress

Panel A of Figure 5 shows that credit from distressed banks fell by around 24% from 2014Q1 to 2016Q4, with a rapid decrease in 2015Q4-2016Q1. However, this drop need not translate into lower overall credit available to distressed banks' borrowers if these are able to substitute credit with other banks. Credit from other banks slightly increased, around 2%, between 2014Q1 and 2016Q1, suggesting that other banks step in and lend more to distressed banks' borrowers. Indeed, Panel B of Figure 5, which tracks credit available over-time to borrowers of distressed banks versus others, shows that the two group of firms move largely in parallel and by the end of 2016 both groups of firms have lost about 2% of credit compared to 2014.

(Insert Figure 5 about here)

The lack of an overall effect on credit is consistent with the evidence provided earlier that borrowers of distressed banks are more likely to apply for credit and be accepted at other banks, especially when they are low-risk firms. If total credit at distressed banks' borrowers does not change much relative to other borrowers, we would also expect limited effects on investment rates. We test for this more formally by running a regression at the firm-year level on growth rate of credit and investment on $SD_{f,2013}$ and other firm characteristics between 2014 and 2017.[21] Results are reported in Table 9. All dependent variables are winsorized at 5th and 95th percentile.

(Insert Table 9 about here)

We find that there is virtually no difference in the growth rate of credit between borrowers of distressed banks and others during the period between 2014 and 2017 (Panel A, Table 9). High-risk (low-risk) borrowers of distressed banks have a growth rate of credit 0.2 percentage points lower (higher) compared to other borrowers, but the difference is not statistically significant. When we investigate the dynamic effects over time we find a significant decrease in credit in 2014, concentrated among high-risk borrowers. The decline in 2015 matches the earlier evidence from Figure 5 showing a marked decline in credit from distressed banks around 2015Q4-2016Q1.

[21] We include 2017 in the real effects analysis to track some long-term effect on credit and investment. After 2017 the distressed banks cease to exist as separate entities since they are acquired by a national bank.

However, the decrease is only temporary and growth rate of credit recovers in later periods: the difference in credit growth between distressed and non-distressed banks' borrowers becomes positive in 2016 for low-risk firms and in 2017 for high-risk firms.

Consistent with the limited effects on overall credit growth, we also find limited impact on firm-level investment rate for distressed banks borrowers (Panel, Table 9). There are heterogeneous effects depending on firm risk: high-risk borrowers of distressed banks have a 0.9 percentage lower (20% compared to mean) investment rate during the overall sample period, but the difference is not statistically significant. We find virtually no effect for low-risk firms. When we split the effect by year, we still fail to find any significant effect across the two groups of firms. We also find no significant effect on other firm outcomes, such as sales or wage growth (see Table A4).

5. Conclusions

In this paper we provide novel evidence on the credit reallocation effects of bank distress. We show that before bank failures actually materialize, high-quality borrowers respond to public news about bank distress by obtaining credit at other banks, either those in their existing relationship set or new ones. This 'borrower run' can spill-over on other banks' balance sheet and affect their lending decisions, leading to a balance sheet cleansing effect: credit to high-risk borrowers of non-distressed banks is reduced.

Our results are informative on the debate on how bank regulators and resolution authorities should wind down banks that are in distress or likely to fail. A common approach in bank resolution, in both theory and practice, is to separate distressed banks' assets in two parts: a 'good' and a 'bad' part', collecting all the non-performing assets in a public 'bad' bank (Beck et al. 2021). Our results suggest that before the regulatory intervention takes place, market forces help credit reallocation by allowing high-quality borrowers to find alternative sources of credit elsewhere.[22] Nonetheless, an outright bank failure may still be suboptimal because it forces authorities to activate the deposit insurance scheme, affecting other banks that contribute to the insurance fund, and potentially undermines depositors' trust in the banking system overall (Brown et al., 2018).

[22] It is important to note that 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 Searches

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 being the peak number of searches.

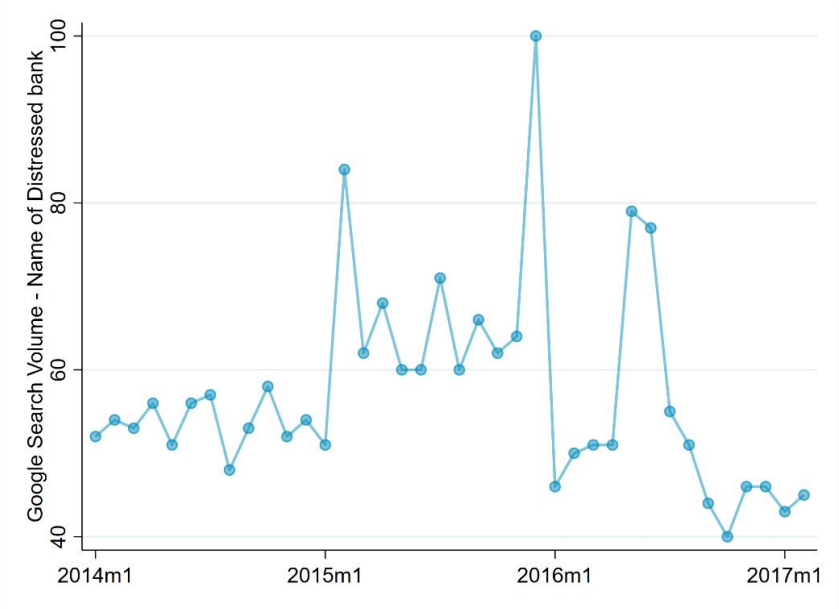
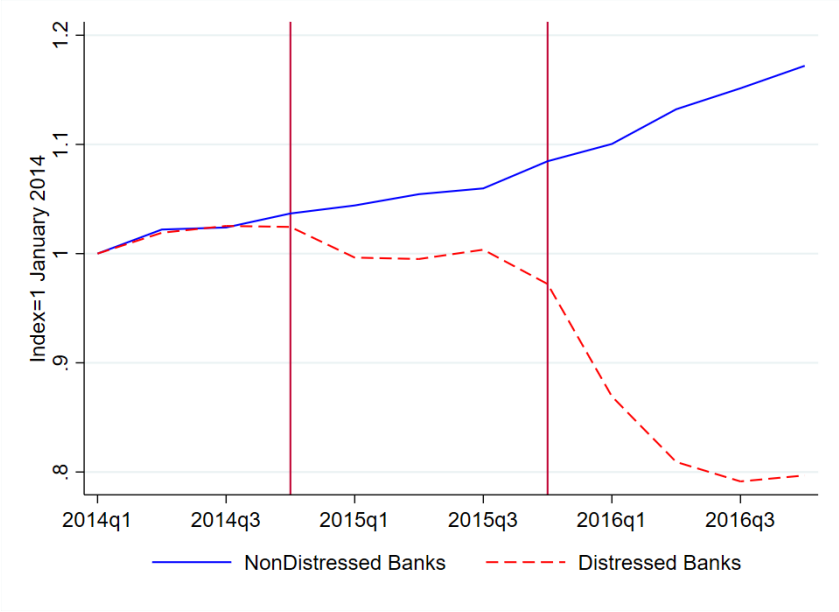


Figure 2. Deposit-runs at the distressed banks

This figure shows the quarterly evolution of total deposits of distressed and non-distressed banks in Panel A and corporate and household deposits of distressed banks in Panel B for from 2014Q1 to 2016Q4. All series have been normalized to be equal to 1 as of 2014Q1.The vertical lines indicate the beginning of the Post1 period (February 2015) and Post2 period (2015Q4).

A. Total deposits of distressed banks and non-distressed banks



B. Corporate vs. household deposits of distressed banks

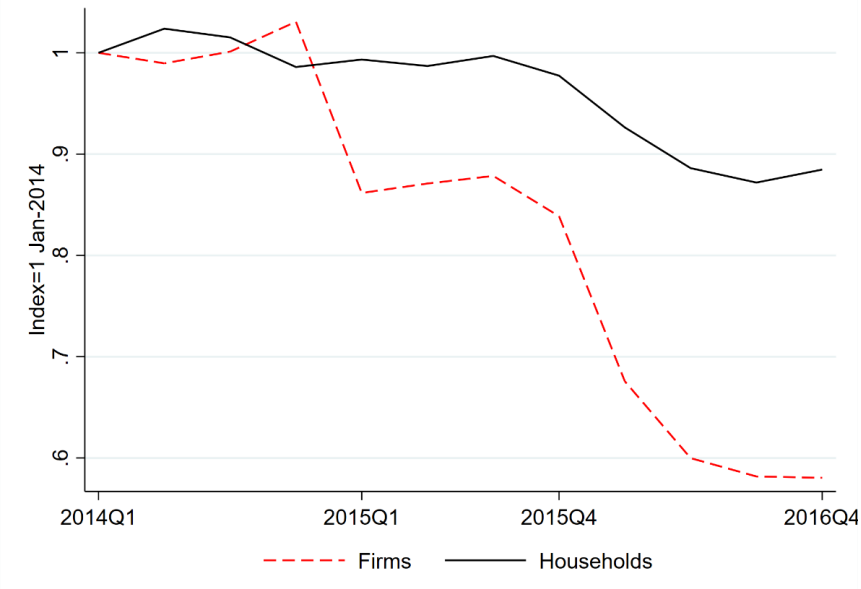


Figure 3. Loan applications to outside banks: Dynamic DiD

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

$$ApplOut_{f,t} = \sum_{t=2014Q1}^{2016Q4} \beta_t \mu_t \times SD_{f,2013} + \gamma X_{f,t-4} + \alpha_{k,p,s,t} + \varepsilon_{f,t}$$

Where $ApplOut_{f,t}$ 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. μ_t is a calendar year quarter dummy. $X_{f,t-4}$ are lagged firm controls and include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. $\alpha_{k,p,s,t}$ are industry×province×size×year quarter and credit score× year quarter fixed effects. Standard errors are clustered at the firm-level.

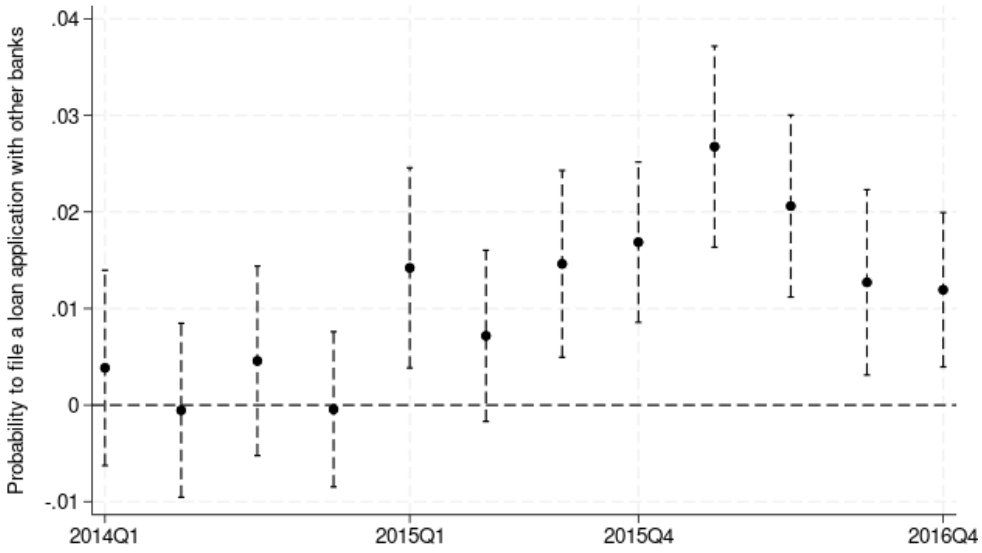


Figure 4. Business lost to other banks

This figure plots the cumulative share of business lost to other banks.

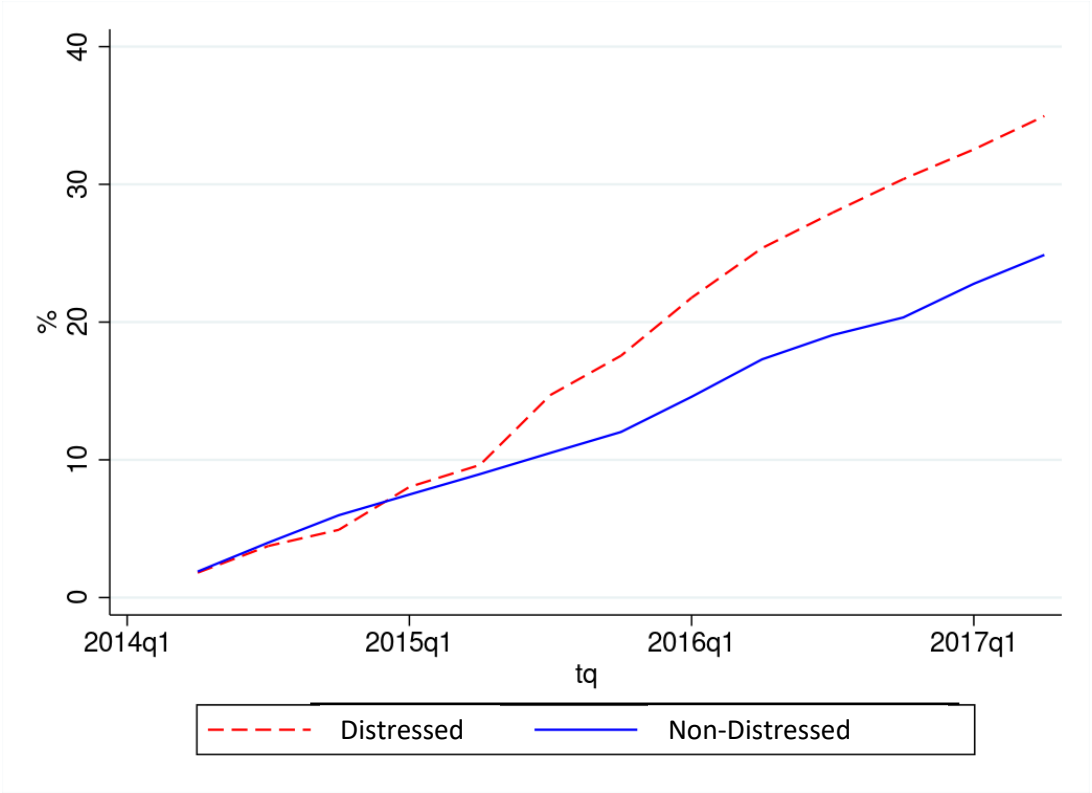
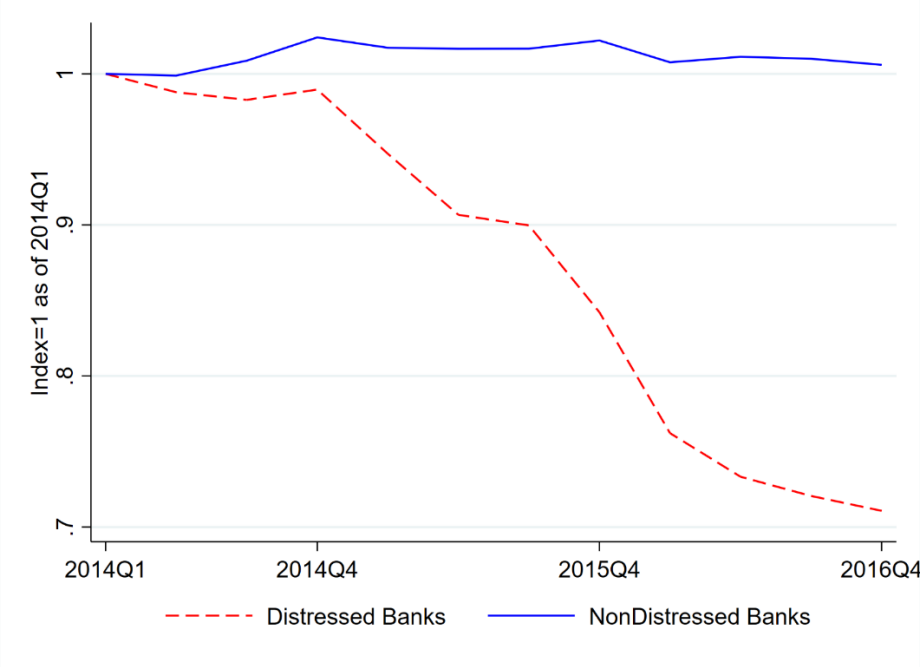


Figure 5: Credit of distressed banks and their borrowers

This figure shows total credit in the affected area from t=-7 to t=+4, where t=0 is the quarter where the major shock happened (last quarter of year T). Panel A shows outstanding credit at distressed banks (dashed line) and non-distressed banks (solid line). Panel B shows credit available at distressed banks' borrowers (dashed line) and non-distressed banks' borrowers (solid line). All series have been normalized to be equal to one in t=-7.

A. Total credit from distressed and non-distressed banks



B. Total credit available to distressed and non-distressed banks borrowers

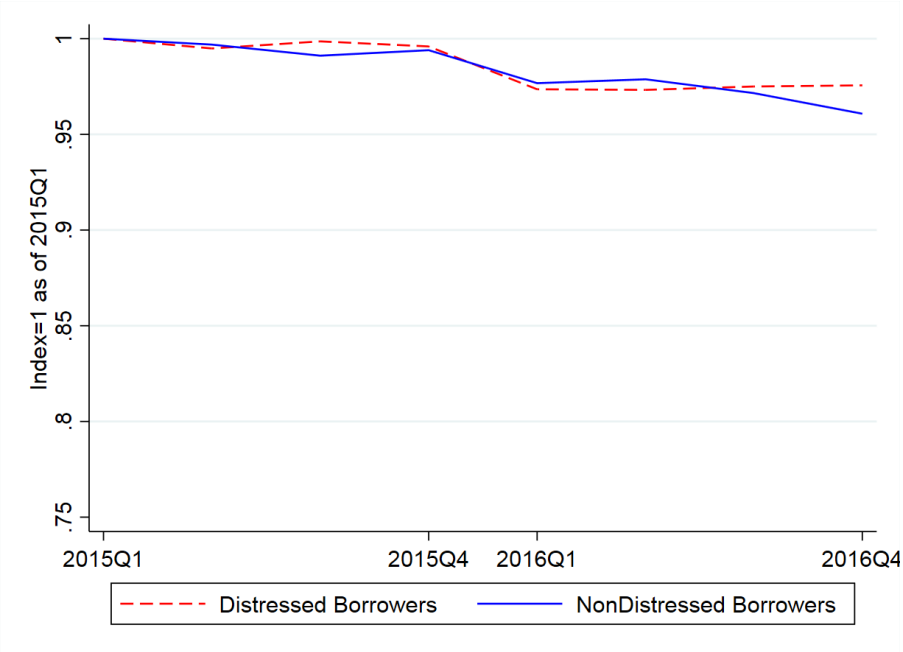


Table 1: Summary statistics

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

	Obs.	Mean	St. Dev.	Median	5th pct.	95th pct.
Panel A. Bank characteristics as of 2013Q4						
Total Assets (€ mil.)	480	5988	48444	503	76	8987
Capital Ratio (%)	480	12.461	3.994	12.045	6.700	19.679
Deposits/Assets (%)	480	42.018	12.515	41.957	20.322	61.431
Firm Deposit Share (%)	480	24.785	14.900	22.372	7.954	51.621
Panel B. Firm characteristics as of 2013Q4						
Total Assets (€ mil.)	56505	4.001	9.687	1.061	0.063	70.668
Sales (€ mil.)	56505	4.007	9.874	1.025	.019	70.917
Age (years)	56505	17.334	11.816	14	2	54
EBITDA/Assets	56505	0.072	0.129	0.069	-0.504	0.467
Altman Z-score	56505	4.921	2.067	5	1	9
High-Risk	56505	0.279	0.0448	0	0	1
Single Relationship Borrower	56505	0.428	0.494	0	0	1
DistressedBorrower	56505	0.266	0.442	0	0	1
ShareDistressed	56505	0.117	0.260	0	0	1
ShareDistressed if DistressedBorrower=1	15033	0.441	0.334	0.322	0.02	1
Panel C. Bank Credit (bank-firm-quarter						
AppOutsideBanks	824388	0.043	0.209	0	0	1
Of which Distressed	615975	0.058	0.234	0	0	1
Of which NonDistressed	208413	0.039	0.191	0	0	1
NewRelationship	36158	0.273	0.445	0	0	1
Of which Distressed	12125	0.293	0.455	0	0	1
Of which NonDistressed	24033	0.262	0.439	0	0	1
Panel D. Firm-year panel, 2014-2017						
Δlog(credit)	174884	-0.022	0.302	0	-0.702	0.638
Investment Rate	174884	0.051	0.390	-0.031	-0.435	1.277
Δlog(sales)	174884	0.012	0.209	0.024	-0.481	0.417
Δlog(wage bill)	159632	0.025	0.172	0.027	-0.378	0.387

Table 2. Deposit runs and reallocation

This table provides the estimates for Eqns. (1) and (2). The sample period is 2014M1-2016M12. In Panel A the unit of observation is at the bank-month and the dependent variable is the log of total deposits by bank *b* in month *t*. Distressed Banks is a dummy equal to one for deposits of the two distressed banks. Post1 is a dummy equal to one between 2015M2 and 2015M11, Post2 is a dummy equal to one between 2015M12 and 2016Q4. In Panel B the unit of observation is at the bank-province-month and the dependent variable is the log of deposits by non-distressed bank *b* in month *t* in province *p*. HighShare is a dummy equal to one if the distressed banks have an above the median share of local corporate deposits in columns (1)-(4) and household deposits in columns (5)-(7). HighCapital is a dummy equal to one if the bank has an above the median capital ratio in 2013, 0 otherwise. LargeBank is a dummy equal to one if the bank has total assets above €100 billion in 2013 (i.e., if it is one of the top five banks in the country). Standard errors are clustered at the bank level in Panel A and province level in Panel B.

Panel A. Bank-month

	Log(deposits of distressed banks)		
	All	Firms	Households
	(1)	(2)	(3)
Distressed Banks × Post1	-0.061*	-0.119***	-0.045
	(0.034)	(0.045)	(0.045)
Distressed Banks × Post2	-0.341***	-0.582***	-0.227***
	(0.077)	(0.104)	(0.072)
Fixed Effects			
Bank	Yes	Yes	Yes
Year-Month	Yes	Yes	Yes
Observations	16,931	16,931	16,931
R-squared	0.999	0.994	0.997

Panel B. Bank-province-month

	Log(deposits of non-distressed banks)						
	Firms				Households		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HighShare × Post1	0.116**						
	(2.39)						
HighShare × Post2	0.219***						
	(2.87)						
HighShare × Post1		0.318***		0.323***	-0.153		-0.077
× HighCapital		(2.99)		(2.99)	(-1.64)		(-0.85)
HighShare × Post2		0.257		0.243	-0.181		-0.113
× HighCapital		(1.63)		(1.51)	(-1.45)		(-0.91)
HighShare × Post1			-0.104*	0.027		0.359***	0.431***
× LargeBank			(-1.97)	(0.60)		(2.69)	(3.58)
HighShare × Post2			-0.197**	-0.084		0.311**	0.376***
× LargeBank			(-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

Table 3. Loan applications to outside banks

This table provides the estimates for Equation (2). The unit of observation is at the firm-quarter and the sample period is 2014Q1-2016Q4. The dependent variable is $ApplOut_{f,t}$ a dummy equal to one if firm *f* applies to an outside bank in quarter *t*. $SD_{f,2013}$ 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. $Post\ 1$ 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 go from 1 (safe) to 9 (risky), are interacted with year-quarter indicator. Standard errors are clustered at the firm level. T-statistics are reported in parentheses.

	Loan Applications to Outside Banks				
	All Firms	Low-Risk		High-Risk	
		Single	Multiple	Single	Multiple
	(1)	(2)	(3)	(4)	(5)
$SD_{f,2013}$	0.001	0.001	-0.004	0.001	0.015*
	(0.05)	(0.22)	(-0.90)	(0.26)	(1.86)
$SD_{f,2013} \times Post\ 1$	0.010***	0.011**	0.012*	0.005	-0.001
	(2.81)	(2.21)	(1.75)	(0.55)	(-0.08)
$SD_{f,2013} \times Post\ 2$	0.018***	0.012***	0.027***	0.014*	0.006
	(6.13)	(2.83)	(4.87)	(1.86)	(0.64)
Fixed effects & Controls					
Industry×Province×Size×Time	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Observations	824,388	199,320	420,895	64,940	134,389
R-squared	0.04	0.078	0.056	0.16	0.105

Table 4. New lending relationships

This table provides the estimates for Equation (3). The unit of observation is a bank-firm-year between 2014-2016. The sample is restricted to firms that file at least one loan in application in a year. The dependent variable is a dummy equal to one if a new bank-firm relationship between borrower *f* and bank *b* is created in the quarter after a loan application, 0 otherwise. $SD_{f,2013}$ 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 Lagged firm controls include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. Credit score dummies, which go from 1 (safe) to 9 (risky), are interacted with year-quarter indicator. Standard errors are clustered at the firm and bank level. T-statistics are reported in parentheses.

	New Lending Relationships				
	All firms	Low-risk	High-risk	Single	Multiple
	(1)	(2)	(3)	(4)	(5)
$SD_{f,2013}$	0.029**	0.037**	0.023	0.032	0.022
	(2.14)	(2.24)	(0.86)	(1.33)	(1.19)
Fixed effects & Controls					
Industry×Province×Size×Time	Yes	Yes	Yes	Yes	Yes
Bank×Year	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Observations	26,826	20,287	6,128	5,029	21,302
R-squared	0.151	0.168	0.258	0.273	0.162

Table 5. New lending relationships: Time-series and bank heterogeneity

This table provides the estimates for Equation (3). The unit of observation is a bank-firm-year between 2014-2016. The sample is restricted to firms that file at least one loan in application in a year. The dependent variable is a dummy equal to one if a new bank-firm relationship between borrower *f* and bank *b* is created in the quarter after a loan application, 0 otherwise. $SD_{f,2013}$ 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. Bank characteristics are: size (log of total assets), capital ratio (total equity over total assets) and quality of loan portfolio (non-performing loans over total assets). Bank characteristics are standardized by removing the mean of each variable Lagged firm controls include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. Credit score dummies, which go from 1 (safe) to 9 (risky), are interacted with year-quarter indicator. Standard errors are clustered at the firm and bank level. T-statistics are reported in parentheses.

	New Lending Relationships							
	All	2014	2015	2016	All	2014	2015	2016
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SD_{f,2013}$	0.029**	-0.001	0.048**	0.046*	0.040**	0.014	0.062*	0.062**
	(2.14)	(-0.06)	(2.09)	(1.93)	(2.21)	(0.57)	(1.87)	(2.13)
$SD_{f,2013} \times CapitalRatio_b$					0.012*	0.015	0.028***	-0.011
					(1.95)	(1.02)	(3.08)	(-0.86)
$SD_{f,2013} \times Log(Assets)_b$					0.016*	0.003	0.048***	-0.013
					(1.91)	(0.29)	(4.19)	(-0.68)
$SD_{f,2013} \times NPL/Loans_b$					0.157	0.278	-0.145	0.051
					(0.86)	(0.63)	(-0.53)	(0.13)
Fixed effects & Controls								
Industry×Province×Size×Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank×Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,826	10,718	8,731	7,377	20,892	8,015	7,093	5,784
R-squared	0.151	0.158	0.155	0.144	0.135	0.144	0.139	0.125

Table 6. Credit volume and loan interest rates

This table provides the estimates for Equation (5). The unit of observation is at the bank-firm-quarter 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 bank *b* to firm *f* in quarter *t*. The variable *Distressed Banks* is a dummy equal to one for credit relationships with the two distressed banks. *Post 1* is a dummy equal to one between 2015Q1 and 2015Q3, *Post 2* is a dummy equal to one between 2015Q4 and 2016Q4. Standard errors are clustered at the bank level.

Panel A:	Log(Credit volume)					
	Borrowers		Low-Risk		High-Risk	
	All	Only multiple	All	Only multiple	All	Only multiple
	(1)	(2)	(3)	(4)	(5)	(6)
Distressed Banks × Post 1	-0.019**	-0.014**	-0.021***	-0.014*	-0.014	-0.008
	(0.0077)	(0.00621)	(0.007)	(0.007)	(0.008)	(0.011)
Distressed Banks × Post 2	-0.097***	-0.092***	-0.097***	-0.088***	-0.097***	-0.101***
	(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	1449628	1238980	1125291	970376	318657	268603
R-squared	0.598	0.756	0.611	0.762	0.577	0.699

Panel B:	Loan interest rates					
	Borrowers		Low-Risk		High-Risk	
	All	Only multiple	All	Only multiple	All	Only multiple
	(1)	(2)	(3)	(4)	(5)	(6)
Distressed Banks × Post 1	-0.056	-0.088	-0.083	-0.120	0.178***	0.108
	(0.142)	(0.131)	(0.155)	(0.138)	(0.0481)	(0.0811)
Distressed Banks × Post 2	0.222	0.156	0.183	0.115	0.483***	0.448**
	(0.364)	(0.339)	(0.396)	(0.356)	(0.136)	(0.188)
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	1053092	916727	951079	828892	96120	87835
R-squared	0.214	0.615	0.214	0.608	0.387	0.566

Table 7. Credit Line Drawdowns

This table provides the estimates for Equation (5) where the dependent variable is the share of drawn over total credit lines granted from bank *b* to firm *f* in quarter *t*. The unit of observation is at the bank-firm-quarter and the sample period is 2014Q1-2016Q4. The variable *Distressed Banks* is a dummy equal to one for credit relationships with the two distressed banks. *Post 1* is a dummy equal to one between 2015Q1 and 2015Q3, *Post 2* is a dummy equal to one between 2015Q4 and 2016Q4. Standard errors are clustered at the bank level.

	Share Credit Drawn					
	Borrowers		Low-Risk		High-Risk	
	All	Only multiple	All	Only multiple	All	Only multiple
	(1)	(2)	(3)	(4)	(5)	(6)
Distressed Banks × 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)
Distressed Banks × 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	1184318	969992	926316	765639	257458	204353
R-squared	0.0776	0.0855	0.0873	0.0810	0.0874	0.0896

Table 8. Credit spillovers effects on other banks in the region

This table provides the estimates for equation (5). The unit of observation is a bank-firm-quarter. The sample excludes credit relationships with distressed banks. The dependent variable is 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 go from 1 (safe) to 9 (risky), are interacted with year-quarter indicator. Standard errors are clustered at the bank level. T-statistics are reported in parentheses.

	ΔLog(Credit)			
	(1)	(2)	(3)	(4)
$Exp_{b,t}$	-0.0062	-0.001		
	(-0.52)	(-0.13)		
$Exp_{b,t} \times Risky_f$		-0.019***	-0.019***	-0.079***
		(-5.54)	(-5.34)	(-2.14)
$Exp_{b,t} \times CapitalRatio_b \times Risky_f$				0.010***
				(2.24)
$Exp_{b,t} \times Log(Ass)_b \times Risky_f$				-0.023
				(-0.57)
$Exp_{b,t} \times Interbank_b \times Risky_f$				-0.095
				(-1.05)
Fixed-effects and controls				
Firm controls	Y	Y	Y	Y
Prov*Sector*Quarter FE	Y	Y	Y	Y
Bank FE	Y	Y	-	-
Bank*Quarter FE	N	N	Y	Y
BankCharacteristics×High-risk	N	N	N	Y
Observations	661,016	661,016	661,016	661,016

Table 9. Total firm credit and real effects

This table provides the estimates on the effects of bank distress total credit and investment. The unit of observation is a firm-year. The dependent variable is the annual growth rate of credit in Panel A and the investment rate (i.e. the change in total fixed assets over lagged total fixed assets) in Panel B. $SD_{f,2013}$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. Lagged firm controls include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. Credit score dummies, which go from 1 (safe) to 9 (risky), are interacted with year-quarter indicator. Standard errors are clustered at the firm level. T-statistics are reported in parentheses.

Panel A. Total Credit	ΔLog(credit)					
	All	High-risk	Low-risk	All	High-risk	Low-risk
	(1)	(2)	(3)	(4)	(5)	(6)
$SD_{f,2013}$	0.004	0.001	0.006*			
	(1.25)	(0.08)	(1.66)			
$SD_{f,2013} \times I(year\ 2014)$				0.012**	0.016	0.011
				(2.00)	(1.42)	(1.50)
$SD_{f,2013} \times I(year\ 2015)$				-0.018***	-0.039***	-0.009
				(-2.72)	(-2.91)	(-1.18)
$SD_{f,2013} \times I(year\ 2016)$				0.014*	-0.007	0.021**
				(1.92)	(-0.47)	(2.57)
$SD_{f,2013} \times I(year\ 2017)$				0.010	0.038**	0.003
				(1.40)	(2.45)	(0.32)
Observations	174884	40011	134487	174884	40011	134487
R^2	0.052	0.101	0.048	0.052	0.102	0.048

Panel B. Real effects	Investment Rate					
	All	High-risk	Low-risk	All	High-risk	Low-risk
	(1)	(2)	(3)	(4)	(5)	(6)
$SD_{f,2013}$	-0.003	-0.009	-0.001			
	(-0.66)	(-1.08)	(-0.29)			
$SD_{f,2013} \times I(year\ 2014)$				-0.009	-0.018	-0.005
				(-1.27)	(-1.42)	(-0.53)
$SD_{f,2013} \times I(year\ 2015)$				-0.006	-0.001	-0.008
				(-0.76)	(-0.05)	(-0.86)
$SD_{f,2013} \times I(year\ 2016)$				-0.003	-0.009	-0.006
				(-0.36)	(-0.53)	(-0.58)
$SD_{f,2013} \times I(year\ 2017)$				0.011	-0.002	0.016
				(1.16)	(-0.12)	(1.45)
Fixed-effects & controls						
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Province×Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
I(CreditScore) × Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	174884	40011	134487	174884	40011	134487
R^2	0.037	0.073	0.042	0.037	0.073	0.042

INTERNET APPENDIX

Figure A1. Total credit to non-financial firms, 2014-2016

This figure plots total credit to non-financial firms for a selected group of European countries (France, Germany, Italy, Portugal and Spain) between January 2014 and December 2016. All series have normalized to 1 in January 2014. Source: ECB SDW (link).

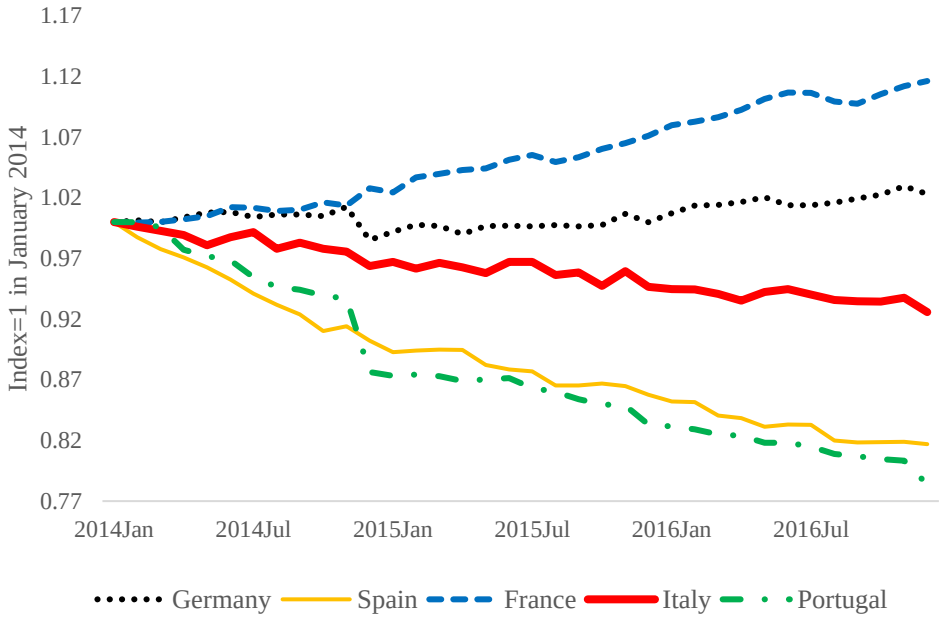


Figure A2. Deposits from distressed banks: Dynamic DiD

This figure plots the β_t coefficients and associated 95% confidence interval from the following regression (Khwaja and Mian, 2008):

$$Log(Deposits)_{f,b,t} = \sum_{t=2014M2}^{2016M12} \beta_t \, \mu_t \times D_b + \mu_t + \alpha_b + \varepsilon_{b,p,t},$$

Where D_b is a dummy equal to one for credit given by distressed banks, μ_t is a year-month calendar dummy and β_t measures the impact in each month from 2014M1 to 2016M12. 2014M1 is the omitted period. We include time and bank fixed-effects, μ_t and α_b. Vertical lines indicate the start of the two distress periods, between February and November 2015 (Post 1) and after December 2015 (Post 2). Standard errors are clustered at the bank level.

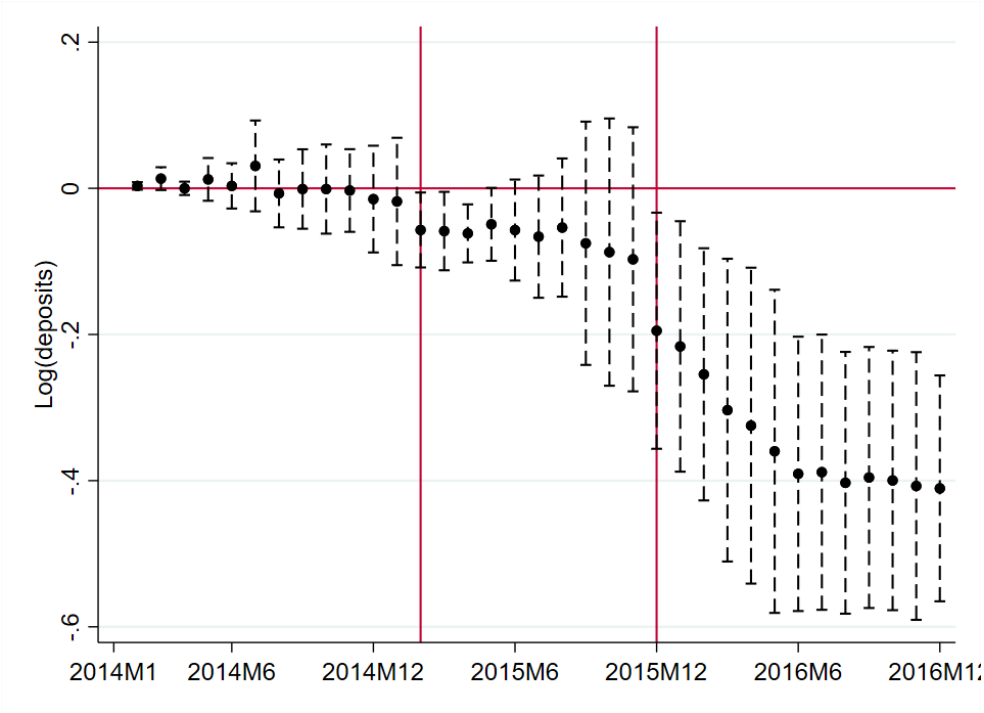


Figure A3. Credit volume from distressed banks: Dynamic DiD

This figure plots the β_t coefficients and associated 95% confidence interval from the following regression:

$$Log(Credit)_{f,b,t} = \sum_{t=2014Q1}^{2016Q4} \beta_t \, \mu_t \times D_b + \alpha_{f,t} + \alpha_b + \varepsilon_{b,p,t},$$

where D_b is a dummy equal to one for credit given by distressed banks, μ_t is a year-quarter calendar dummy and β_t measures the impact in each quarter from 2014Q1 to 2016Q4. We include firm-time and bank fixed-effects, $\alpha_{f,t}$ and α_b. Standard errors are clustered at the bank level.

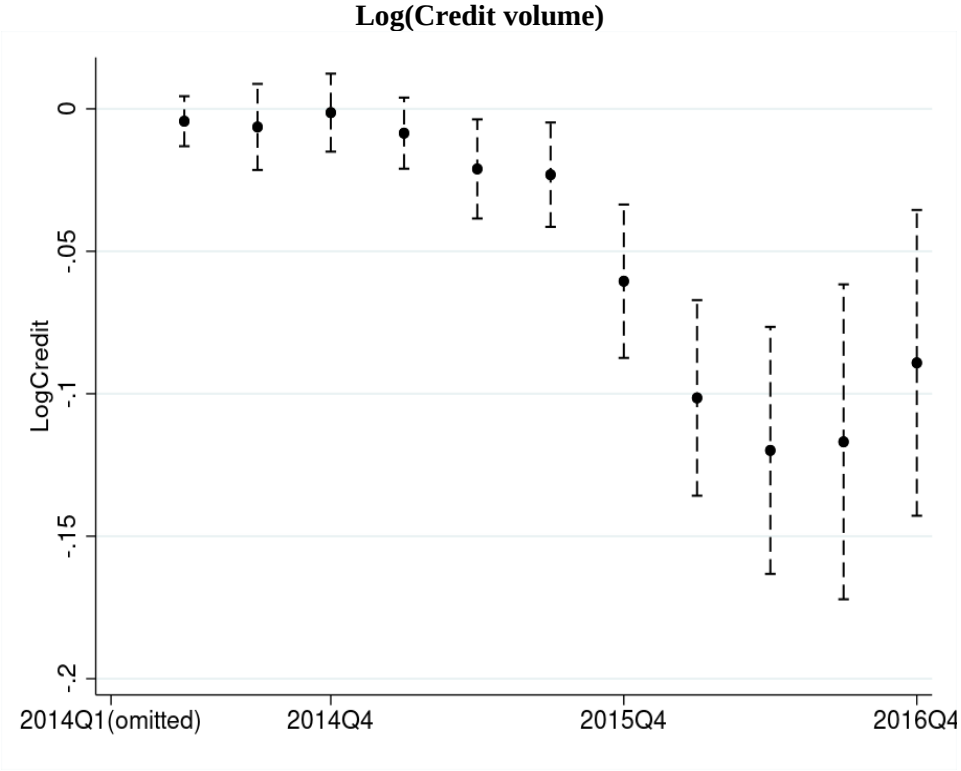


Table A1. Deposit Reallocation: Robustness

This table provides the estimates for Equation (1) using the continuous share of deposits in 2013 instead of $HighShare_{p,2013}$ which is based on the median value. The sample period is 2014M1-2016M12. The unit of observation is at the bank-province-month and the dependent variable is the log of deposits by non-distressed bank *b* in month *t* in province *p*. *Share* the share of share of local firm deposits in columns (1)-(4) and of household deposits in columns (5)-(7). *HighCapital* is a dummy equal to one if the bank has an above the median capital ratio in 2013, 0 otherwise. *LargeBank* is a dummy equal to one if the bank has total assets above €100 billion in 2013 (one of the top five banks in Italy). Standard errors are clustered at the province level.

	Log(deposits of non-distressed banks)						
	Firms				Households		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share × Post 1	0.305						
	(0.76)						
Share × Post 2	1.221**						
	(2.22)						
Share × Post1		1.762*		1.776*	-0.252		-0.205
× HighCapital		(1.75)		(1.71)	(-0.29)		(-0.23)
Share × Post2		2.893**		2.772**	1.349		1.380
× HighCapital		(2.29)		(2.12)	(1.29)		(1.31)
Share × Post1			-0.507	0.112		0.333	0.265
× LargeBank			(-1.09)	(0.21)		(1.11)	(1.17)
Share × Post2			-1.682**	-0.692		-0.268	0.133
× LargeBank			(-2.40)	(-0.83)		(-0.56)	(0.34)
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	188139	188139	188139	188139	166623	166623	166623
R-squared	0.475	0.480	0.480	0.480	0.438	0.438	0.438

Table A2. Balance of firm characteristics

This table reports the average values of firm characteristics as of December of 2013 from the shock computed for distressed and non-distressed bank borrowers. Manufacturing, Retail & Wholesale Trade and Constructions are dummies equal to one if the firm belongs to one of those 1-digit sectors. Numbers in parentheses are the normalized differences (the difference between the averages in the two groups, normalized by the square root of the sum of the corresponding variances, see Imbens and Wooldridge 2009). Numbers exceeding 0.25 indicate an unbalanced sample in that covariate.

	Distressed Banks Borrowers	Non-Distressed Banks Borrowers
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)
HighRisk	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)

Table A3. Are single relationship borrowers less risky?

This table provides the estimates on the riskiness of single relationship borrowers. The unit of observation is a firm in 2013Q4. The dependent variable is a dummy equal to one for firms that have only one bank relationship at the beginning of the sample period (2013Q4), 0 if more than one. *HighRisk* is a dummy equal to one if the Altman Z-score is above 7. Standard errors are robust. T-statistics are reported in parentheses.

	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	61493	58197	57485	57437
R^2	0.276	0.293	0.263	0.272

Table A4. Real effects: sales and wage growth

This table provides the estimates on the effects of bank distress. The unit of observation is a firm-year. The dependent variable is the annual growth rate of sales in Panel A and annual growth rate of wages in Panel B. $ShareDistressed_f$ is the share of credit from distressed banks in year=-2. Lagged firm controls include: the log of total assets, the log of firm age, the ratio of EBITDA over assets. Credit score dummies, which go from 1 (safe) to 9 (risky), are interacted with year-quarter indicator. Standard errors are clustered at the firm level. T-statistics are reported in parentheses.

Panel A. Sales growth	ΔLog(NetSales)					
	All	High-	Low-	All	High-	Low-
	(1)	(2)	(3)	(4)	(5)	(6)
$ShareDistressed_f$	-0.001	0.001	-0.002			
	(-0.23)	(0.18)	(-0.92)			
$ShareDistressed_f \times I(year\ 2014)$				-0.000	0.002	-0.005
				(-0.08)	(0.24)	(-0.93)
$ShareDistressed_f \times I(year\ 2015)$				0.000	0.005	-0.002
				(0.08)	(0.53)	(-0.43)
$ShareDistressed_f \times I(year\ 2016)$				0.005	0.004	0.004
				(1.10)	(0.43)	(0.82)
$ShareDistressed_f \times I(year\ 2017)$				-0.008*	-0.011	-0.007
				(-1.75)	(-1.04)	(-1.32)
Observations	174884	40011	134487	174884	40011	134487
R^2	0.080	0.147	0.075	0.080	0.147	0.075

Panel B. Wage growth	ΔLog(Wages)					
	All	High-	Low-	All	High-	Low-
	(1)	(2)	(3)	(4)	(5)	(6)
$ShareDistressed_f$	0.001	0.002	0.000			
	(0.55)	(0.41)	(0.03)			
$ShareDistressed_f \times I(year\ 2014)$				0.001	-0.004	0.003
				(0.34)	(-0.43)	(0.78)
$ShareDistressed_f \times I(year\ 2015)$				0.002	0.010	-0.002
				(0.54)	(1.09)	(-0.41)
$ShareDistressed_f \times I(year\ 2016)$				0.004	0.006	0.002
				(0.90)	(0.63)	(0.41)
$ShareDistressed_f \times I(year\ 2017)$				-0.003	-0.003	-0.004
				(-0.67)	(-0.27)	(-0.86)
Fixed-effects & controls						
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Province×Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
I(CreditScore) × Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	159632	34959	124257	159632	34959	124257
R^2	0.072	0.124	0.067	0.072	0.124	0.067