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The Role of Structural Funding for Stability in the German Banking Sector

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The Role of Structural Funding for Stability in the German Banking Sector*

Fabian Schupp Leonid Silbermann

Abstract

We analyze whether, and if so by how much, stable funding would have contributed to the financial soundness of German banks in the time period between 1995 and 2013, before the Basel III liquidity regulation to address excessive maturity mismatches in the wake of the financial crisis via the Net Stable Funding Ratio can be expected to have been fully implemented. Using a dataset that contains information on critical events of German banks, we find that financing loans using fewer customer deposits would have been associated with a higher probability of financial distress for savings banks and credit cooperatives. A one percent rise in the loan-to-deposit ratio from 1995 to 2013 corresponds to an increase in the probability of experiencing a critical event, implying approximately two additional savings banks and two additional credit cooperatives in financial distress. No such effect can be detected for commercial banks (excluding big banks), which are found to be far more heterogeneous with respect to their business models.

Keywords: Banks, financial distress, stable funding, Basel III liquidity regulation, NSFR, financial stability, panel data, random effects logit

JEL classification: G21, G28, C23, C25.

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1 Introduction

The financial crisis revealed a large vulnerability of banks originating from money market funding. It showed that liquidity problems were among the main causes of distress in the global financial sector as banks failed to prepare themselves for short-term liquidity stress. As countermeasures, the Basel Committee on Banking Supervision (BCBS) introduced the *Liquidity Coverage Ratio* (LCR) and the *Net Stable Funding Ratio* (NSFR). While the former requires banks to hold enough unencumbered highly liquid assets to withstand a 30 day liquidity stress scenario, the latter stipulates that banks procure sufficient stable funding over a time horizon of one year. Although a full assessment of how successful the NSFR might be at addressing excessive maturity mismatches in the banking sector is not feasible at this stage, we investigate what the impact of stable funding on the probability of banks experiencing financial distress has been in the past. To this end, we use supervisory data on critical events of financial institutions spanning a time period of 19 years and combine it with balance sheet data as well as other supervisory data in order to estimate the effect of stable funding on banks' probabilities of financial distress. Due to the fact that the NSFR cannot be calculated exactly for the time period prior to its implementation, we use the loan-to-deposit ratio and the loan-to-interbank-liabilities ratio as proxies for stable funding. As a result of our empirical work, we find evidence that stable funding makes critical events significantly less likely for savings banks and credit cooperatives, suggesting a stabilizing effect of the NSFR. This effect cannot be found for the banking group of commercial banks. We corroborate our findings in a series of robustness checks.

The remainder of this paper is organized as follows. Section 2 discusses the related theoretical and empirical literature. Section 3 describes the data, presents the estimation approach, the results, and provides a critical discussion of our findings. Section 4 concludes.

2 Literature

The most recent experience during the financial crisis serves as anecdotal evidence for the importance of funding structures, including in Europe. At the beginning of the crisis, major strains on European money markets were observed (BIS (2008)) to which the ECB reacted by providing €95 bn of funding into the interbank market (Brunnermeier (2009)). Northern Rock is one of the most prominent examples of how funding freezes can put otherwise sound institutions on the brink of bankruptcy. Money market withdrawals caused severe trouble at Northern Rock, long before the bank's depositors even anticipated its financial problems (Shin (2009)).[1] For the German Hypo Real Estate, trouble began with its subsidiary DEPFA plc having problems rolling over its wholesale funding following the Lehmann collapse (Deutscher Bundestag (2009)). In response, the regulator decided that banks should therefore make themselves more resilient against stress on the interbank

[1] Northern Rock funded its rapid growth mainly through wholesale funding. While the bank's deposit share basically stagnated, its wholesale funding share declined to merely 23% by July 2007, which was well before the depositor run. The latter occurred despite the public announcement of the liquidity assistance by the government. Also, 2/3 of the drained deposits are accounted for by postal, telephone or internet accounts and only 1/3 by classic bank accounts (Shin (2009)).

funding market. Building on past experience, the NSFR considers interbank funding with maturities below one year to be unstable and incentivizes banks to fund themselves using more stable sources of funding like deposits from households and non-financial corporations. These deposits are considered stable despite their short-term maturity due to very low run-off rates.

a) Stable funding in theoretical literature

In theory, wholesale funding, especially owing to its short-term maturity structure, is often thought to have a disciplining effect on banks as it prompts them to rollover their debt frequently. Given their high expertise, wholesale investors would also be expected to provide better and closer monitoring than depositors would; at the same time opening up more investment opportunities for banks (Brunnermeier (2009), Calomiris and Kahn (1991), Huang and Ratnovski (2011)).

However, a sufficiently high degree of wholesale funders' seniority might force otherwise financially sound banks into inefficient liquidation given publicly available but imprecise information like market prices and credit ratings. Using a noisy negative public signal on banks' project quality, wholesale investors have the incentive to reduce their monitoring and withdraw their funds if their seniority governing the division of banks' liquidation value is sufficiently high. This holds true especially for large and publicly traded banks, while traditional banks holding opaque and non-tradable loans should still profit from wholesale funding and its disciplining character.[2] A higher share of deposit funding (along with a higher precision of the public signal) might even fortify this mechanism, given that more deposits incentivize early withdrawals by wholesale creditors, as they raise the liquidation value (Huang and Ratnovski (2011)).

Another source of instability of wholesale funding that is transmitted through the interbank market structure which is prone to sudden market freezes, as could be observed during the financial crisis, are the so called *liquidity spirals* (Brunnermeier and Pedersen (2009)). A major part of wholesale funding is obtained by borrowing against assets subject to haircuts. Operating at the edge of being equity constrained, these haircuts determine a bank's maximum leverage[3], so that rising haircuts force banks to either raise more equity or deleverage by selling off assets in order to hold their leverage constant.[4] If there is a general increase in haircuts due to rising volatility in the market, the banking system

[2] This is especially relevant when analyzing the German banking system, as savings banks and credit cooperatives are a lot more opaque for outside investors than many commercial banks. Of course, there is also a high degree of heterogeneity within the commercial banking sector itself. Small institutions, in particular, do not necessarily disclose much information on their business, and thus, are not any more easily monitored than are savings banks and credit cooperatives.

[3] Brunnermeier (2009) describes how banks maximize their leverage under the constraints implied by haircuts.

[4] Shin (2009) provides an easy example of this mechanism. Assuming a bank holds assets worth 100 units and the haircut applied is 2%. This means, that the bank can borrow 98 units against this asset and has to obtain 2 units of equity funding. Its leverage would then be $100/2 = 50$. Were the haircut to rise to 4%, equity would have to double to 4 to reach the new maximum leverage of 25. However, increasing equity would probably be even harder in times of stress. Alternatively, the bank can sell off assets. According to Shin, they usually decide on the latter. Additionally, banks always hold enough equity to cover their *Value-at-Risk* which amplifies the mechanism even more and adds to its procyclicality, as *Value-at-Risk* and leverage are inversely related (see Shin (2009)).

might experience extreme funding stress.

On the other hand, due to very low run-off rates, deposits are perceived to be a very stable form of funding in the Basel accords on liquidity regulation (BCBS (2014)).[5] This can be attributed to the switching costs that depositors incur whenever they move money to a new bank, as well as to deposit insurances (Flannery (1982), Sharpe (1997), Diamond and Dybvig (1983)). However, insured deposits might also destabilize banks by being less disciplining than market funding (Billett, Garfinkel, and O'Neal (1998) and Demirgüç-Kunt and Detragiache (1998)).[6]

Another reason why deposits are stable relates to liquidity services provided by the bank which, in a distress event, make depositors withdraw later than wholesale creditors. It is also argued that there is a link between a bank's assets and its choice of funding. Banks that engage primarily in relationship lending rely more on deposits due to their lower risk of sudden withdrawal (Song and Thakor (2007)).[7] This is not exactly in line with the argument brought forward by Huang and Ratnovski (2011), which is that banks with intransparent assets should profit more from wholesale funding as wholesale investors' greater monitoring effort imposes market discipline.

b) Stable funding in empirical literature

Theory points towards a relevant but to some extent arbitrary effect of more stable funding for systemic stability. Empirical evidence can be found in Hong et al. (2014) who find a small but significant stabilizing effect of the NSFR. In their study, they examine the role of stable funding by using monthly bank-level balance sheet data from the *call reports* published by the Fed. Their dependent variable in a dynamic discrete-time hazard model[8] is a failure dummy constructed from data on bank failures available from the *Federal Deposit Insurance Corporation* (FDIC).[9] They emphasize the role of the NSFR in lowering systemic risk, in particular. Similarly, Bologna (2015) finds a positive impact of the foreseen regulation on bank stability by using the same data sources in a pooled multivariate logit estimation.[10] In his work, the failure dummy as the dependent variable is regressed on a set of different bank performance indicators and on a loan-to-deposit ratio as a measure for stable funding. He concludes that a greater deposit base for loans would have led to fewer bank defaults in the US between 2007 and 2009. However, the

[5] Hong, Huang, and Wu (2014) confirm the run-off rates applied by the LCR and NSFR regulation quantitatively.

[6] See also Bologna (2015) who, by further differentiating between different types of deposits, can show that depending on whether one regards core deposits or brokered deposits and whether they are small or large, they differ in their stability, with small core deposits being the most stable kind.

[7] Song and Thakor (2007) also show that banks might deviate from that behaviour when exposed to more competition, which then raises the riskiness of the bank.

[8] Their model is based on the Moody's RiskCalc Model.

[9] The FDIC defines defaults "[...] with respect to an insured depository institution any adjudication or other official determination by any court of competent jurisdiction, the appropriate Federal banking agency, or other public authority pursuant to which a conservator, receiver, or other legal custodian is appointed for an insured depository institution or, in the case of a foreign bank having an insured branch, for such branch.", see the FDIC's website, https://www.fdic.gov/regulations/laws/rules/1000-400.html, December 2015.

[10] The approach followed by Bologna (2015) is adapted in this paper. In particular, his proxy for the NSFR, the loan-to-deposit ratio, is central to our empirical analysis.

economic significance of the effect of funding on the probability of default clearly trails the effects of higher capitalization, higher profitability and lower asset risk.

Peresetsky, Karminsky, and Golovan (2004) combine quarterly balance sheet data with macro variables and construct a failure dummy to run a logit estimation for Russian banks with a sample spanning the period from 1997 to 2003. They find a higher share of deposit funding to be beneficial with regard to lowering the default risk of small, but not of large banks in Russia. This emphasizes the need to control for bank size when examining the effect of stable funding. According to Wong, Fong, Li, and Choi (2010), in Hong Kong the NSFR also reduces the probability of banking distress. Their results are based on a linear regression of an estimated banking distress probability on aggregated bank balance sheet measures accounting for capital adequacy and funding structure as well as macro variables accounting for inflation and output covering the period from 1998 to 2010.

Focusing on macro effects of the new regulation in the U.K., Yan, Hall, and Turner (2012) find a negative impact on GDP in the short run, mainly based on bank lending rates. The effect on bank profitability in the long run is, however, positive. Utilizing a binary response model, they estimate the probability of a banking crisis occuring conditional on aggregate bank capital adequacy, the NSFR and macro variables. They conclude that the NSFR helps to reduce the probability of banking crises and expect it to have a positive impact on output in the long run.

Using a CoVaR approach[11] López-Espinosa, Moreno, Rubia, and Valderrama (2012) address systemic risks, finding wholesale funding to be a key determinant in triggering systemic risk episodes. This is true even from a global perspective, according to which money markets can be considered an important distribution channel of risk across countries. The authors used disaggregated data on 54 international banks from 18 countries covering the period from July 2001 until December 2009.

Gobat, Yanase, and Maloney (2014) deliver some insights into the extent to which banks have adjusted to the upcoming implementation of the new funding regulation to date. They calculate the NSFR for over 2000 banks in 128 countries including Germany at end-2012. They show that at that point in time more than half of all German banks included had already addressed their funding risk by fulfilling the NSFR minimum requirements.[12] If those results could be generalized, this would suggest that the final implementation of the new regulation will not lead to much further change in the German banking sector.

To the best of the authors' knowledge, there is no study that quantifies the impact of stable funding on bank stability in Germany. However, Porath (2006) analyzes the effect of other potential risk drivers found on banks' balance sheets and those caused by changes in the macro environment. He finds the main drivers to be capitalization, return, credit risk, market risk as well as different business cycle indicators and macroeconomic price variables. The author gathers critical events experienced by the German banks from the same supervisory dataset as we use in this paper. Another study that uses these data is Kick and Koetter (2007). In their study, the authors show how the different events recorded by the supervisor can be clustered in different categories of severity in order to estimate a generalized ordered logit model. Their main result is that the probability of

[11]This risk measure has first been proposed by Adrian and Brunnermeier (2011).

[12]This is also true for the majority of banks in the entire sample. Their results suggest that large banks tend to have the greatest need for adjustment to comply with the NSFR.

the respective critical events responds differently to given changes in the financial profiles of banks.

3 Empirical analysis

3.1 Data

In order to answer the question of whether stable funding has been conducive to the overall stability of German banks in the past, we use unique supervisory data that contain information on critical events of German monetary financial institutions, which we combine with banks' balance sheets, profit and loss accounts, and additional supervisory data. We eliminate from our sample branches of foreign banks, special purpose banks, mortgage banks as well as building and loan associations. Branches of foreign banks from the EU and some other jurisdictions are not supervised by the German Federal Financial Supervisory Authority, building and loan associations and special purpose banks have very specific business models that do not focus on traditional loans to consumers and/or firms that are financed by deposits from the private non-financial sector. As far as the mortgage banks are concerned, we do not have data on profitability for almost half of the observations. On average, the remaining banks' loans and deposits account for approximately 95% of the loans and deposits of German monetary financial institutions. Depending on the year, the number of banks in our sample ranges from 3,269 to 1,619.

3.1.1 Financial distress events

We have access to a dataset that contains information on critical events of German banks from 1995 to 2013 at an annual frequency.[13] The data have been put together by the Deutsche Bundesbank for microprudential supervisory purposes[14] and have also been used in academic studies (see Koetter, Bos, Heid, Kolari, Kool, and Porath (2007), Kick and Koetter (2007), Porath (2006)). Critical events of banks that comprise the dataset vary with respect to their severity. It is possible for a bank to experience one (several) event(s) in consecutive years as well as several different events in one year. Once a bank has entered into a critical state, subsequent critical events recorded by the supervisor are not treated as new events in the following. Banks are labeled as "cured" in the data only after a one year waiting period. After this time banks might again experience critical events. We map the different critical events listed below to one single category of financial distress events.[15] A financial distress event is classified as such if for bank i in period t at least one of the following critical events occurs:

- Disclosure of facts[16] pursuant to section 29(3) of the Banking Act (BA)

[13]There is also a variable indicating whether or not for a certain bank critical events took place prior to 1995.

[14]The data are used to maintain and validate SRP ratings (SRP: supervisory review process) of banks from several banking groups.

[15]This, of course, is a simplified view and disregards different degrees of severity of the critical events. However, for the sake of having as large a sample size as possible and practicability of our empirical approach, we find it feasible to treat each critical event as a financial distress event. Later on, we confirm this approach in several robustness checks.

[16]This refers to the auditor becoming aware of facts that jeopardize the existence of the institution

- Operating loss in excess of 25% of liable capital
- Losses of liable capital amounting to at least 25% pursuant to section 24(1) of the BA
- Forbiddance of granting of loans/large exposures pursuant to sections 45 or 46 of the BA
- Moratoriums pursuant to section 4a of the BA
- Capital preservation measures
- Restructuring caused by mergers[17]
- Liquidation or insolvency
- Financial Market Stabilisation Fund (Sonderfonds Finanzmarktstabilisierung: SoFFin) recapitalisation measures and guarantees.[18]

This definition is very closely related to what constitutes a financial distress event of a bank according to Porath (2006) and covers all events indicating that a bank is in danger of ceasing to exist as a going concern[19] without outside intervention. A broad definition of financial distress events as opposed to restricting the analyses to liquidation or insolvency events is necessary for our study as, in particular, savings banks and credit cooperatives are well protected against full-blown defaults which are usually prevented by internal rescue mechanisms.[20]

The critical events are collected by the local banking supervisors on a yearly basis. The exact dates on which these events occurred cannot be retrieved in all cases. For all following analyses, we only consider those bank years in which a bank experiences a critical event after being considered financially healthy for at least one year, while

or fundamentally impair its development. However, for the supervisor, this leads to the recording of a critical event only if at least one of the other events described above occurs in the following year.

[17]Only mergers that come about as a result of at least one bank experiencing financial difficulties are recorded. Ordinary M&A activities are not part of the dataset.

[18]These are measures taken by the Financial Market Stabilisation Fund, that aim to stabilize the financial system in Germany. The guarantees apply to newly issued debt securities and justified other debt issued by financial institutions. The SoFFin recapitalisation measures and guarantees are not an integral part of the data on critical events of German banks. We augment the original dataset by the SoFFin data whenever there is a SoFFin recapitalisation measure or a guarantee for a bank and none of the above criteria has been met to trigger an entry into the original dataset. This applies to Commerzbank in 2008 and BayernLB in 2009. See the Federal Agency for Financial Market Stabilisation (FMSA) website, http://www.fmsa.de/export/sites/standard/downloads/20140630_Overview_of_SoFFin_measures.pdf, April 2015.

[19]In case of a liquidation or insolvency, a bank is a gone concern.

[20]Savings banks in Germany collectively hold funds and reserves to guarantee the liquidity and solvency of all members of the *Sparkassen Finanzgruppe* in which all savings banks are included. In this way, they guarantee deposits even beyond the legal minimum of €100.000 (see the *Finanzgruppe and Deutsche Sparkassen- und Giroverbund* website, http://www.dsgv.de/de/sparkassen-finanzgruppe/haftungsverbund/, April 2015 and Simpson (2013)). Credit cooperatives have a similar arrangement: A fund guaranteeing all deposits as well as debt held by customers and by investment companies as long as these liabilities relate to parts of the fund assets (Bundesverband der Deutschen Volksbanken und Raiffeisenbanken (2014)).

subsequent years already in financial distress are omitted. This is essential because once a bank experiences a critical event, it must be expected that this event affects balance sheet data in the following periods, which leads to endogeneity concerns in the model.

In our estimation, we use 637 critical events (without subsequent critical events), 105 of which were commercial banks, 76 savings banks and Landesbanken, and 456 credit cooperatives and their regional institutions.[21] Appendix A.3 presents a brief descriptive analysis of the critical events used in this study. As far as the nature of critical events is concerned, almost half of the events are capital preservation measures. The second most frequent critical event is restructuring caused by mergers, which could be observed in over 30% of the financial distress events, followed by operating losses in excess of 25% of liable capital in over 10% of the critical events. Table A2 in Appendix A.1 contains a breakdown of the financial distress events experienced by the German banks from 1995 to 2013 by event type and banking group.

3.1.2 Exogenous variables of interest

Our aim is to investigate whether stable funding - as envisioned by the Basel Committee on Banking Supervision - would have made German banks safer in the time period before the liquidity regulation was expected to come into force. Within the framework of the Basel III liquidity regulation, the *Net Stable Funding Ratio* (NSFR) was introduced. According to the BCBS (2014), the NSFR relates *Available Stable Funding* (ASF) to *Required Stable Funding* (RSF) and is formally defined as

$$\text{NSFR} = \frac{Available\ Stable\ Funding}{Required\ Stable\ Funding} = \frac{ASF}{RSF} \geq 100\%.$$

RSF consists of banks' assets, off-balance sheet items and other selected activities that are weighted by the RSF factors based on supervisory assumptions regarding the respective liquidity profile of each exposure. The corresponding RSF factors are the amounts of each exposure that supervisors think should be supported with stable funding reflecting the relative market illiquidity of the respective assets and off-balance sheet items. Funding is regarded as stable if it can be expected not to be withdrawn in an extended period of stress. When determining a bank's ASF, each funding source is assigned a factor between 0 and 1. Funding with a factor of 1 includes Tier 1 and Tier 2 capital as well as secured and unsecured funding with a residual maturity of at least one year. Retail deposits of small customers and small non-financial corporations with a residual maturity of less than one year are assigned a factor of 0.95 or 0.9 depending on their respective run-off rate which may lie between 3% and 10% or above 10%[22]. Deposits which are covered by a deposit insurance scheme are also regarded as stable. Unsecured money market funding is seen as much less stable and is assigned a factor of only 0.5. Similarly, deposits of non-banks, governments, central banks, multilateral development

[21] The number of critical events is conditional on available observations for our explanatory variables. Throughout the entire sample there are 719 financial distress events. However, in 82 cases, observations for at least one exogenous variable used in the estimation are missing.

[22] See BCBS (2013) and BCBS (2014). The exact run-off rate is determined by the responsible regulator and is supposed to mirror the behavior of depositors in the respective jurisdiction in a period of stress.

banks as well as other public institutions with a residual maturity of less than one year are assigned a factor of 0.5. Money market funding with a residual maturity of less than 6 months is regarded as unstable and is assigned a factor of zero. In each period, banks' ASF should be at least equal to their RSF, or put differently, the ratio of ASF over RSF should be equal to or greater than 100%. The aim of the NSFR is

> "[...] to limit over-reliance on short-term wholesale funding during times of buoyant market liquidity and encourage better assessment of liquidity risk across all on- and off-balance sheet items" (BCBS (2014)).

Ideally, we would calculate the Net Stable Funding Ratio according to the Basel III formula using data from the past.[23] However, the data at our disposal are not granular enough, and hence, do not allow us to do so. Therefore, we use the *loan-to-deposit ratio (LTD)*[24] and the *loan-to-interbank-liabilities ratio ($LTIBL$)* as our main variables of interest to proxy banks' stable funding.

Our LTD is very similar to that used by Bologna (2015) and is constructed as the ratio of all loans to the non-financial sector over all unsecured liabilities towards non-banks.

$$LTD_{it} = \frac{Loans_{it}}{Deposits_{it}} \cdot 100. \tag{1}$$

The LTD is a simple, balance sheet-based measure of stable funding that is established in the literature (see, for example, Bank of England (2014), Van den End (2013)).[25] According to the European Systemic Risk Board, limits on the LTD can be used as one of the macroprudential instruments to address excessive maturity mismatches by increasing the stability of banks' funding base.[26] There is also some empirical evidence that the LTD can be a good predictor of funding vulnerabilities (European Systemic Risk Board (2014)).[27]

Since the NSFR of a bank is a decreasing function of its loans and an increasing function of its deposits, the LTD is related to the NSFR in an inverse fashion. The lower the LTD and the higher the NSFR, the more stable the funding of a bank is. If the LTD

[23]In the literature some direct approaches are discussed to get a good approximation of the NSFR. They rely on assumptions about the share of certain asset and liability categories as classified by the NSFR regulation (i.e. categories relating to the maturity and stability of these assets) within the categories reported (Hong et al. (2014), Wong et al. (2010) and Yan et al. (2012)).

[24]The LTD can be regarded as a simple variant of the NSFR (European Systemic Risk Board (2014)).

[25]The drawback of this measure, however, is that it does not completely capture the maturity transformation as it only focuses on certain parts of banks' balance sheets (European Systemic Risk Board (2014)).

[26]As part of the programme on economic and financial assistance, Banco de Portugal introduced an indicative target of 120% for the LTD of the eight largest banking groups to be reached by 2014 as one of several measures to achieve a more balanced funding profile for the banking sector. A mandatory cap of 100% for banks' LTD was introduced in South Korea in the aftermath of the financial crisis and came into force in 2012.

[27]The LTD seems to be used as a measure of stable funding by bank managers as well. According to Moorad Choudhry, the former Head of Business Treasury, Global Banking and Markets at the Royal Bank of Scotland, the LTD "[...] is a standard and commonly used metric, typically reported monthly. It measures the relationship between lending and customer deposits, and is a measure of the self-sustainability of the bank (or the branch or subsidiary). A level above 100% is an early warning sign of excessive asset growth; of course, a level below 70% implies excessive liquidity and implies a potentially inadequate return on funds" (Choudhry (2011)).

of a bank rises (either on account of falling deposits or because loans have increased or both), then the NSFR decreases[28] according to the ASF and the RSF factors outlined in the Basel III liquidity regulation.[29]

As wholesale funding is not the residual when equity and deposits are subtracted from liabilities, we also consider the $LTIBL$, defined as

$$LTIBL_{it} = \frac{Loans_{it}}{Interbank\ Liabilities_{it}} \cdot 100. \tag{2}$$

It should be noted that the relation between the $LTIBL$ and the NSFR is not as clear-cut as in the case of the LTD, as depending on the maturity, an increase in certain interbank liabilities can either lead to an increase or a decrease in the NSFR. The data at our disposal do not allow us to make the relevant distinction.

Appendix A.4 provides a descriptive analysis of our exogenous variables of interest.

3.2 Econometric specification

Our starting point is the underlying latent-variable model:

$$y^*_{it} = \boldsymbol{x_{i,t-1}}'\boldsymbol{\beta} + \boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma} + \delta RD_i + \boldsymbol{TD}'\boldsymbol{\zeta} + \alpha_i + u_{it}, \qquad i = 1, \ldots, n; t = 2, \ldots, T_i$$

$$y_{it} = \begin{cases} 1 & \text{if } y^*_{it} > 0 \\ 0 & \text{otherwise.} \end{cases}$$

y^*_{it} is a latent, continuous variable that reflects bank i's financial health in an inverse fashion, i.e. the larger y^*_{it} is, the closer bank i is to default. The observable dummy y_{it} takes on the value one if bank i experiences financial problems in period t, and zero if it is financially healthy in t. $\boldsymbol{x_{i,t-1}}$ is a vector of lagged measures of banks' stable funding, i.e. it contains our main exogenous variables of interest.[30] Depending on the specification, it either consists of the loan-to-deposit ratio LTD as defined in (1) or the loan-to-interbank liabilities ratio $LTIBL$ as defined in (2), or both.[31] Standard deviations in Table A3 in Appendix A.1 reveal that there are several very large values in both ratios, particularly for commercial banks and the group of credit cooperatives. These come about as a consequence of certain banks' business models that use almost no deposits or interbank liabilities to fund loans. Winsorizing both ratios is one possible solution, but this might give rise to a sample selection bias, as specific business models reflected by particularly large or small values of either one of the ratios could be related to financial distress. The fact that the share of bank years in financial distress is higher for the largest 1% of the LTD values than for the overall sample suggests that this might indeed be the case. For this reason, we take the (natural) logarithm of both ratios. Doing so compresses the respective distributions somewhat, such that extremely large values do not drive the

[28] A lower deposit base reduces the ASF, while a greater volume of loans increases the RSF.

[29] Wong et al. (2010) estimate the correlation of the NSFR and their LTD for banks in Hong Kong and find a significant negative linear relation between the two variables.

[30] The exact details and definitions of the variables used in the econometric analysis can be found in Appendix A.2.

[31] Whenever only one measure of stable funding is used, the vector naturally becomes a scalar $x_{i,t-1}$.

results so much.[32] Apart from avoiding possible endogeneity problems, this approach is more efficient, as it utilizes all available observations. The vector $\boldsymbol{z_{i,t-1}}$ of lagged explanatory variables contains the following control variables: the return on assets ROA as a measure of banks' profitability[33], the capital ratio CR[34] in order to account for banks' capacity to absorb losses, the loan loss ratio LLR to measure the quality of banks' assets, the administrative expenses ratio $AdminR$ as a proxy for banks' efficiency, relative liquid assets $Liquid$ to capture banks' market liquidity[35], $Total\ Assets$ as a proxy for banks' size, and the $Z-Score$ or the distance to default[36] to proxy banks' risk profile as is common in the literature (see, for example, Boyd, Graham, and Hewitt (1993), Laeven and Levine (2009), Demirgüç-Kunt and Huizinga (2010)). We take the (natural) logarithm of all explanatory variables[37] but the ROA and the $Z-Score$ because the logarithm cannot be computed, as in some cases, negative returns render both variables negative. We use lagged explanatory variables to mitigate endogeneity concerns and avoid reverse causality. Since it is impossible for us to tell when exactly the financial distress incident took place during a certain year, using lagged explanatory variables is absolutely necessary to make sure that a certain period of time lies between the date on which balance sheet items are disclosed and the financial distress event. Additionally, we control for geographical effects using regional dummies RD[38] as well as macroeconomic effects that impact all banks' financial health in a given year (e.g. regulatory changes) captured by the vector of time dummies $\boldsymbol{TD}$. The stochastic error term consists of a time-varying, idiosyncratic component u_{it} and a time-constant, bank-specific unobserved heterogeneity α_i. To model the probability for the observed Bernoulli-distributed dummy-variable y_{it}, we use the logistic function, i.e. we estimate the following random effects logit model:

$$\begin{aligned} Pr(y_{it}=1|\boldsymbol{x_{i,t-1}},\boldsymbol{z_{i,t-1}},RD_i,\boldsymbol{TD},\alpha_i) &= \Lambda(\boldsymbol{x_{i,t-1}}'\boldsymbol{\beta}+\boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma}+\delta RD_i+\boldsymbol{TD}'\boldsymbol{\zeta}+\alpha_i) \\ &= \frac{exp(\boldsymbol{x_{i,t-1}}'\boldsymbol{\beta}+\boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma}+\delta RD_i+\boldsymbol{TD}'\boldsymbol{\zeta}+\alpha_i)}{1+exp(\boldsymbol{x_{i,t-1}}'\boldsymbol{\beta}+\boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma}+\delta RD_i+\boldsymbol{TD}'\boldsymbol{\zeta}+\alpha_i)}, \end{aligned} \tag{3}$$

[32] Winsorizing all explanatory variables in $\boldsymbol{x_{i,t-1}}$ and $\boldsymbol{z_{i,t-1}}$ at the 1% and 99% level, respectively, leads to qualitatively similar estimation results.

[33] We prefer the ROA to the return on capital measure of profitability because the former is insensitive to banks' choice of their capital structure.

[34] Due to the fact that for the period before 2008, Tier 1 capital can only be approximated, we use equity from banks' balance sheets to measure their capital.

[35] CR, LLR, $AdminR$, ROA and $Liquid$ are the so-called **CAMEL** control variables that were applied in a rating system by US regulators and are extensively used in the literature (see, for example, Wheelock and Wilson (2000)). **CAMEL** stands for **C**apital adequacy, **A**sset quality, **M**anagerial efficiency, **E**arnings and **L**iquidity.

[36] The $Z-Score$ is the number of standard deviations that a bank's ROA has to fall to trigger default. To include banks' risk-taking might be important as shown by Vázquez and Federico (2012).

[37] Note that for the LLR there are 618 zeros. In order to compute the respective logarithm, we replace these with $\epsilon = 1 \cdot 10^{-10}$. Using the ratios in place of logarithms does not change the results.

[38] In our case, the term region applies to the German federal states in which banks are headquartered. The regional dummies are supposed to capture region-specific, structural effects that might be relevant for banks' financial health and do not vary over time, e.g. structural unemployment. For banks that operate across different federal states the implicit assumption is that the fraction of activities taking place outside the federal region in which the respective bank is headquartered is relatively small as time-invariant, regional conditions in other federal states are not picked up by the regional dummy associated with the respective bank.

$$u_{it}|\boldsymbol{x_{i,t-1}}, \boldsymbol{z_{i,t-1}}, RD_i, \boldsymbol{TD}, \alpha_i \sim \mathcal{L}(0;\pi^2/3)^{39}, \qquad \alpha_i|\boldsymbol{x_{i,t-1}}, \boldsymbol{z_{i,t-1}}, RD_i, \boldsymbol{TD} \sim \mathcal{N}(0;\sigma_\alpha^2),$$

where Λ is the cdf of the error term u_{it} that follows the logistic distribution conditional on the regressors. $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ (including an intercept), δ, $\boldsymbol{\zeta}$ are the parameters to be estimated. The bank-specific unobserved heterogeneity α_i is assumed to be conditionally normally distributed around zero with the variance σ_α^2.

We prefer a logit to a probit model mainly because the logistic functional form allows us to use the log of the odds-ratio[40] and interpret the estimated coefficients directly. Ideally, we would like to compute and interpret the marginal effects, but since they are a function of the unobserved heterogeneity α_i, one needs to make assumptions about it, which is why it is convenient to have a superior alternative. Apart from that, we estimate a (conditional) fixed effects logit model to robustify our findings and it seems more natural to use a random effects logit model instead of a random effects probit model[41]. However, applying the random effects probit model yields very similar results.

3.3 Estimation results

Our main specification (3) is estimated via maximum likelihood.[42] Note that we do not use robust standard errors of the estimated coefficients for inference.[43] First, we estimate (3) using the entire sample, and hence, additionally include banking group dummies letting commercial banks be our reference group. Table 1 summarizes the main results and contains the estimated coefficients as well as the corresponding marginal effects. In a (random effects) logit model, the marginal effect on the probability of a bank experiencing a critical event induced by a small change in an exogenous variable such as stable funding in the form of the LTD is given by

$$\frac{\partial Pr(y_{it} = 1|\boldsymbol{x_{i,t-1}}, \boldsymbol{z_{i,t-1}}, RD_i, \boldsymbol{TD}, \alpha_i)}{\partial LTD_{i,t-1}} = \beta^{LTD} \cdot \Lambda(\bullet) \cdot [1 - \Lambda(\bullet)], \qquad (4)$$

[39] The scale parameter is set to one.

[40] The odds ratio is defined as the probability that a bank runs into financial difficulties over the probability that a bank remains financially healthy, and for the random effects logit model its natural logarithm is $log\{Pr(y = 1)/[1 - Pr(y = 1)]\} = \boldsymbol{x_{i,t-1}}'\boldsymbol{\beta} + \boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma} + \delta RD_i + \boldsymbol{TD}'\boldsymbol{\zeta} + \alpha_i$.

[41] In contrast to the conditional fixed effects logit model, a fixed effects probit model cannot be estimated consistently due to the incidental parameters problem introduced by the unobserved heterogeneity (see, for example, Baltagi (2008)).

[42] The unobserved heterogeneity is integrated out of the likelihood function using a method proposed by Butler and Moffitt (1982).

[43] This is guided by the theoretical consideration that in a binary outcome model such as ours the entire conditional distribution $Pr(y_{it} = 1|\boldsymbol{x_{i,t-1}}, \boldsymbol{z_{i,t-1}}, RD_i, \boldsymbol{TD}, \alpha_i)$ including all conditional moments is specified. Thus, it is not possible to correctly model the conditional expected value and at the same time incorrectly specify the conditional variance, which is one of the reasons for using robust standard errors in an OLS-type model (Cameron and Trivedi (2005)). If the random sampling assumption were violated, then cluster-robust standard errors would be required. Also, in a panel model, robust standard errors might be called for to address serial correlation. However, given our sample, we deem the random sampling assumption justified and serial correlation is taken into account by including the unobserved heterogeneity α_i in the model. Hence, there is no need to resort to the robust standard errors. While, in a random effects logit model, the robust estimator of the variance-covariance matrix is also asymptotically consistent and could, in principle, be applied, it is also more computationally intensive, which is why we choose not to use it.

and always has the same sign as the estimated coefficient β^{LTD}.[44] A statistically significant positive β^{LTD} in Table 1 means that a larger LTD of a bank increases its probability of becoming financially distressed, and (4) tells us by how much. Since the unobserved heterogeneity is one of the arguments in $\Lambda(\bullet)$, the marginal effect in (4) is also a function of α_i. To compute the marginal effect, the assumed conditional expected value $\alpha_i = 0$ is used. As this can be a nonrepresentative evaluation point, we have to interpret the marginal effects with caution. For this reason, we take advantage of the specific functional property of the logit model and use the log of the odds ratio, as defined in footnote 40, to interpret the estimated coefficients directly.

The estimated coefficient for the lagged LTD in column (1) equals 0.3302. Since we take the log of $LTD_{i,t-1}$, the interpretation of the marginal effect is that an approximate relative percentage change in stable funding in the form of LTD of bank i, given by $\Delta log(LTD_{i,t-1}) \cdot 100$, increases the log of the ratio of the probability of this bank experiencing a critical event over the probability that the bank remains financially healthy by $\frac{\beta^{LTD}}{100} \cdot [\Delta log(LTD_{i,t-1}) \cdot 100]$. That is, a 1% rise in the LTD from 1995 to 2013 increases the log of the odds ratio by 0.003302. Since (the log of) the odds ratio is a non-linear function of the probability of becoming financially distressed, the magnitude of the effect crucially depends on this probability. The predicted mean share of banks experiencing a critical event for the first time, which can be interpreted as a non-parametric empirical distribution measure for the unknown conditional expected value, amounts to 1.2792%, implying 519 bank years in distress.[45] Given the sample of 40,572 bank years, an increase in the log of the odds ratio of 0.003302 implies a rise in the mean share of bank years in distress of 0.000041767, i.e. approximately two additional banks become financially distressed.[46] Similarly, a 1% decrease in the $LTIBL$ in column (2) leads to an even greater rise in the log of the odds ratio of 0.003319 implying an increase in the mean share of bank years in distress of 0.000042458 or stated differently, almost two more banks experience a critical event. Both estimated coefficients are statistically significant indicating the importance of stable funding for the German banking sector. The likelihood ratio test rejects the null that the coefficient on the lagged LTD ($LTIBL$) is zero. The estimated marginal effects suggest a similar effect. If the LTD rises (the $LTIBL$ falls) by one percent, the conditional probability of a bank experiencing a critical event increases by

[44]The marginal effect in a (random effects) logit model depends on the estimated coefficient and the probability density function of $\Lambda(\bullet)$. Since $\Lambda(\bullet)$ is a strictly increasing cdf, the probability density function is always greater than zero, i.e the marginal effect has the same sign as the estimated coefficient. In (4), the marginal effect is expressed in terms of the cdf itself.

[45]The actual mean share of banks experiencing a critical event for the first time in all bank years throughout the entire sample, which can be interpreted as a point estimate of the unconditional probability of a bank in distress in the underlying population, is 1.57%. If our model were perfect, then the model-implied mean share of bank years in distress would equal the actual mean share. Taking the actual mean share of banks in distress as a point estimate for the unknown probability of experiencing financial distress would be inappropriate, as the probability used in the odds ratio in the context of our model is a conditional one.

[46]If the estimated mean share of banks in financial difficulties of 1.2792% is used, then the log of the odds ratio is -4.34606. An increase of 0.003302 leads to a new log of the odds ratio of -4.34276, which corresponds to an odds ratio of 0.0130006. This yields a (conditional) predicted probability of a bank running into financial difficulties for the first time of 0.012834 and a (conditional) predicted probability of a bank staying financially healthy of 0.987166. For the sample of 40,572 bank years, this means that approximately 521 (instead of the model-implied 519) bank years will turn out to be financially distressed.

Table 1: RE logit estimation – all banks (no subsequent critical events)

Explanatory variables	(1) Estimates	Marginal effects	(2) Estimates	Marginal effects	(3) Estimates	Marginal effects
$log(LTD_{i,t-1})$	0.3302***	0.0040***			0.2715***	0.0033***
	(0.0624)	(0.0008)			(0.0642)	(0.0008)
$log(LTIBL_{i,t-1})$			−0.3319***	−0.0041***	−0.3049***	−0.0037***
			(0.0560)	(0.0007)	(0.0604)	(0.0008)
$ROA_{i,t-1}$	−0.2922***	−0.0036***	−0.2616***	−0.0032***	−0.3264***	−0.0040***
	(0.0378)	(0.0005)	(0.0339)	(0.0004)	(0.0421)	(0.0006)
$log(CR_{i,t-1})$	−0.9843***	−0.0120***	−0.8341***	−0.0102***	−1.0080***	−0.0122***
	(0.1754)	(0.0022)	(0.1703)	(0.0022)	(0.1800)	(0.0023)
$log(LLR_{i,t-1})$	0.0514***	0.0006***	0.0804***	0.0010***	0.0670***	0.0008***
	(0.0194)	(0.0002)	(0.0204)	(0.0003)	(0.0205)	(0.0002)
$log(AdminR_{i,t-1})$	0.9195***	0.0112***	0.8458***	0.0104***	0.9559***	0.0116***
	(0.1477)	(0.0020)	(0.1389)	(0.0018)	(0.1508)	(0.0019)
$log(Liquid_{i,t-1})$	0.1961***	0.0024***	0.0997	0.0012	0.1834**	0.0022**
	(0.0724)	(0.0009)	(0.0682)	(0.0008)	(0.0723)	(0.0009)
$log(Total\ Assets_{i,t-1})$	0.1326***	0.0016***	0.1168***	0.0014***	0.1115**	0.0014**
	(0.0431)	(0.0005)	(0.0433)	(0.0005)	(0.0439)	(0.0005)
$Z-Score_{i,t-1}$	0.0001	$8.04 \cdot 10^{-7}$	0.0001*	$9.90 \cdot 10^{-7*}$	0.0001	$8.58 \cdot 10^{-7}$
	(0.0001)	$(6.13 \cdot 10^{-7})$	(0.0000)	$(5.21 \cdot 10^{-7})$	(0.0000)	$(5.89 \cdot 10^{-7})$
$Constant$	−6.2626***		−2.7561***		−4.0733***	
	(0.8469)		(0.8606)		(0.9441)	
Time dummies	Yes		Yes		Yes	
Regional dummies	Yes		Yes		Yes	
Number of banks	3,497		3,500		3,490	
Number of observations	40,572		40,432		40,378	
Pseudo R^2	0.09		0.09		0.10	

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients, the corresponding marginal effects and standard errors (in parentheses) using the random effects logit model (3) (augmented by banking group dummies). Standard errors of the marginal effects are calculated using the delta method. In column (1), the (natural) log of the loan-to-deposit ratio LTD as defined in (1) is used as a lagged measure of banks' stable funding $\boldsymbol{x_{i,t-1}}$, in column (2), the (natural) log of the loan-to-interbank liabilities ratio $LTIBL$ as defined in (2) is employed, and in column (3), both measures are used. See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

0.0040 (0.0041) percentage points. Again, if we take the predicted mean share of 1.2792% (1.29308%), then an increase (a decrease) in the probability of 0.0040 (0.0041) percentage points implies approximately two (one) additional bank years in financial distress.[47]

[47] Alternatively, we can calculate the estimated conditional probability of experiencing a critical event for each bank by keeping all the regressors as they are (using $\alpha_i = 0$), except for the vector of lagged measures of banks' stable funding $\boldsymbol{x_{i,t-1}}$, for which we increase (decrease) the LTD ($LTIBL$) by one percent in every period t. These estimated probabilities for individual banks can be used to determine the new overall conditional probability of a bank year becoming financially distressed by taking the mean over the individual ones. The new predicted mean share of 1.283248% (1.297159%) again implies approximately two (one) more banks experiencing financial distress.

In column (3), both stable funding variables are used simultaneously in order to examine which funding variable is more important for bank distress. It turns out that the estimated effects of both variables retain their relative importance and statistical significance, although both coefficients are slightly smaller.

The estimated coefficients on most control variables are in line with what is expected for these variables in terms of the sign of the respective coefficients. More profitable banks[48], banks holding more capital and banks with qualitatively better credit exposures are associated with a smaller probability of experiencing a critical event. Managerial efficiency negatively affects the likelihood of distress. A bank's size appears to be positively related to the probability of distress. In column (1) (column (2)), liquidity (banks' risk-taking) is significantly different from zero and has a positive sign. As far as liquidity is concerned, banks might accumulate liquid assets when they anticipate financial difficulties. The positive coefficient of the $Z - Score$ is economically immaterial.

Descriptive statistics in Appendix A.1, Table A3 readily show that the German banking sector is very heterogeneous and there are big differences in the bank-specific characteristics across banking groups. To illustrate this from yet another perspective, Figure A4 in Appendix A.5 depicts the evolution of the size of the German banking sector[49] and the shares of the total assets of different banking groups in the total assets of the whole banking sector at three different points in time. Between 1994 and 2012, the total assets of German banks more than doubled from approximately three trillion euro to almost seven trillion euro. However, marked differences in the shares of the total assets of different banking groups have emerged over time. Most strikingly, between 1994 and 2012, the share of commercial banks' total assets increased from approximately 35% to over 50%, which was mostly due to the growth of big banks, and the share of the Landesbanken grew from 24% to 30% between 1994 and 2003 and then decreased to almost 15% between 2003 and 2012. The relative size of credit cooperatives as well as their regional institutions has remained relatively constant, whereas the relative size of savings banks has steadily fallen from almost 24% in 1993 to 15% in 2012. Dynamics-related considerations aside, a look at the proportions shown in Figure A4, Appendix A.5 suggests that it might be appropriate to treat big banks, other commercial banks, the Landesbanken, savings banks, the regional institutions of credit cooperatives and credit cooperatives as separate banking groups.[50] We corroborate this visual conjecture by employing the Mann-

[48] Note that the effect of profits has been found to be ambiguous in the literature. Behn, Detken, Peltonen, and Schudel (2013) find that large profits in the banking sector can be associated with excessive risk-taking leading to increased vulnerability and subsequent banking crises (see also Drehmann, Borio, and Tsatsaronis (2011)). This underscores the importance of including a proxy for risk-taking such as the $Z - Score$.

[49] The German banking sector is approximated by the banks in our sample. As explained in Section 3.1, we have excluded a few banking groups for different reasons. The share of the total assets of the banks in our sample in the total assets of monetary financial institutions in Germany amounts to about 80%. In terms of loans/deposits, the share of banks in our sample in the loans/deposits of German monetary financial institutions is around 95%, respectively.

[50] The Landesbanken were founded to act as a sort of central bank for savings banks, thereby also taking care of payment transactions. Only over time have new tasks been added to their portfolio, such as liquidity management, large value credits, securities settlement, foreign transactions etc. (Gubitz (2013)). Over time, their business models have evolved towards that of big banks (Deutsche Bundesbank (2015)). Very similar services are provided by the regional institutions of credit cooperatives to credit cooperatives. These banks are, however, not in public hand (Guinnane (2013)). The big banks can also

Whitney-Wilcoxon test and the Kolmogorov-Smirnov test[51] to see whether each of the variables LTD, $LTIBL$, relative loans (LR), relative deposits (DR) and relative interbank liabilities ($IBLR$)[52] comes from the same underlying distribution for the subgroups of big banks vs. other commercial banks, Landesbanken vs. savings banks and regional institutions of credit cooperatives vs. credit cooperatives, respectively. For each pairing, the null of the same underlying distribution is rejected for almost every variable.[53] As the non-parametric tests confirm that these six subgroups are different from each other with respect to the funding variables, it seems reasonable to assume that the way stable funding affects the probability of financial distress might differ across banking groups as well. Ideally, we would estimate our model for each banking group separately. Unfortunately, samples consisting of just Landesbanken or central institutions of credit cooperatives or big banks turn out to be too small to yield meaningful results. Hence, we exclude all Landesbanken, regional institutions of credit cooperatives as well as big banks from all following analyses.

We re-estimate our main specification (3) for the groups of other commercial banks, savings banks and credit cooperatives respectively.[54] Table 2 shows the results for the group of commercial banks without big banks. Most notably, both stable funding variables are not significantly different from zero, i.e. the funding profile does not appear to be of primary importance for explaining distress events for these banks. The only significant variables across all specifications are profitability, managerial efficiency and banks' risk-taking. Commercial banks with a higher ROA are less prone to financial distress. Counterintuitively, a greater distance to default is associated with a higher probability of distress. However, the effect is economically negligible. Note that the number of observations is smaller than the number reported in Table A3 in Appendix A.1. This is due to the fact that no critical events could be observed for commercial banks in the year 2003 or in three federal states. The corresponding observations cannot be used in the estimation because the dependent variable does not display any variation for those values.

The estimation output in Table 3 refers to the results for savings banks. As reported in column (1), the estimated coefficient of the LTD is 3.4244, i.e. given 8,423 bank years for savings banks,[55] an increase in the LTD of one percent implies that approximately two

be argued to have a fundamentally different business model from the much smaller other commercial banks which are much less internationally oriented.

[51] As both these tests are non-parametric tests, they do not require any distributional assumptions and are robust to outliers.

[52] Banks' relative loans, deposits and interbank liabilities are each calculated as a share in the total assets.

[53] The only exception is the LTD for big banks and other commercial banks. The null that the LTD for each subgroup stems from the same distribution cannot be rejected using the Mann-Whitney-Wilcoxon test. However, it is rejected when the Kolmogorov-Smirnov test is applied.

[54] The alternative is to apply interaction terms involving our stable funding measures and banking groups. However, the interpretation of the interaction effects associated with the interaction terms is more complicated because the interaction effect is not equal to the marginal effect of the interaction term and may have different signs for different values of the independent variables involved (see Ai and Norton (2003)).

[55] Again, the number of observations used in the estimation is smaller than the number reported in Table A3 in Appendix A.1 because there were no critical events for savings banks in the year 2011 or in four federal states. The corresponding 918 bank years cannot be used in the estimation because the dependent variable is zero throughout and does not vary for those values.

Table 2: RE logit estimation: main specification – commercial banks without big banks (no subsequent critical events)

Explanatory variables	(1) Estimates	(1) Marginal effects	(2) Estimates	(2) Marginal effects	(3) Estimates	(3) Marginal effects
$log(LTD_{i,t-1})$	-0.0701	-0.0022			-0.0921	-0.0031
	(0.0747)	(0.0024)			(0.0785)	(0.0026)
$log(LTIBL_{i,t-1})$			0.0074	0.0002	0.0057	-0.0002
			(0.0578)	(0.0019)	(0.0584)	(0.0019)
$ROA_{i,t-1}$	-0.1190^{***}	-0.0038^{***}	-0.1355^{***}	-0.0044^{***}	-0.1188^{***}	-0.0040^{***}
	(0.0304)	(0.0010)	(0.0346)	(0.0012)	(0.0343)	(0.0012)
$log(CR_{i,t-1})$	-0.4542^{**}	-0.0145^{**}	-0.3748^{*}	-0.0122^{*}	-0.3447	-0.0115
	(0.2113)	(0.0070)	(0.2142)	(0.0072)	(0.2189)	(0.0075)
$log(LLR_{i,t-1})$	-0.0034	-0.0001	-0.0023	-0.0001	-0.0010	-0.0000
	(0.0144)	(0.0005)	(0.0148)	(0.0005)	(0.0151)	(0.0005)
$log(AdminR_{i,t-1})$	0.6037^{***}	0.0193^{***}	0.4644^{***}	0.0151^{***}	0.5358^{***}	0.0178^{***}
	(0.1621)	(0.0054)	(0.1511)	(0.0050)	(0.1621)	(0.0056)
$log(Liquid_{i,t-1})$	-0.1233	-0.0039	-0.0553	-0.0018	-0.1229	-0.0041
	(0.0904)	(0.0029)	(0.0816)	(0.0027)	(0.0919)	(0.0031)
$log(Total\ Assets_{i,t-1})$	-0.0748	-0.0024	-0.0468	-0.0015	-0.0497	-0.0017
	(0.0887)	(0.0029)	(0.0916)	(0.0030)	(0.0917)	(0.0031)
$Z-Score_{i,t-1}$	0.0002^{**}	$6.00 \cdot 10^{-6*}$	0.0002^{***}	$7.33 \cdot 10^{-6***}$	0.0002^{**}	$6.51 \cdot 10^{-6**}$
	(0.0001)	$(3.18 \cdot 10^{-6})$	(0.0001)	$(2.77 \cdot 10^{-6})$	(0.0001)	$(3.24 \cdot 10^{-6})$
$Constant$	-1.4096		-2.2967		-1.6442	
	(1.5877)		(1.6904)		(1.7136)	
Time dummies	Yes		Yes		Yes	
Regional dummies	Yes		Yes		Yes	
Number of banks	295		291		283	
Number of observations	2,644		2,488		2,443	
Pseudo R^2	0.13		0.13		0.12	

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients, the corresponding marginal effects and standard errors (in parentheses) using the random effects logit model (3) on the sample of commercial banks excluding big banks. Standard errors of the marginal effects are calculated using the delta method. In column (1), the (natural) log of the loan-to-deposit ratio LTD as defined in (1) is used as a lagged measure of banks' stable funding $\boldsymbol{x_{i,t-1}}$, in column (2), the (natural) log of the loan-to-interbank liabilities ratio $LTIBL$ as defined in (2) is employed, and in column (3), both measures are used. See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

more savings banks experience a critical event from 1995 to 2013. The effect of the $LTIBL$ in column (2) is not significant, meaning that interbank funding is not crucial for savings banks. This finding is corroborated in column (3) when both stable funding variables are employed simultaneously.[56] While the $LTIBL$ remains statistically insignificant, the effect of the LTD becomes slightly greater. Interestingly, the coefficient estimated for the CR is not significant either, suggesting that profitability is much more important

[56]Again, the likelihood ratio test rejects the null that the coefficient on the lagged LTD is zero.

Table 3: RE logit estimation: main specification – savings banks (no subsequent critical events)

Explanatory variables	(1)		(2)		(3)	
	Estimates	Marginal effects	Estimates	Marginal effects	Estimates	Marginal effects
$log(LTD_{i,t-1})$	3.4244***	0.0247***			3.4645***	0.0250***
	(0.7199)	(0.0057)			(0.7335)	(0.0058)
$log(LTIBL_{i,t-1})$			−0.2574	−0.0019	0.1507	0.0011
			(0.4603)	(0.0034)	(0.5035)	(0.0036)
$ROA_{i,t-1}$	−1.9704***	−0.0142***	−2.1775***	−0.0161***	−1.9739***	−0.0142***
	(0.4225)	(0.3300)	(0.4062)	(0.0033)	(0.4307)	(0.0033)
$log(CR_{i,t-1})$	−1.1776	−0.0085	−1.5009	−0.0111	−1.2902	−0.0093
	(0.9539)	(0.0069)	(0.9662)	(0.0072)	(1.0258)	(0.0075)
$log(LLR_{i,t-1})$	0.8525***	0.0062***	0.9248***	0.0068***	0.8522***	0.0062***
	(0.2963)	(0.0022)	(0.2838)	(0.0022)	(0.2968)	(0.0022)
$log(AdminR_{i,t-1})$	0.1092	0.0008	−1.0792	−0.0080	0.0191	0.0001
	(0.9952)	(0.0072)	(1.0480)	(0.0078)	(1.0404)	(0.0075)
$log(Liquid_{i,t-1})$	0.7875***	0.0057***	0.5009*	0.0037*	0.7813***	0.0056***
	(0.2753)	(0.0021)	(0.2681)	(0.0020)	(0.2767)	(0.0021)
$log(Total\ Assets_{i,t-1})$	−0.2596	−0.0019	−0.4127***	−0.0030**	−0.2616	−0.0019
	(0.1592)	(0.0012)	(0.1591)	(0.0012)	(0.1594)	(0.0012)
$Z - Score_{i,t-1}$	−0.0175*	−0.0001*	−0.0157	−0.0001	−0.0179*	−0.0001*
	(0.0099)	(0.0001)	(0.0098)	(0.0001)	(0.0100)	(0.0001)
$Constant$	−17.9799***		2.1228		−18.7967***	
	(5.0768)		(3.5074)		(5.7791)	
Time dummies	Yes		Yes		Yes	
Regional dummies	Yes		Yes		Yes	
Number of banks	601		601		601	
Number of observations	8,423		8,423		8,423	
Pseudo R^2	0.29		0.26		0.29	

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients, the corresponding marginal effects and standard errors (in parentheses) using the random effects logit model (3) on the sample of savings banks. Standard errors of the marginal effects are calculated using the delta method. In column (1), the (natural) log of the loan-to-deposit ratio LTD as defined in (1) is used as a lagged measure of banks' stable funding $\boldsymbol{x_{i,t-1}}$, in column (2), the (natural) log of the loan-to-interbank liabilities ratio $LTIBL$ as defined in (2) is employed, and in column (3), both measures are used. See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

for savings banks than capital.[57] A lower quality of the assets increases the likelihood of becoming financially distressed, as do more liquid assets[58]. Finally, risk-taking – as proxied by the $Z - Score$ – slightly increases the probability of financial distress, even though the effect is economically not very large.

Table 4 contains the results for credit cooperatives. Stable funding positively affects

[57]However, this might be because we are using equity from banks' balance sheets, which is only a proxy for regulatory capital.

[58]This might reflect savings banks anticipating financial difficulties.

the likelihood of staying financially healthy. Given 26,940 observations[59] on credit cooperatives, a 1% increase in the LTD corresponds to two more credit cooperatives experiencing critical events from 1995 to 2013. The estimated effect of the $LTIBL$ is similar, albeit weaker. The results do not change much when both proxies for stable funding are used in column (3). That is, for credit cooperatives, more stable deposits as well as fewer interbank liabilities appear to reduce the chances of becoming financially distressed.[60] Again, the expected effects for the ROA, CR, LLR and the $AdminR$ are found in the estimation. The estimated coefficient of liquidity suggests that more liquid assets are associated with a higher probability of experiencing financial distress, which might be due to credit cooperatives accumulating liquidity in anticipation of financial difficulties. Contrary to the findings for savings banks, size does seem to matter for credit cooperatives, whereas risk-taking does not.

Since both measures of stable funding are ratios, it is insightful to examine whether the numerator or the denominator or both impacts the probability of experiencing a critical event. To that end, we estimate (3) using the relative loans (LR), relative deposits (DR) and relative interbank liabilities ($IBLR$) as defined in footnote 52 in place of the LTD and the $LTIBL$. The results in Appendix A.6, Table A6, Table A7 and Table A8 show that for savings banks and credit cooperatives, both the numerator and the denominator of both stable funding measures are statistically significant and have the expected sign, i.e. more loans, fewer deposits and more interbank liabilities are associated with a higher probability of becoming financially distressed.

All in all, it appears to be crucial to differentiate between banking groups when assessing the importance of stable funding. Stable deposits reduce the likelihood of financial distress for savings banks and credit cooperatives, whereas stable funding does not seem to be important for the more heterogeneous group of commercial banks at all. Credit cooperatives also seem to benefit from relying less on interbank funding.

We conduct several robustness checks to examine how sensitive our findings are. We check whether or not our findings are sensitive to different estimation techniques, more conservative assumptions/definitions of variables as well as alternative/additional variables, and we show that the main results remain unchanged. The exact details can be found in Appendix A.7.

3.4 Discussion of the results

We now turn to the discussion of the presented results. As shown above, the effect of stable funding differs across banking groups. Perhaps surprisingly, our findings for commercial banks excluding big banks suggest that neither the LTD nor the $LTIBL$ has a significant effect on the probability of occurrence of critical events. This raises questions regarding possible explanations for this result. To begin with, the sample of commercial banks used in the analysis is the most heterogeneous of all three banking groups. Commercial banks can differ a lot in their respective business models, in size and also in their funding

[59] As is the case with commercial banks and savings banks, 1,111 bank years cannot be used in the estimation procedure because no financial distress events are available for the year 2013 or in one federal state.

[60] The likelihood ratio statistics are large enough for the test to reject the null that the coefficients on the lagged LTD and/or $LTIBL$ are zero.

Table 4: RE logit estimation: main specification – credit cooperatives (no subsequent critical events)

Explanatory variables	(1) Estimates	(1) Marginal effects	(2) Estimates	(2) Marginal effects	(3) Estimates	(3) Marginal effects
$log(LTD_{i,t-1})$	0.5830***	0.0086***			0.4481***	0.0067***
	(0.1170)	(0.0017)			(0.1220)	(0.0018)
$log(LTIBL_{i,t-1})$			−0.5292***	−0.0081***	−0.4076***	−0.0061***
			(0.1158)	(0.0018)	(0.1201)	(0.0018)
$ROA_{i,t-1}$	−0.2584***	−0.0038***	−0.2410**	−0.0037***	−0.2363**	−0.0035***
	(0.0937)	(0.0013)	(0.0946)	(0.0013)	(0.0941)	(0.0013)
$log(CR_{i,t-1})$	−1.7972***	−0.0267***	−1.5026***	−0.0230***	−1.6737***	−0.0251***
	(0.2949)	(0.0047)	(0.2807)	(0.0046)	(0.2916)	(0.0046)
$log(LLR_{i,t-1})$	0.9746***	0.0145***	0.9957***	0.0152***	0.9594***	0.0144***
	(0.0859)	(0.0017)	(0.0852)	(0.0017)	(0.0860)	(0.0017)
$log(AdminR_{i,t-1})$	1.0634***	0.0158***	1.2009***	0.0184***	1.1316***	0.0169***
	(0.2801)	(0.0042)	(0.2779)	(0.0043)	(0.2813)	(0.0043)
$log(Liquid_{i,t-1})$	0.3045***	0.0045***	0.1813*	0.0028*	0.3011***	0.0045***
	(0.1040)	(0.0016)	(0.1003)	(0.0016)	(0.1031)	(0.0016)
$log(Total\ Assets_{i,t-1})$	0.1710***	0.0025***	0.1933***	0.0030***	0.1741***	0.0026***
	(0.0558)	(0.0008)	(0.0559)	(0.0009)	(0.0560)	(0.0009)
$Z-Score_{i,t-1}$	−0.0001	$-6.72 \cdot 10^{-7}$	−0.0000	$-3.91 \cdot 10^{-7}$	−0.0000	$-5.31 \cdot 10^{-7}$
	(0.0002)	$(3.19 \cdot 10^{-6})$	(0.0002)	$(2.49 \cdot 10^{-6})$	(0.0002)	$(2.87 \cdot 10^{-6})$
$Constant$	−7.1787***		−1.7262		−4.1824**	
	(1.0733)		(1.1497)		(1.3558)	
Time dummies	Yes		Yes		Yes	
Regional dummies	Yes		Yes		Yes	
Number of banks	2,543		2,542		2,541	
Number of observations	26,940		26,890		26,885	
Pseudo R^2	0.15		0.15		0.15	

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients, the corresponding marginal effects and standard errors (in parentheses) using the random effects logit model (3) on the sample of credit cooperatives. Standard errors of the marginal effects are calculated using the delta method. In column (1), the (natural) log of the loan-to-deposit ratio LTD as defined in (1) is used as a lagged measure of banks' stable funding $\boldsymbol{x_{i,t-1}}$, in column (2), the (natural) log of the loan-to-interbank liabilities ratio $LTIBL$ as defined in (2) is employed, and in column (3), both measures are used. See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

strategy. As discussed above, for commercial banks in particular, both funding ratios display several very large values, which might give rise to statistical insignificance. These stem from banks' business models that use almost no deposits or interbank liabilities to fund their assets. Although taking the log of both ratios mitigates this problem, it does not alter the results. However, this does not necessarily mean that wholesale funding poses no risk to commercial banks. Even after the log transformation, extreme values still greatly impact the empirical distribution of the LTD and the $LTIBL$, which is apparent when the first two moments of the respective empirical LTD and $LTIBL$ distributions for different banking groups are examined.[61] However, the results do not change much when the sample of commercial banks is restricted to financial institutions whose share of loans and deposits in total assets is at least 15%. This means that extreme values are not the reason why the results for commercial banks are different. Therefore, in future work, the analysis of the German commercial banking sector should put more emphasis on heterogeneity across different financial institutions and the different business models associated with this heterogeneity.

In contrast to the findings for the group of other commercial banks, the results for savings banks and credit cooperatives are in line with the literature on the stability of deposits. For these banks, stable funding is associated with a lower probability of experiencing a critical event and this effect is statistically highly significant.[62] In order to better understand the channel of impact of funding, we have examined how these banks' funding structures have evolved over time ahead of a critical event, conditioning on banks experiencing financial distress.[63] Savings banks and credit cooperatives that experience a critical event tend to constantly increase the share of loans financed through liabilities other than deposits in the periods up until that event.[64] In a complementary manner, the $LTIBL$ tends to decrease in the lead-up to the critical events, which means that the share of interbank funding increases as the event approaches, even though this trend does not exactly mirror the development of the LTD. What remains to be explained is how these findings fit in with the institutional set-up of savings banks and credit cooperatives. Both banking groups have established insurance funds that protect each member's solvency and liquidity, which should reduce incentives for early withdrawals. Furthermore, to our knowledge, no bank runs took place in Germany between 1995 and 2013. The reason why we still find significant effects might stem from the fact that the largest share of interbank funding is obtained from within the respective banking group, so that those who provide funding simultaneously guarantee the corresponding liabilities. In this case, the guarantee might not protect the bank from sudden funding withdrawals. Because of this specific feature of both banking groups' interbank funding, the result that credit cooperatives benefit from a higher $LTIBL$ while savings banks do not has to be interpreted with extreme caution. For the most part, interbank liabilities of these two banking groups consist of liabilities vis-à-vis regional institutions of credit cooperatives or Landesbanken and to a lesser extent vis-a-vis other banks and the central bank. That is, it is conceivable that the results are (partly) driven by the liquidity services provided by the regional institutions and Landesbanken as described in footnote 50 in the run-up to the respective distress events. Unfortunately, the available data do not allow us to reliably differentiate between credit cooperatives' and savings banks' interbank liabilities vis-à-vis their regional institutions or Landesbanken and vis-à-vis other banks or the central bank throughout the entire sample.[65] Another conjecture is that funding positions other than deposits are

[61]The mean of $log(LTD)$ ($log(LTIBL)$) for commercial banks equals 4.6624 (5.6531), while it is 4.4767 (5.8122) for savings banks and 4.3553 (6.3327) for the group of credit cooperatives. The standard deviations for the respective banking groups amount to 1.8523 (1.9872), 0.3305 (0.4708), and 0.3422 (0.6670).

[62]Note that the data do not allow us to identify exogenous liquidity shocks in order to estimate a causal effect on the probability of financial distress of stable funding.

[63]The plots are available from the authors upon request.

[64]This pattern can also be observed for the group of commercial banks.

[65]For the available observations, it turns out that for credit cooperatives the effect of the $LTIBL$ is not significant when only liabilities vis-à-vis their central institutions are considered, whereas the significant

associated with more risks, which are not sufficiently captured by the $Z - Score$. Also, it is conceivable that the ability of savings banks and credit cooperatives to attract deposits varies across regions and that our regional federal state-level dummies are too imprecise to take this into account. All in all, the understanding of the mechanisms through which less stable funding leads to financial distress needs to be further developed. We leave that for future research, as identifying and analyzing those channels is beyond the scope of this paper.

As is apparent in Appendix A.5, Figure A4, savings banks and credit cooperatives account for around 30% of the German banking sector's size.[66] However, there are several reasons why this perspective understates the implications of both banking groups being more stable. Figure A5 in Appendix A.5 shows that in terms of credit exposures, the share of savings banks and credit cooperatives is considerably higher.[67] Moreover, savings banks and credit cooperatives play an important role when it comes to providing loans to small and medium-sized enterprises, which comprise the largest portion of all firms in the German economy by far (Behr, Foos, and Norden (2015), IMF (2016)). Apart from that, there is some evidence that savings banks contribute to enhancing local economic development in underdeveloped regions (Hakenes, Hasan, Molyneux, and Xie (2015)). All of the above suggests that the benefits of having more stable savings banks and credit cooperatives are substantially greater than it might seem at the first glance.

4 Conclusion

The recent financial crisis has highlighted the importance of stable funding for banks. The regulatory response on the part of the BCBS to the problems caused by the lack of ample liquidity buffers and excessive maturity mismatches has been to introduce the LCR and the NSFR. Although it is difficult at this point to assess whether and to what extent the new regulatory requirements will be instrumental in adequately addressing the problems associated with unstable funding structures in the banking sector, it is possible to infer from the past what difference stable funding has made with respect to the financial health of banks. Quantifying this difference and thus approximating one effect of the NSFR on the probability of banks experiencing financial distress is this paper's main objective.

Our results suggest that for Germany, financial institutions associated with the banking groups of savings banks and credit cooperatives, respectively, have benefited greatly from financing their loans with stable deposits, as they have had a lower probability of experiencing a distress event. Our results, at least partly, confirm the empirical findings in the literature. This suggests that the introduction of the NSFR can be expected to be conducive to the financial health of the corresponding financial institutions, even though

negative effect remains when the liabilities vis-à-vis the central institutions are excluded. For savings banks, regressions based on the available observations reveal a significant negative effect of the $LTIBL$ once central bank credit is excluded, while the effect of the $LTIBL$ based solely on central bank credit is significantly positive, suggesting that savings banks financing their loans to a greater extent via the central bank, have experienced fewer critical events. This result could not be found for credit cooperatives.

[66]This share varies between 25% and 38%, depending on the time period. Overall, the relative share of assets of savings banks and credit cooperatives has declined over time.

[67]Over the time horizon of the entire sample, the share of loans of savings banks and credit cooperatives in the overall loans of the entire German banking sector lies between 33% and 45%.

a comprehensive analysis of the impact of Basel III liquidity requirements on the German banking sector is beyond the scope of this study.[68] This finding has implications for savings banks' and credit cooperatives' business practices as well as the supervisory process for these banking groups. No positive effect of stable funding could be found for the overall stability of commercial banks (excluding big banks), which are found to be far more heterogeneous with respect to their business models.

[68] The caveat that Goodhart's law, according to which a statistical regularity/measure loses its property as an indicator of economic developments as soon as it is used for regulatory purposes (Goodhart (1975), Daníelsson (2002)), might also apply to the introduction of the NSFR is, of course, valid.

A Appendix

A.1 Descriptive statistics

Table A1: Critical events – breakdown by banking group and over time

	Number of critical events			
Year	**All banks**	**Commercial banks**	**Savings banks and Landesbanken**	**Credit cooperatives and regional institutions**
1995	48	5	1	42
1996	55	5	4	46
1997	64	7	2	55
1998	59	5	5	49
1999	62	4	1	57
2000	54	3	6	45
2001	79	16	13	50
2002	52	12	11	29
2003	24	0	7	17
2004	29	2	3	24
2005	19	9	2	8
2006	13	6	1	6
2007	17	3	6	8
2008	20	8	5	7
2009	21	9	6	6
2010	7	5	1	1
2011	7	3	0	4
2012	5	2	1	2
2013	2	1	1	0
Total	637	105	76	456

Note: This table shows the breakdown of financial distress events (without subsequent critical events) as defined in Section 3.1.1.

Table A2: Critical events – breakdown by event type and banking group

	Types of critical events			
Critical event	**All banks**	**Commercial banks**	**Savings banks and Landesbanken**	**Credit cooperatives and regional institutions**
• Disclosure of facts pursuant to section 29(3) of the Banking Act	37	4	11	22
• Operating loss in excess of 25% of liable capital	64	47	10	7
• Losses of liable capital amounting to at least 25% pursuant to section 24(1) of the Banking Act;	16	11	2	3
• Forbiddance of granting of loans/ large exposures pursuant to sections 45 or 46 of the Banking Act;	1	0	1	0
• Moratoriums pursuant to section 4a of the Banking Act	3	3	0	0
• Capital preservation measures	302	29	23	250
• Restructuring caused by mergers	211	9	28	174
• Liquidation or insolvency	1	1	0	0
• SoFFin recapitalisation measures and guarantees	2	1	1	0
Total	637	105	76	456

Note: This table shows the breakdown of financial distress events (without subsequent critical events) as defined in Section 3.1.1.

Table A3: Summary statistics for the explanatory variables by banking group

	obs	mean	sd	p25	p50	p75
All banks:						
LTD	40,572	535.4192	21,589.21	68.17	83.45	99.13
LTIBL	40,432	6,340.52	341,041.7	314.81	446.01	657.49
ROA	40,572	0.470	0.86	0.26	0.42	0.62
CR	40,572	5.400	3.8503	4.108	4.872	5.7857
LLR	40,572	1.2877	59.4566	0.3784	0.69	1.108
AdminR	40,572	2.2954	1.8202	1.851	2.146	2.479
Liquid	40,572	6.5506	6.2029	3.5149	5.2630	7.6378
Total Assets	40,572	2,321,599	25,300,000	93,872	260,516	793,913.5
$Z - Score$	40,572	49.119	391.2474	17.971	26.043	38.251
LR	40,572	58.5889	14.3476	51.873	60.855	67.69
DR	40,572	71.1947	13.8737	66.367	73.529	79.622
IBLR	40,572	15.1961	10.9056	8.5771	13.251	18.962
AbnormLoangr	40,503	439.598	80,523.85	-2.78	0.203	3.738
RegLoangr	40,521	4.8343	7.0057	0.998	4.626	8.561
RegDepositgr	40,521	4.2528	5.3036	1.89	4.64	7.2738
Commercial banks:						
LTD	2,925	5,959.35	79,937.39	52.36	95.472	167.048
LTIBL	2,837	65,095.63	1,157,305	119.1138	238.1039	625.1888
ROA	2,925	0.7331	2.8153	0.1438	0.506	1.08199
CR	2,925	10.365	12.2051	4.3618	6.7173	10.6906
LLR	2,925	7.179	221.371	0.29819	0.91512	1.94705
AdminR	2,925	3.6854	6.277	1.3608	2.1686	3.6961
Liquid	2,925	13.5809	17.2984	3.3019	7.2596	15.3905
Total Assets	2,925	13,400,000	84,400,000	166,094	593,997	2,738,188
$Z - Score$	2,925	85.88697	736.3427	9.28747	16.66133	36.0171
LR	2,925	49.7006	30.0829	23.2836	50.8555	75.0138
DR	2,925	50.8411	28.4837	26.6283	55.4350	76.1873
IBLR	2,925	25.876	25.2452	4.97376	17.5633	40.8104
AbnormLoangr	2,863	6,186.53	302,861.3	-8.1221	1.627684	15.108
RegLoangr	2,881	4.6042	7.280282	0.91212	4.697908	8.95849
RegDepositgr	2,881	4.732009	6.290622	1.73019	4.979391	7.69307
Savings banks and Landesbanken:						
LTD	9,547	94.42401	31.78976	76.6321	92.6413	109.812
LTIBL	9,547	372.8428	238.9239	237.932	319.6606	435.328
ROA	9,547	0.385896	0.284273	0.23059	0.389409	0.54895
CR	9,547	4.353592	1.106071	3.63853	4.196681	4.9825
LLR	9,547	0.913744	0.684155	0.47663	0.746607	1.13857
AdminR	9,547	1.790906	0.333592	1.64744	1.820822	1.98297
Liquid	9,547	4.12525	2.24523	2.5143	3.6706	5.1991
Total Assets	9,547	4,306,836	20,500,000	637,385	1,182,540	2,234,355
$Z - Score$	9,547	51.67706	370.1547	20.0120	28.09728	41.7210
LR	9,547	59.02045	12.44403	53.0218	61.35803	67.2348
DR	9,547	65.64215	11.14319	60.1952	66.9744	72.9850
IBLR	9,547	19.81646	9.16117	13.0233	18.59369	25.3852
AbnormLoangr	9,540	1.869788	16.86038	-2.44011	-0.15700	2.37632
RegLoangr	9,540	4.631268	7.669494	0.91233	3.928161	8.38486
RegDepositgr	9,540	3.968659	5.414738	1.45309	4.177924	7.098978
Credit cooperatives and regional institutions:						
LTD	28,100	120.657	2,174.201	66.88138	80.48493	93.98087
LTIBL	28,048	2,428.84	178,489	376.2305	506.2593	733.5483
ROA	28,100	0.471442	0.4619707	0.273917	0.429250	0.623472
CR	28,100	5.238987	1.588457	4.333921	5.025113	5.855574
LLR	28,100	0.801447	0.7775164	0.347934	0.648863	1.052757
AdminR	28,100	2.322089	0.5979904	2.02234	2.28186	2.572058
Liquid	28,100	6.64278	3.943463	4.10359	5.79627	8.11926
Total Assets	28,100	497,499	4,988,774	69,652.5	150,143	346,242
$Z - Score$	28,100	44.42201	343.342	18.18525	25.93646	37.05751
LR	28,100	59.36753	11.89746	52.68924	60.98778	67.64254
DR	28,100	75.19988	9.036758	70.2444	75.8834	81.16526
IBLR	28,100	12.51462	7.111397	7.789638	11.78918	16.23078
AbnormLoangr	28,100	2.675052	14.92909	-2.75043	0.3104994	3.880392
RegLoangr	28,100	4.926823	6.734028	1.07077	4.74772	8.60905
RegDepositgr	28,100	4.300131	5.147798	2.127622	4.746625	7.233285

Continued on next page

Table A3: Summary statistics for the explanatory variables by banking group

	obs	mean	sd	p25	p50	p75
Continued from previous page						
Commercial banks without big banks:						
LTD	2,850	6,113.686	80,976.99	51.24802	94.88831	168.5997
$LTIBL$	2,713	68,034.12	1,183,384	120.381	245.6303	640.1249
ROA	2,850	0.7484081	2.849657	0.1463988	0.524051	1.111011
CR	2,850	10.55456	12.30643	4.448797	6.904447	10.83442
LLR	2,850	7.340622	224.2636	0.2935469	0.9217868	1.98661
$AdminR$	2,850	3.742417	6.348221	1.386909	2.204323	3.746095
$Liquid$	2,850	13.76577	17.47942	3.252019	7.380536	15.93746
$Total\ Assets$	2,850	3,649,987	11,000,000	160,582	553,710	2,363,413
$Z-Score$	2,850	87.46222	745.8858	9.455287	16.73799	36.12203
LR	2,850	49.94104	30.35443	22.91734	51.86193	75.80461
DR	2,850	50.93529	28.7441	25.36346	56.28352	76.58227
$IBLR$	2,850	25.89813	25.51466	4.769899	17.11728	42.22281
$AbnormLoangr$	2,788	6,352.532	306,907.6	-8.137938	1.444487	15.22671
$RegLoangr$	2,806	4.588322	7.272036	0.9121202	4.697908	8.958492
$RegDepositgr$	2,806	4.705173	6.277733	1.73019	4.932129	7.693069
Savings banks:						
LTD	9,341	92.4525	27.98149	76.33772	92.07174	108.4497
$LTIBL$	9,341	378.556	238.3254	243.555	323.4473	438.4264
ROA	9,341	0.391578	0.2820592	0.2384984	0.3946473	0.5523934
CR	9,341	4.383198	1.059563	3.669632	4.216748	4.997026
LLR	9,341	0.920699	0.6864677	0.481417	0.7543242	1.14727
$AdminR$	9,341	1.821882	0.262044	1.661232	1.82774	1.986176
$Liquid$	9,341	4.156886	2.247618	2.548492	3.694542	5.224406
$Total\ Assets$	9,341	1,896,822	2,673,656	629,465	1,155,496	2,123,026
$Z-Score$	9,341	50.51807	368.6469	20.00154	28.01303	41.21417
LR	9,341	59.47948	12.10679	53.79467	61.60516	67.36791
DR	9,341	66.59475	9.145858	60.6842	67.23883	73.11214
$IBLR$	9,341	19.46697	8.845534	12.90444	18.38236	24.86764
$AbnormLoangr$	9,335	1.812651	16.81694	-2.431434	-0.178719	2.329706
$RegLoangr$	9,335	4.620632	7.678773	0.9123301	3.843997	8.384861
$RegDepositgr$	9,335	3.957975	5.405501	1.45309	4.14274	7.098978
Credit cooperatives:						
LTD	28,051	120.566	2,176.096	66.8373	80.46535	93.92933
$LTIBL$	27,994	2,433.46	178,661	376.9081	506.7944	734.1421
ROA	28,051	0.471725	0.4622086	0.2742768	0.4294842	0.6238908
CR	28,051	5.242896	1.586864	4.337416	5.028328	5.857646
LLR	28,051	0.800216	0.7770149	0.3473533	0.6477177	1.051515
$AdminR$	28,051	2.325377	0.5932935	2.023904	2.282674	2.572609
$Liquid$	28,051	6.648329	3.944079	4.107282	5.800634	8.125089
$Total\ Assets$	28,051	346,188	922,339.5	69,518	149,608	344,755
$Z-Score$	28,051	44.45206	343.6403	18.19842	25.94434	37.05887
LR	28,051	59.44084	11.77585	52.75204	61.01212	67.65944
DR	28,051	75.31134	8.64041	70.28384	75.90201	81.17254
$IBLR$	28,051	12.42895	6.805807	7.78218	11.77123	16.19441
$AbnormLoangr$	28,051	2.670382	14.92728	-2.74899	0.307313	3.870427
$RegLoangr$	28,051	4.925159	6.73288	1.07077	4.74772	8.60905
$RegDepositgr$	28,051	4.297801	5.145128	2.117221	4.713122	7.192748

Table A4: Summary statistics for the stable funding variables by financial distress status and banking group

	obs	mean	sd	p25	p50	p75
All banks:						
Financially healthy bank years:						
LTD_{t-1}	39,935	538.8685	21,755.18	68.1275	83.3344	98.97538
$LTIBL_{t-1}$	39,801	6,428.339	343,733.4	316.1534	447.069	659.1206
Bank years in financial distress:						
LTD_{t-1}	637	319.1731	3,882.533	70.7362	89.4694	107.7242
$LTIBL_{t-1}$	631	801.3614	4,625.522	250.2943	356.9962	545.52
Commercial banks:						
Financially healthy bank years:						
LTD_{t-1}	2,820	6,148.353	81,393.8	53.0595	95.95023	167.6354
$LTIBL_{t-1}$	2,738	67,356.81	1,177,986	119.8324	238.8741	622.6769
Bank years in financial distress:						
LTD_{t-1}	105	883.3319	7,451.497	37.61707	88.56574	119.599
$LTIBL_{t-1}$	99	2,559.385	11,526.53	92.87137	174.4209	1,166.667
Savings banks and Landesbanken:						
Financially healthy bank years:						
LTD_{t-1}	9,471	94.20008	31.52169	76.59752	92.53974	109.5798
$LTIBL_{t-1}$	9,471	373.777	239.2048	238.9864	320.3487	436.0388
Bank years in financial distress:						
LTD_{t-1}	76	122.3301	48.69925	91.1165	116.4177	146.9507
$LTIBL_{t-1}$	76	256.4203	164.4315	176.2266	227.1395	285.2223
Credit cooperatives and regional institutions:						
Financially healthy bank years:						
LTD_{t-1}	27,644	118.9838	2,160.675	66.81621	80.39054	93.84774
$LTIBL_{t-1}$	27,592	2,460.544	179,957.7	377.7126	508.2645	736.9607
Bank years in financial distress:						
LTD_{t-1}	456	222.0753	2,879.134	72.34592	87.70964	102.3842
$LTIBL_{t-1}$	456	510.5087	443.8209	301.3046	412.1315	566.3138

Note: This table shows the summary statistics of the stable funding measures (loan-to-deposit ratio LTD as defined in (1) and loan-to-interbank liabilities ratio $LTIBL$ as defined in (2)) by financial distress status (without subsequent critical events as defined in Section 3.1.1) in the following period and banking group.

A.2 List of variables

Table A5: Definition of variables used in various estimations

Variable	Units	Definition
Loan-to-deposit ratio	%	$LTD_{it} = \frac{Loans_{it}}{Deposits_{it}} \cdot 100$
Loan-to-interbank liabilities ratio	%	$LTIBL_{it} = \frac{Loans_{it}}{Interbank\ Liabilities_{it}} \cdot 100$
Return on assets	%	$ROA_{it} = \frac{Return_{it}}{Total\ Assets_{it}} \cdot 100$
Capital ratio	%	$CR_{it} = \frac{Equity_{it}}{Total\ Assets_{it}} \cdot 100$
Loan loss ratio	%	$LLR_{it} = \frac{Provisions\ and\ allowances\ for\ credit\ losses_{it}}{Total\ Assets_{it}} \cdot 100$
Administrative expenses ratio	%	$AdminR_{it} = \frac{Personnel\ expenses\ and\ other\ administrative\ expenses_{it}}{Total\ Assets_{it}} \cdot 100$
Liquid assets	%	$Liquid_{it} = \frac{Cash,\ central\ bank\ deposits_{it}\ and\ overnight\ interbank\ loans_{it}}{Total\ Assets_{it}} \cdot 100$
Size	€ thousand	$Total\ Assets_{it}$

Continued on next page

Table A5: Definition of variables used in various estimations

Continued from previous page

Variable	**Units**	**Definition**
Distance to default	–	$Z-Score_{it} = \frac{CR_{it}+ROA_{it}}{\sigma_{ROA_{it}}}$[69]
Loans ratio	%	$LR_{it} = \frac{Loans_{it}}{Total\ \ Assets_{it}} \cdot 100$
Deposits ratio	%	$DR_{it} = \frac{Deposits_{it}}{Total\ \ Assets_{it}} \cdot 100$
Interbank liabilities ratio	%	$IBLR_{it} = \frac{Interbank\ \ Liabilities_{it}}{Total\ \ Assets_{it}} \cdot 100$
Abnormal loan growth	Percentage points	$AbnormLoangr_{it} = Growth\ rate\ of\ loans_{it} - Median\ growth\ rate\ of\ loans_t$
Regional loan growth	%	$RegLoangr_{it} = \frac{\sum_i^{N^{reg}} Loans_{it} - \sum_i^{N^{reg}} Loans_{i,t-1}}{\sum_i^{N^{reg}} Loans_{i,t-1}} \cdot 100$
Regional deposit growth	%	$RegDepositsgr_{it} = \frac{\sum_i^{N^{reg}} Deposits_{it} - \sum_i^{N^{reg}} Deposits_{i,t-1}}{\sum_i^{N^{reg}} Deposits_{i,t-1}} \cdot 100$

[69]The standard deviation of the return on assets $\sigma_{ROA_{it}}$ is computed using all available observations on ROA up to the respective period t, i.e. for a given bank i, $\sigma_{ROA_{it}}$ is different for every available period t because with each new period an additional observation is used to calculate the standard deviation. At least two observations are needed to compute $\sigma_{ROA_{it}}$ for bank i.

A.3 A descriptive analysis of the critical events used in the study

As can be seen in Figure A1, during the period from 1995 to 2013 there were 637 critical events (without subsequent critical events)[70], 105 of which were commercial banks, 76 savings banks and Landesbanken, and 456 credit cooperatives and their regional institutions[71], i.e. in absolute numbers most critical events have been recorded for the banking group of credit cooperatives.[72]

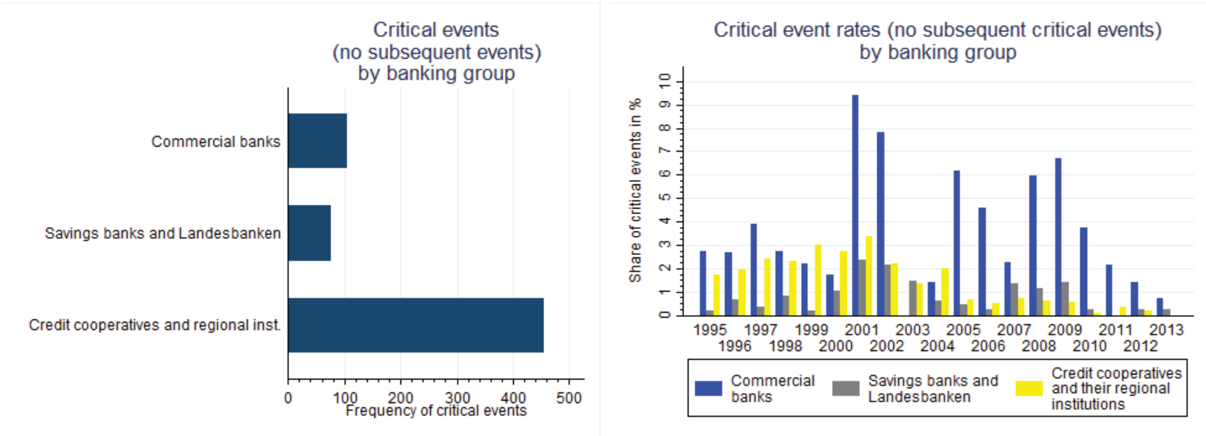

Figure A1: Critical events by banking group and over time

For credit cooperatives, the highest annual shares of banks in distress were recorded between 1995 up until 2001.[73] After that period, the share of credit cooperatives experiencing critical events went down to 0.5% in 2006 from over 3% in 2001. Credit cooperatives endured the financial crisis fairly well with a share of banks in distress that hardly rose.[74]

[70]As stated in footnote 21, the number of critical events is conditional on available observations for our explanatory variables. There were 719 critical events during the period from 1995 to 2013, but for 82 of them at least one regressor is missing.

[71]Commercial banks or private banks, public banks (savings banks and Landesbanken), and cooperatives (credit cooperatives and their regional institutions) constitute the three pillars of the German banking sector (see, for example, Berger, Bouwman, Kick, and Schaeck (2016), IMF (2016)).

[72]The exact breakdown of critical events by banking group and over time can be found in Appendix A.1, Table A1.

[73]The structural change in the German banking sector in the 1990s had a particularly severe impact on the cooperatives sector which led to a strong consolidation process within the banking group and the relatively high share of credit cooperatives experiencing critical events between 1995 and 2001 (see Guinnane (2013)).

[74]The dataset on critical events also contains information on bank closures. Since this label also applies to financially healthy banks that have been taken over by other banks, closures are not tantamount to critical events. There are 272 bank years in which banks were closed after they were healthy for a number of years prior to the closure, even though they had experienced at least one critical event before becoming financially healthy for at least one year. In 441 cases, a closure is immediately preceded by at least one less severe critical event. In theory, it is conceivable that a bank's financial condition deteriorates so quickly that the bank has to be liquidated within one year. However, this is highly improbable. We conservatively omit those 272 bank years in which banks were closed, whenever those banks were healthy in the years prior to the closure. Because of this, the critical event rates displayed in Figure A1 might be slightly higher than they actually were. Keeping these observations in the dataset and treating them

The share of commercial banks experiencing critical events was similarly high between 1995 and 2001. However, during the years of the dot-com bubble, the share sharply rose towards 9% which implied an increase of more than 400%. While there were not many new events in the years after the bubble for any of the banking groups, commercial banks clearly had the highest share of banks whose status changed from financially healthy to distressed for the first time during that period. The savings banks have emerged to be the most stable sector in Germany over the 19 years observed. On average, their share of institutions in financial distress is below 1%. Only over the course of the dot-com bubble did the share notably rise, but never much higher than 2%. Since then, it has stayed constantly low and just like credit cooperatives, the largest portion of all savings banks got through the financial crisis very much unharmed.

as financially healthy bank years has no bearing on our results.

A.4 A descriptive analysis of the loan-to-deposit ratio and the loan-to-interbank liabilities ratio

The LTD reveals great differences in the share of loans in deposits across the banking groups in Germany. This particularly refers to the comparison between commercial banks, on the one hand, and savings banks and credit cooperatives on the other. Table A3 in Appendix A.1 shows that the distribution of the LTD of commercial banks has a very large mean of 5,959%. This is mainly due to very high LTDs in the 99th percentile. Very large values can be explained by some commercial banks' business models that rely only on a very small deposit base for funding. This is true, for example, for many investment banks. The median values across the banking groups are relatively close to one another, with the median of commercial banks amounting to 95%, and that of savings banks and credit cooperatives being equal to 93% and 80% respectively. However, the respective distributions of the LTD for savings banks and credit cooperatives are characterized by far fewer extreme values.

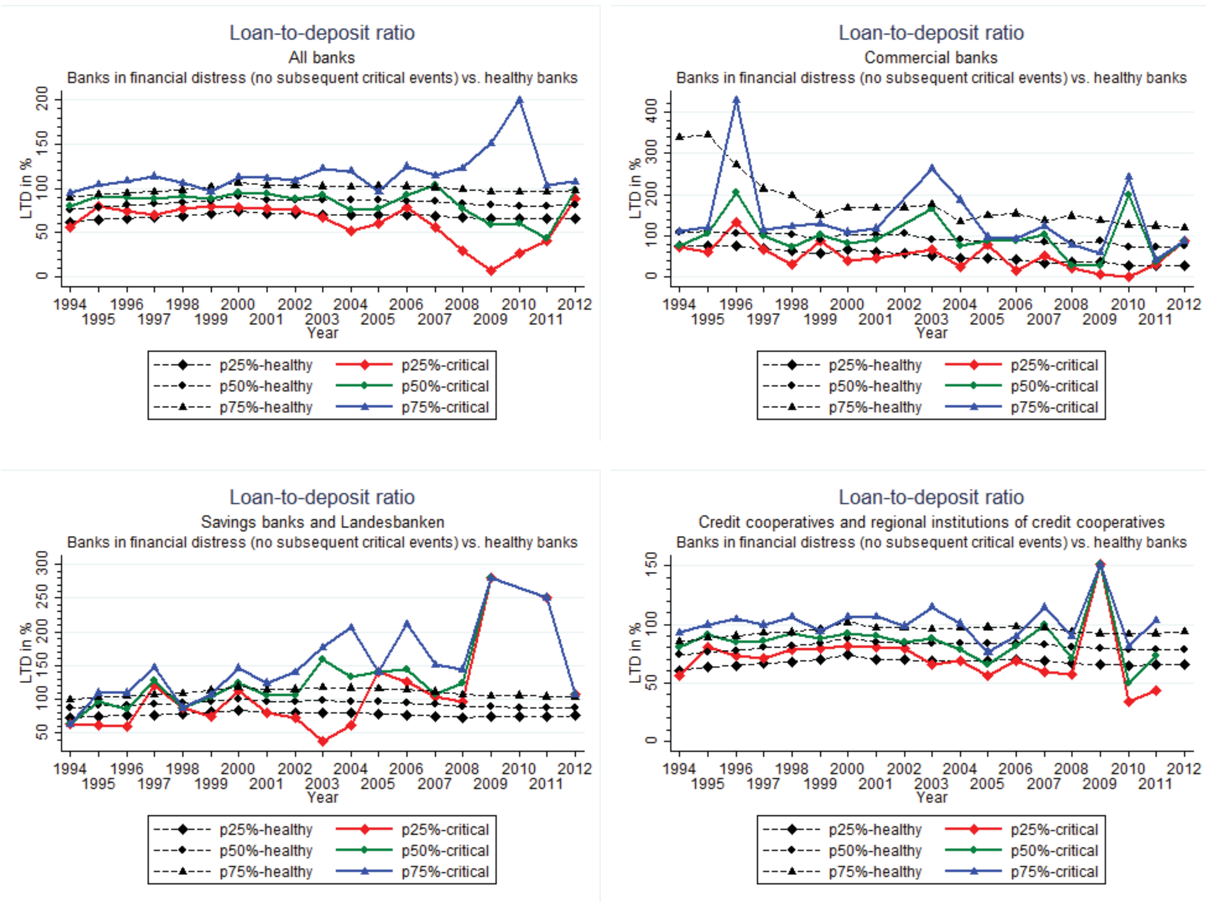

Figure A2: Loan-to-deposit ratio by banking group and over time

Figure A2 displays the quartiles and the median of the LTD for banks that become financially distressed in the following year (solid lines) and healthy ones (dashed lines), for each year from 1994 to 2012.[75] The subfigures show the respective percentiles for all banks and for each banking group separately.[76]

The complete sample shows that for the healthy banks, the distribution of the LTD is fairly stable. By contrast, the distribution of the LTD for banks experiencing critical events is far more volatile and this volatility increases in the second half of the 2000s. This is due to a much smaller sample size, but it also suggests that funding is not necessarily the main driver of each critical event. However, for most of the time periods the LTD of banks in critical states lies above that of the healthy banks.[77] This difference is especially pronounced in the 75th percentile. The breakdown by banking group reveals that the picture looks different depending on which banking group is considered. For commercial banks, the distribution of the LTD of banks in critical states tends to lie below that of the healthy banks. This gives rise to the assumption that funding problems have not been the main cause of trouble for this banking group. As far as savings banks are concerned, the distribution of the LTD of banks in financial distress clearly lies above that of the healthy banks in most years. This suggests that savings banks that experience financial distress often turn out to have financed a larger part of their loan portfolio through sources other than deposits, which, in general, is uncommon behavior for savings banks.[78] Indeed, there seems to be some relation between this behavior and the likelihood of critical events in this sector. A similar picture emerges for credit cooperatives. Especially at the beginning of the sample and up until 2002, the LTD of banks in financial distress seems to systematically lie above that of the healthy banks in all considered percentiles. After that period, the distribution displays more volatility over the years which is mainly due to the significantly lower number of critical events. However, there are still a number of banks in critical states that have a higher LTD than most healthy banks.

As for the $LTIBL$, there are vast differences in the use of wholesale funding across banking groups. As would be expected, it is most widely used by commercial banks. Over the period between 1994 and 2012, the mean of the ratio of interbank liabilities to total assets is 26%, as opposed to a mean of 20% for savings banks and 13% for credit cooperatives. However, commercial banks' standard deviation of this ratio is also the largest. The median of commercial banks' $LTIBL$ amounts to 238%. Again, the distribution of commercial banks is driven by extreme values, while it also shows a large variance pointing towards more heterogeneity in the sector of commercial banks. The 99th percentile is 435,833% which basically means no wholesale funding at all. Slightly fewer extreme values are recorded for the group of credit cooperatives. Their mean still stands at a high 2,429%, the 99th percentile is 5,358%. The median of the $LTIBL$ of credit cooperatives is 506% and more than twice as large as that of commercial banks. For savings banks, this ratio is distributed a lot more narrowly. The mean is 373% and

[75] One has to keep in mind that the figures merely show the quartiles and the median of the LTD for the respective subgroup of banks at each point in time, i.e. the percentiles should not be regarded as time series. As the overall number of banks in distress varies over time, any relation between two points in time is of little informative value.

[76] Table A4 in Appendix A.1 contains a breakdown of the LTD by financial distress status in the following period and banking group.

[77] This is not true for the lower quartile and the median in most of the second half of the 2000s.

[78] Savings banks finance the largest part of their loan growth via deposits (Gubitz (2013)). This is also true for credit cooperatives. The correlation of loan growth and deposit growth is 0.878 for savings banks and 0.697 for credit cooperatives. By contrast, for commercial banks, this correlation is only 0.128.

the median amounts to 320%. Overall, savings banks are a lot less active on the interbank market than are commercial banks, but more active than credit cooperatives.[79]

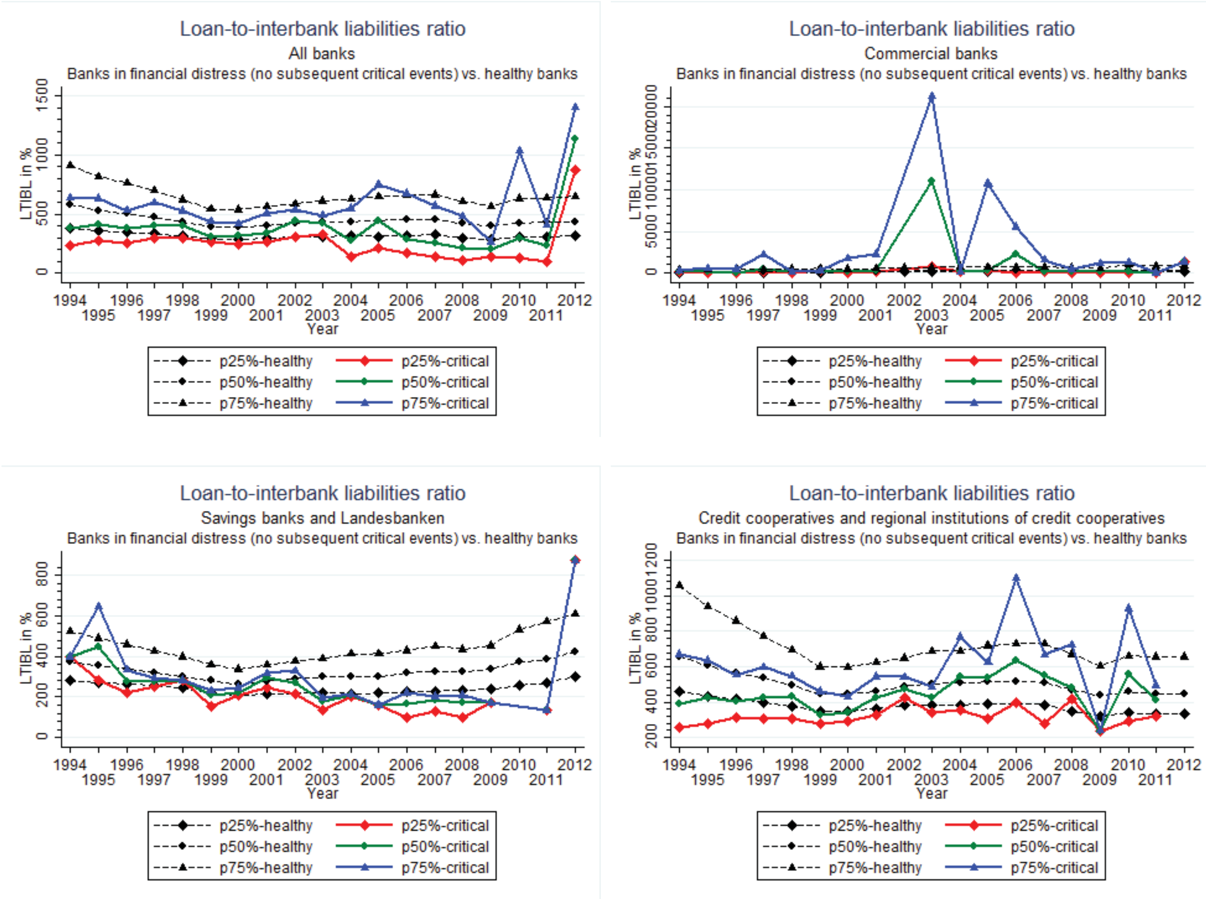

Figure A3: Loan-to-interbank liabilities ratio by banking group and over time

Subfigures in Figure A3 show the quartiles and the median of the $LTIBL$ for banks that become financially unhealthy in the following period (solid lines) and healthy ones (dashed lines) for the entire sample and for each banking group for each year from 1994 to 2012.[80] For the whole sample, unhealthy banks tend to have a lower $LTIBL$, which means that they finance their loans with more funding obtained from the interbank market than do healthy banks. Since banks' financial distress is often associated with liquidity problems, this is not surprising. However, there are marked differences across banking groups. The $LTIBL$ in the commercial banking sector, in particular, can be observed to display a different pattern. Here, the distribution of the $LTIBL$ for banks in financial distress lies above that of healthy banks in most years. This suggests that wholesale funding is not the main cause of their problems. For savings banks, the distribution of the $LTIBL$ of banks in critical states is below that of healthy banks, showing that banks in

[79]It should be noted that the German interbank market is highly segmented. The counterparties that savings banks are most heavily engaged in interbank credit relationships with are other savings banks and the *Landesbanken*. The same is true of credit cooperatives and their central institutions.

[80]Table A4 in Appendix A.1 reports a breakdown of the $LTIBL$ by financial distress status in the following period and banking group.

financial distress financed a higher share of their loan portfolio through wholesale funding. The same holds true for credit cooperatives, although this can most notably be observed for the period from 1995 up until 2003. Thereafter, this relation is reversed in several years, but one must keep in mind that, as can be seen in Appendix A.1, Table A1, from 2005 on, the number of banks in financial distress is much smaller.

A.5 Additional figures

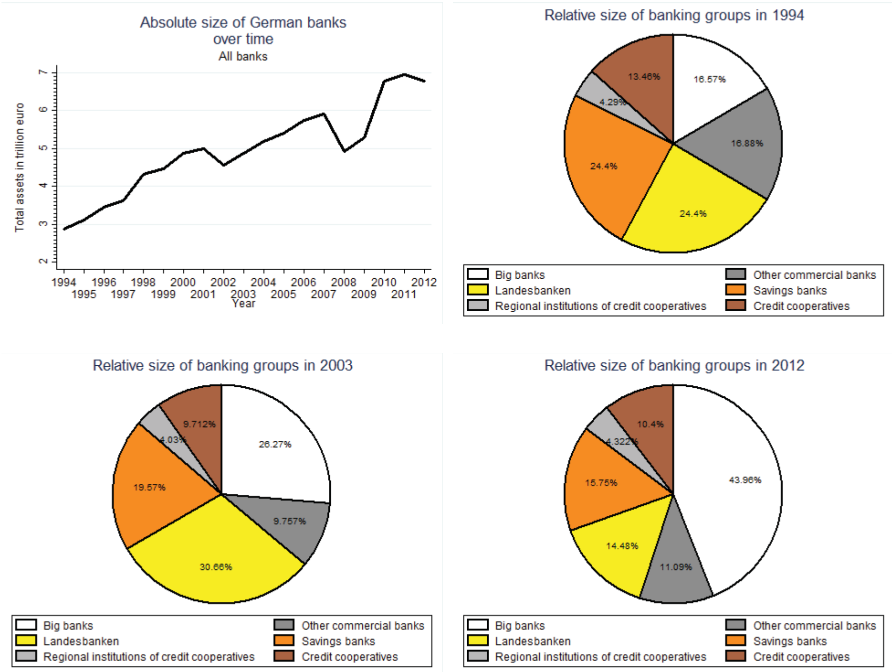

Figure A4: Evolution of the size of the German banks in the sample by banking group and over time

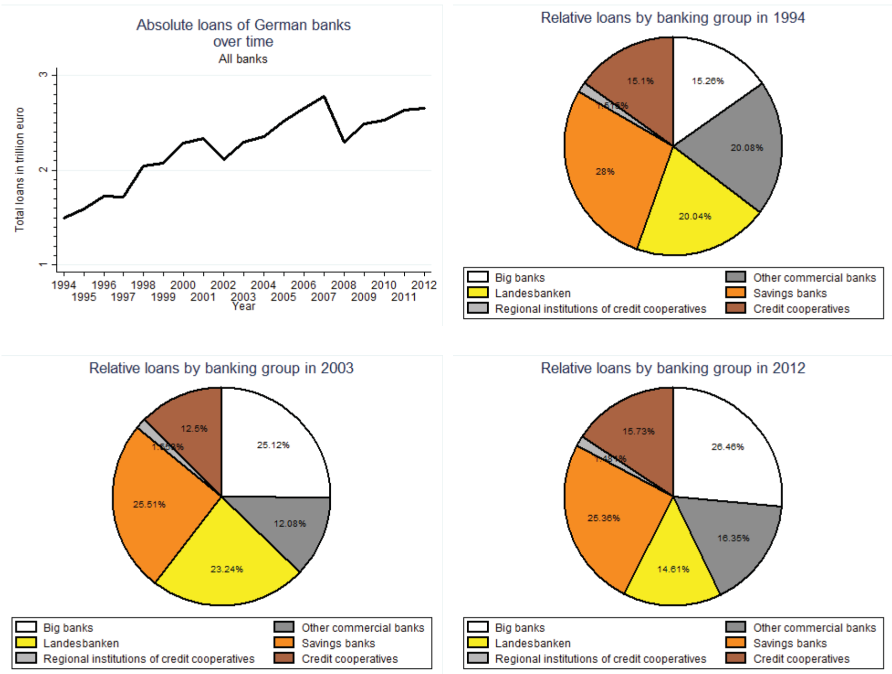

Figure A5: Evolution of the relative loans to the non-financial sector of the German banks in the sample by banking group and over time

A.6 Additional estimation output

Table A6: RE logit estimation: specification using relative loans in place of the stable funding variables – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(LR_{i,t-1})$	0.0745	4.2409***	2.1489***
	(0.0951)	(1.0672)	(0.3218)
$ROA_{i,t-1}$	−0.1327***	−2.0766***	−0.2293***
	(0.0320)	(0.4234)	(0.0673)
$log(CR_{i,t-1})$	−0.4706*	−2.1176**	−1.8168***
	(0.2128)	(0.9447)	(0.2911)
$log(LLR_{i,t-1})$	−0.0087	0.8743***	1.0035***
	(0.0148)	(0.2977)	(0.0854)
$log(AdminR_{i,t-1})$	0.6250***	−1.2156	1.1073***
	(0.1650)	(0.9359)	(0.2796)
$log(Liquid_{i,t-1})$	−0.0760	0.6588**	0.2393**
	(0.0864)	(0.2741)	(0.1015)
$log(Total\ Assets_{i,t-1})$	−0.0792	−0.2955*	0.1406**
	(0.0896)	(0.1618)	(0.0554)
$Z - Score_{i,t-1}$	0.0002*	−0.0180*	−0.0000
	(0.0001)	(0.0099)	(0.0002)
$Constant$	−2.0353	−17.5358**	−12.8806***
	(1.6326)	(5.6336)	(1.5649)
Time dummies	Yes	Yes	Yes
Number of banks	295	601	2,543
Number of observations	2,644	8,423	26,940
Pseudo R^2	0.13	0.28	0.15

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3). See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

Table A7: RE logit estimation: specification using relative deposits in place of the stable funding variables – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(DR_{i,t-1})$	0.1743	-4.3928^{***}	-0.3758^{**}
	(0.1018)	(1.2356)	(0.1498)
$ROA_{i,t-1}$	-0.1266^{***}	-2.0374^{***}	-0.2631^{***}
	(0.0307)	(0.4146)	(0.0945)
$log(CR_{i,t-1})$	-0.3704	-0.5537	-1.6752^{***}
	(0.2209)	(0.9710)	(0.2887)
$log(LLR_{i,t-1})$	-0.0076	0.8948^{***}	1.0058^{***}
	(0.0145)	(0.2839)	(0.0854)
$log(AdminR_{i,t-1})$	0.6023^{***}	0.4170	1.1091^{***}
	(0.1672)	(1.0817)	(0.2751)
$log(Liquid_{i,t-1})$	-0.1420	0.6889^{**}	0.1988^{*}
	(0.0909)	(0.2693)	(0.1035)
$log(Total\ Assets_{i,t-1})$	-0.0693	-0.3522^{**}	0.1902^{***}
	(0.0905)	(0.1544)	(0.0555)
$Z-Score_{i,t-1}$	0.0002	-0.0153	-0.0000
	(0.0001)	(0.0097)	(0.0002)
$Constant$	-2.4928	16.2331^{**}	-3.2526^{**}
	(1.6553)	(5.1032)	(1.1342)
Time dummies	Yes	Yes	Yes
Number of banks	295	601	2,543
Number of observations	2,644	8,423	26,940
Pseudo R^2	0.13	0.27	0.14

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3). See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

Table A8: RE logit estimation: specification using relative interbank liabilities in place of the stable funding variables – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(IBLR_{i,t-1})$	0.0206	1.3056**	0.6890***
	(0.0696)	(0.5442)	(0.1095)
$ROA_{i,t-1}$	−0.1384***	−2.1013***	−0.2111**
	(0.0356)	(0.4177)	(0.0937)
$log(CR_{i,t-1})$	−0.3849*	−0.8630	−1.5479***
	(0.2145)	(0.9851)	(0.2792)
$log(LLR_{i,t-1})$	−0.0022	0.9088***	0.9763***
	(0.0146)	(0.2924)	(0.0852)
$log(AdminR_{i,t-1})$	0.4685**	−0.3014	1.2062***
	(0.1521)	(1.0581)	(0.2786)
$log(Liquid_{i,t-1})$	−0.0528	0.6455**	0.2334**
	(0.0820)	(0.2773)	(0.1003)
$log(Total\ Assets_{i,t-1})$	−0.0558	−0.3553**	0.1766***
	(0.0929)	(0.1659)	(0.0556)
$Z-Score_{i,t-1}$	0.0002***	−0.0147	−0.0000
	(0.0001)	(0.0098)	(0.0002)
$Constant$	−2.1980	−5.3731	−6.4957***
	(1.6015)	(4.0390)	(0.9932)
Time dummies	Yes	Yes	Yes
Number of banks	291	601	2,542
Number of observations	2,488	8,423	26,890
Pseudo R^2	0.13	0.27	0.15

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3). See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

A.7 Robustness checks

We conduct several robustness checks to examine how sensitive our findings are. A random effects logit model relies on several restrictive assumptions that are needed for obtaining a tractable likelihood function and in order for the estimator to be consistent.[81] One crucial assumption is $\alpha_i|\boldsymbol{x_{i,t-1}}, \boldsymbol{z_{i,t-1}}, RD_i, \boldsymbol{TD} \sim \mathcal{N}(0; \sigma_\alpha^2)$, i.e. conditional on the regressors, the time-invariant unobserved heterogeneity is independent of the vector of the explanatory variables (and follows a normal distribution). However, instances are conceivable where regressors and the bank-specific unobserved heterogeneity might be (at least) correlated. For example, if α_i captures bank managers' (constant fraction of) risk appetite, then it might be related to the values of regressors such as the capital ratio, the return on assets or the loan-to-deposit ratio, for example. There are several ways around this assumption. In our robustness checks we resort to the (conditional) fixed effects logit model and the linear probability model with fixed effects.[82]

Because of their non-linear nature, it is not possible in binary response models to treat α_i as 'fixed' effects, i.e. not making any assumption about how α_i and $\boldsymbol{x_{i,t-1}}$, $\boldsymbol{z_{i,t-1}}$ might be related and thus allowing them to be correlated, by transforming the data to deviations from banks-specific means over time like it is in the linear regression case. The alternative is to estimate the unobserved heterogeneity parameters for each bank, which can be shown to render the maximum likelihood estimator inconsistent, given small T_i (Greene (2012)). However, one can circumvent this incidental parameters problem and still 'eliminate' the unobserved heterogeneity using a conditional logit model, which is an advantage over a probit model. The term 'conditional' refers to the finding that once we condition on $\sum_{t=2}^{T_i} y_{i,t-1}$, the likelihood function is no longer a function of α_i, i.e. in a logit model for panel data $\sum_{t=2}^{T_i} y_{i,t-1}$ is a minimum sufficient statistic for the unobserved heterogeneity (Chamberlain (1980)). Essentially, this means that we condition on banks which change their financial distress status at least once. Observations belonging to all the other banks contribute no additional information to the likelihood function, and hence end up being discarded. Results from the estimation of the model via the conditional fixed effects procedure can be found in Table A9. At least for credit cooperatives, the positive impact on the likelihood of becoming financially distressed of the LTD can be confirmed. However, one has to keep in mind that only 418 banks (out of 2,541) change their status, which is why we are merely interested in the sign of the estimated coefficient. For savings banks, it is positive but statistically insignificant, presumably because only 66 (out of 601) savings banks could be used in the estimation.[83]

While the fixed effects logit model has its merits, it is not without drawbacks. Because we have to condition on banks that have been in financial distress, the number of

[81] For a discussion of the assumptions, see Wooldridge (2002).

[82] Alternatively, one might still use the random effects model, but assume that the unobserved heterogeneity is a certain function of the regressors. Mundlak (1978) proposes that α_i depends on the bank-specific time average of $\boldsymbol{v}_{i,t-1}$, where $\boldsymbol{v}_{i,t-1}$ is a vector containing $\boldsymbol{x_{i,t-1}}$, $\boldsymbol{z_{i,t-1}}$, RD_i and $\boldsymbol{TD}$, i.e $\alpha_i = \psi + \overline{\boldsymbol{v}_i}'\boldsymbol{\xi} + c_i$, $\overline{\boldsymbol{v}_i} = \frac{1}{T_i}\sum_{t=2}^{T_i} \boldsymbol{v}_{i,t-1}$. The assumption then becomes $\alpha_i|\boldsymbol{v}_{i,t-1} \sim \mathcal{N}(\psi + \overline{\boldsymbol{v}_i}'\boldsymbol{\xi}; \sigma_c^2)$. While one very restrictive assumption is essentially being replaced by another, some dependence between α_i and $\boldsymbol{v}_{i,t-1}$ is allowed. We corroborated our findings using this model as well. The results are available upon request.

[83] Because so many observations are discarded, a Hausmann-Test of whether or not the random effects model is justified is not sensible.

Table A9: Conditional FE logit estimation: main specification – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(LTD_{i,t-1})$	0.0611	5.3394	3.0843***
	(0.2899)	(8.8898)	(1.0049)
$log(LTIBL_{i,t-1})$	0.0570	−1.6933	−0.5395
	(0.1593)	(2.7358)	(0.3483)
$ROA_{i,t-1}$	−0.3090	−1.2604	−0.9173***
	(0.1956)	(1.5566)	(0.2663)
$log(CR_{i,t-1})$	−1.0515*	−2.7563	−1.9062
	(0.4396)	(5.9443)	(1.2746)
$log(LLR_{i,t-1})$	0.0503	1.0931	0.6684***
	(0.0476)	(1.7358)	(0.1408)
$log(AdminR_{i,t-1})$	1.5853*	−1.9126	2.4189**
	(0.6231)	(3.7123)	(1.1194)
$log(Liquid_{i,t-1})$	−0.1695	0.6638	0.1178
	(0.3024)	(1.0659)	(0.1432)
$log(Total\ Assets_{i,t-1})$	0.1593	−1.1134	−2.4494***
	(0.5592)	(3.7678)	(0.5766)
$Z-Score_{i,t-1}$	0.0001	−0.0251	−0.0001
	(0.0051)	(0.0411)	(0.0039)
Time dummies	Yes	Yes	Yes
Number of banks	76	66	418
Number of observations	696	670	3,686

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients and bootstrapped standard errors (in parentheses) using the conditional fixed effects logit model (3). See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

observations is substantially reduced. That is why we deploy the linear probability model with fixed effects to estimate the effect of stable funding on the financial distress of banks. Since we are not interested in predicting probabilities of banks getting into financial difficulties, the problem that coefficients from the estimated linear probability model might result in predicted probabilities that are greater than one and/or less than zero is not a serious concern.[84] We estimate the following model using OLS with fixed effects:

$$y_{it} = \boldsymbol{x_{i,t-1}}'\boldsymbol{\beta} + \boldsymbol{z_{i,t-1}}'\boldsymbol{\gamma} + \boldsymbol{TD}'\boldsymbol{\delta} + \alpha_i + u_{it}, \quad i = 1, \ldots, n; t = 2, \ldots, T_i \tag{A1}$$

Note that (A1) does not explicitly contain regional dummies, as they do not vary over time and cannot be distinguished from the bank-specific fixed effects.[85] For this reason, they are part of α_i and are 'eliminated' when the variables are transformed to deviations from banks-specific means over time. The results in Table A10 corroborate our earlier findings with respect to the loan-to-deposit ratio. For the group of other commercial banks, the coefficient is not statistically different from zero, for savings banks and credit cooperatives the effect is positive and larger than in the baseline estimation (3).[86] For savings banks (credit cooperatives), a relative rise in the LTD of one percent is associated with an increase in the expected value of critical events of 0.000344 (0.000418) from 1995 to 2013. The $LTIBL$ is found to have no effect on the probability of experiencing financial distress for either banking group. Interestingly, the estimated coefficient on size is negative for credit cooperatives, so the positive effect reported in Table 4 cannot be corroborated.

As far as different functional forms for modelling the probability parameter are concerned, it might be argued that the employed random effects logit model might not work very well because there are too few critical events.[87] When one of the outcomes is rare, the complementary log-log model is called for (Cameron and Trivedi (2005)).[88] Table A11 reports the results, which are very similar to our benchmark findings.

One important assumption needed for the random effects logit model is that the regressors are strictly exogenous (conditional on the unobserved heterogeneity). For one, strict exogeneity rules out past dependent variables in $\boldsymbol{x_{i,t-1}}$, $\boldsymbol{z_{i,t-1}}$, but it also means that y_{it} values cannot be correlated with the future realizations of the regressors. However, it is conceivable that once a bank is in financial distress, certain measures are taken that systematically affect future balance sheet variables of that bank. We take this assumption seriously and estimate (3) without observations that follow any distress event, i.e. we consider all observations of banks that remain healthy throughout the sample and observations up until the first distress event of banks (including that event) which experience financial difficulties. Doing so leaves us with 556 bank years in financial distress.[89] Table A12 shows that the results basically remain the same.

[84] Another disadvantage of a linear probability model like (A1) is that the marginal effects are constant, regardless of the regressor values.

[85] The same is true for the conditional fixed effects logit model.

[86] Note that the number of observations is larger than the number reported in Table 2, Table 3 and Table 4. This is because the within transformation generates variation across banks even for years/federal states for which no critical events could be observed.

[87] As previously mentioned, the mean share of banks in financial difficulties throughout the entire sample is 1.57%.

[88] In the complementary log-log model, the error term follows a conditional extreme-value Gumbel distribution and the cdf, given by $Pr(y_{it} = 1 | \boldsymbol{x_{i,t-1}}, \boldsymbol{z_{i,t-1}}, RD_i, \boldsymbol{TD}, \alpha_i) = 1 - exp(-exp(\boldsymbol{x_{i,t-1}}'\boldsymbol{\beta} + \boldsymbol{z_{i,t-1}}'\gamma + \delta RD_i + \boldsymbol{TD}'\boldsymbol{\zeta} + \alpha_i))$, is not symmetric around zero.

[89] There are 66 critical events for the group of other commercial banks, 67 for savings banks, and 423 for credit cooperatives.

Table A10: FE OLS estimation: main specification – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(LTD_{i,t-1})$	0.0006	0.0344***	0.0418***
	(0.0036)	(0.0101)	(0.0089)
$log(LTIBL_{i,t-1})$	0.0028	0.0034	0.0009
	(0.0038)	(0.0037)	(0.0018)
$ROA_{i,t-1}$	−0.0076**	−0.0288***	−0.0198***
	(0.0031)	(0.0076)	(0.0041)
$log(CR_{i,t-1})$	−0.0209	−0.0232	−0.0094
	(0.0162)	(0.0147)	(0.0081)
$log(LLR_{i,t-1})$	0.0008	0.0035	0.0009***
	(0.0012)	(0.0021)	(0.0002)
$log(AdminR_{i,t-1})$	0.0254*	−0.0029	0.0182**
	(0.0137)	(0.0304)	(0.0088)
$log(Liquid_{i,t-1})$	−0.0047	0.0028	0.0024
	(0.0048)	(0.0031)	(0.0021)
$log(Total\ Assets_{i,t-1})$	−0.0020	0.0042	−0.0192***
	(0.0099)	(0.0087)	(0.0050)
$Z - Score_{i,t-1}$	0.0000	−0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
$Constant$	0.0444	−0.1958	0.0342
	(0.1483)	(0.1265)	(0.0721)
Time dummies	Yes	Yes	Yes
Number of banks	295	632	2,545
Number of observations	2,709	9,342	27,994
R^2 within	0.04	0.02	0.02
R^2 between	0.01	0.02	0.00
R^2 overall	0.03	0.02	0.01

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients and robust standard errors (in parentheses) using the fixed effects OLS regression (A1). See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

Table A11: Complementary log-log estimation: main specification – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(LTD_{i,t-1})$	-0.0798	3.3755^{***}	0.4109^{***}
	(0.0733)	(0.7032)	(0.1079)
$log(LTIBL_{i,t-1})$	-0.0100	0.1916	-0.3872^{***}
	(0.0558)	(0.4901)	(0.1145)
$ROA_{i,t-1}$	-0.0841^{***}	-1.8314^{***}	-0.0922
	(0.0235)	(0.3984)	(0.0548)
$log(CR_{i,t-1})$	-0.3227	-1.3802	-1.6710^{***}
	(0.2091)	(0.9915)	(0.2734)
$log(LLR_{i,t-1})$	-0.0016	0.8011^{**}	0.9613^{***}
	(0.0143)	(0.2857)	(0.0823)
$log(AdminR_{i,t-1})$	0.5054^{**}	0.2171	1.0422^{***}
	(0.1536)	(1.0060)	(0.2560)
$log(Liquid_{i,t-1})$	-0.1126	0.7011^{**}	0.2948^{**}
	(0.0878)	(0.2641)	(0.0969)
$log(Total\ Assets_{i,t-1})$	-0.0521	-0.2489	0.1696^{**}
	(0.0903)	(0.1546)	(0.0536)
$Z-Score_{i,t-1}$	0.0002^{*}	-0.0176	-0.0000
	(0.0001)	(0.0097)	(0.0002)
$Constant$	-1.7665	-18.6937^{***}	-4.0604^{**}
	(1.6812)	(5.6000)	(1.2964)
Time dummies	Yes	Yes	Yes
Number of banks	283	601	2,541
Number of observations	2,443	8,423	26,885
Pseudo R^2	0.13	0.29	0.15

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects complementary log-log model. See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

Table A12: RE logit estimation: specification using financially healthy bank years and only the first distress event of the respective banks experiencing financial distress – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(LTD_{i,t-1})$	-0.1172	3.6078***	0.6382***
	(0.1803)	(0.7567)	(0.1670)
$log(LTIBL_{i,t-1})$	0.0918	0.1245	-0.4452**
	(0.1264)	(0.5145)	(0.1360)
$ROA_{i,t-1}$	-0.2029**	-1.9910***	-0.3289**
	(0.0767)	(0.4388)	(0.1155)
$log(CR_{i,t-1})$	-1.3031*	-1.2920	-1.7679***
	(0.5858)	(1.0472)	(0.3468)
$log(LLR_{i,t-1})$	0.0240	0.8541**	0.9880***
	(0.0346)	(0.3038)	(0.0945)
$log(AdminR_{i,t-1})$	1.1802*	0.1451	1.4626***
	(0.4697)	(1.0661)	(0.3420)
$log(Liquid_{i,t-1})$	-0.1861	0.9007**	0.3150**
	(0.1961)	(0.2821)	(0.1145)
$log(Total\ Assets_{i,t-1})$	0.2201	-0.2433	0.2350***
	(0.2148)	(0.1615)	(0.0680)
$Z-Score_{i,t-1}$	0.0004	-0.0175	-0.0000
	(0.0002)	(0.0100)	(0.0002)
$Constant$	-8.2906*	-19.7221***	-5.9947***
	(4.0103)	(5.9332)	(1.7281)
Time dummies	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes
Number of banks	256	599	2,486
Number of observations	1,951	8,300	25,272
Pseudo R^2	0.14	0.26	0.15

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time, and zero if it is financially healthy in t. The estimation only uses observations of banks that remain healthy throughout the sample and observations up until the first distress event of banks (including that event) which experience financial difficulties. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3). See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

As previously mentioned, we lag the explanatory variables to make certain that balance sheet data precede financial distress events. However, since we do not have information on when exactly critical events took place during a year, it is possible that very little time lies between the date on which balance sheet items are disclosed and the financial distress event. For this reason, we re-estimate (3) and use two lags for the explanatory variables. The results that are reported in Table A13 in are not much different from the ones for the baseline specification.

When defining financial distress events in Section 3.1, we have explained that there are several types of critical events with varying severity. Even though we believe that our definition captures all relevant instances in which a bank should be labeled financially distressed, we re-estimate (3) using a very conservative definition of financial distress. We only regard bank years as critical if capital preservation measures and/or restructuring caused by mergers and/or liquidation/insolvency and/or SoFFin recapitalisation measures and guarantees have taken place. Bank years with less severe events are omitted for the purpose of this robustness check. Applying this definition reduces the number of bank years in financial distress to 513. Table A14 demonstrates that restricting the analysis to conservatively defined critical events hardly alters the results.

Another potential concern is that the 'operating loss in excess of 25% of liable capital' – as one of the criteria constituting a critical event – is related to a reduction in capital, which is also a right-hand side variable in our model. In order to exclude the possibility that our results are driven by this mechanical statistical association, we estimate (3) again, additionally including a dummy that is one whenever the (negative) return on capital[90] in a given year is less than -25%. The estimation output is reported in Table A15. Not surprisingly, the estimated coefficient for the dummy is positive and highly significant and accordingly, the estimated coefficient on ROA becomes lower and insignificant for credit cooperatives.[91] The effect of the stable funding variables on the likelihood of encountering financial difficulties remains unchanged.

It can also be argued that the $Z-Score$ – as a backward-looking measure of risk – does not adequately account for banks' risk profiles. In this check we employ an alternative. We use the lagged abnormal loan growth to capture bank risk. The abnormal loan growth is defined as the difference between the growth rate of bank i's loans at time t and the median growth rate of loans over all banks in that year. The idea is that loan growth is not necessarily risky per se, but if in a given year, the growth rates are higher than that year's median loan growth, it might be an indication of excessive credit growth and high risk, especially if lending standards and/or collateral requirements are lowered. Apart from that, banks exhibiting higher loan growth rates may attract more risky customers that have been denied loans by their competitors with more moderate loan growth (Foos, Norden, and Weber (2010)). We employ the abnormal loan growth instead of the $Z-Score$ in (3). The results in Table A16 corroborate our earlier findings.[92] Similar to the $Z-Score$, our alternative measure does not suggest that there is a noteworthy effect of

[90]The return on capital is defined as the ratio of banks' returns over their respective capital from the balance sheet.

[91]For savings banks, the ROA is still highly significant.

[92]Except for credit cooperatives, the number of bank years is slightly less than in the baseline estimation. This is because generating growth rates requires two consecutive observations for each cross-sectional unit.

Table A13: RE logit estimation: specification using two lags for the explanatory variables – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(LTD_{i,t-2})$	0.0118	4.2432***	0.7100***
	(0.0903)	(0.9549)	(0.1391)
$log(LTIBL_{i,t-2})$	0.0185	0.4095	−0.3780**
	(0.0694)	(0.5404)	(0.1221)
$ROA_{i,t-2}$	−0.0963*	−1.4788**	−0.1429
	(0.0401)	(0.5125)	(0.0811)
$log(CR_{i,t-2})$	−0.4224	−1.7569	−1.3147***
	(0.2592)	(1.1592)	(0.3060)
$log(LLR_{i,t-2})$	−0.0141	1.0976***	0.5594***
	(0.0175)	(0.3302)	(0.0831)
$log(AdminR_{i,t-2})$	0.5129**	−0.0111	0.6536*
	(0.1940)	(1.1394)	(0.2788)
$log(Liquid_{i,t-2})$	−0.0783	0.2625	0.4593***
	(0.1169)	(0.3016)	(0.1082)
$log(Total\ Assets_{i,t-2})$	−0.1280	−0.4317*	0.1959***
	(0.1053)	(0.1859)	(0.0592)
$Z-Score_{i,t-2}$	0.0003*	−0.0054	−0.0001
	(0.0001)	(0.0065)	(0.0003)
$Constant$	−2.6502	−19.5669**	−8.2200***
	(2.2792)	(6.7155)	(1.6827)
Time dummies	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes
Number of banks	260	559	2,448
Number of observations	2,149	7,473	24,175
Pseudo R^2	0.12	0.23	0.12

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3). See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

a risk-taking variable on the probability of becoming financially distressed.

Another possibility is that the results are influenced by regional economic booms where

Table A14: RE logit estimation: specification using a conservative definition of financial distress – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(LTD_{i,t-1})$	0.0286	4.1655***	0.4050**
	(0.1133)	(0.9494)	(0.1307)
$log(LTIBL_{i,t-1})$	0.0254	0.7522	−0.4432***
	(0.0831)	(0.5881)	(0.1245)
$ROA_{i,t-1}$	−0.0851*	−2.3320***	−0.2541**
	(0.0421)	(0.5046)	(0.0973)
$log(CR_{i,t-1})$	−0.2521	−1.0467	−1.6935***
	(0.3219)	(1.2236)	(0.2996)
$log(LLR_{i,t-1})$	−0.0011	0.7482*	0.9392***
	(0.0220)	(0.3422)	(0.0883)
$log(AdminR_{i,t-1})$	0.2109	0.2122	1.4243***
	(0.2322)	(1.2359)	(0.2956)
$log(Liquid_{i,t-1})$	0.0305	1.0466**	0.2827**
	(0.1413)	(0.3284)	(0.1063)
$log(Total\ Assets_{i,t-1})$	0.0049	−0.2160	0.1841**
	(0.1254)	(0.1863)	(0.0576)
$Z - Score_{i,t-1}$	0.0002	−0.0153	−0.0000
	(0.0001)	(0.0105)	(0.0002)
$Constant$	−4.2445	−25.5586***	−3.9976**
	(2.4504)	(7.5977)	(1.4047)
Time dummies	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes
Number of banks	255	547	2,533
Number of observations	1,806	6,863	26,740
Pseudo R^2	0.07	0.30	0.15

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. In this estimation, financially distressed bank years comprise the following critical events: capital preservation measures or restructuring caused by mergers or liquidation/insolvency or SoFFin recapitalisation measures and guarantees. The less severe bank years are omitted. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3). See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

Table A15: RE logit estimation: specification including a dummy that is one whenever the return on capital is less than -25% – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(LTD_{i,t-1})$	-0.0648	3.3684***	0.4299**
	(0.0816)	(0.8607)	(0.1347)
$log(LTIBL_{i,t-1})$	0.0129	-0.0832	-0.4027**
	(0.0616)	(0.5686)	(0.1247)
$ROA_{i,t-1}$	-0.0373	-1.9265***	-0.0518
	(0.0338)	(0.5104)	(0.0885)
$log(CR_{i,t-1})$	-0.3330	-0.7229	-1.7160***
	(0.2323)	(1.1487)	(0.3096)
$log(LLR_{i,t-1})$	-0.0034	0.6480*	0.9235***
	(0.0160)	(0.3239)	(0.0888)
$log(AdminR_{i,t-1})$	0.4620**	-0.2889	1.3128***
	(0.1756)	(1.1709)	(0.2908)
$log(Liquid_{i,t-1})$	-0.1911*	0.9504**	0.3200**
	(0.0966)	(0.3090)	(0.1085)
$log(Total\ Assets_{i,t-1})$	-0.0754	-0.3268	0.2118***
	(0.0961)	(0.1868)	(0.0600)
$Z-Score_{i,t-1}$	0.0002*	-0.0180	-0.0000
	(0.0001)	(0.0110)	(0.0002)
$Dummy_{Capital\ Loss<-25\%}$	3.4216***	4.8773***	4.1247***
	(0.4371)	(0.6936)	(0.2958)
$Constant$	-1.4905	-17.7408**	-5.0040***
	(1.7614)	(6.5204)	(1.4397)
Time dummies	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes
Number of banks	283	601	2,541
Number of observations	2,443	8,423	26,885
Pseudo R^2	0.21	0.37	0.20

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. $Dummy_{Capital\ Loss<-25\%}$ is a dummy that is one whenever a bank's (negative) return on capital in a given year is less than -25%, and zero otherwise. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3). See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

banks fund regional projects (i.e. increase their supply of credit) and finance them with an increased share of wholesale funding. In order to address this issue, we additionally

Table A16: RE logit estimation: specification using the abnormal loan growth in place of the $Z - Score$ – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(LTD_{i,t-1})$	-0.0644	3.3997^{***}	0.4480^{***}
	(0.0822)	(0.7326)	(0.1220)
$log(LTIBL_{i,t-1})$	0.0172	0.0412	-0.4073^{***}
	(0.0602)	(0.5077)	(0.1201)
$ROA_{i,t-1}$	-0.1788^{***}	-2.2335^{***}	-0.2381^{*}
	(0.0433)	(0.4094)	(0.0944)
$log(CR_{i,t-1})$	-0.3394	-1.3736	-1.6732^{***}
	(0.2296)	(1.0260)	(0.2917)
$log(LLR_{i,t-1})$	-0.0026	0.9059^{**}	0.9588^{***}
	(0.0157)	(0.2985)	(0.0861)
$log(AdminR_{i,t-1})$	0.5452^{**}	0.0727	1.1339^{***}
	(0.1678)	(1.0155)	(0.2818)
$log(Liquid_{i,t-1})$	-0.1128	0.7862^{**}	0.3012^{**}
	(0.0935)	(0.2765)	(0.1032)
$log(Total\ Assets_{i,t-1})$	-0.0340	-0.2967	0.1761^{**}
	(0.0929)	(0.1592)	(0.0562)
$AbnormLoangr_{i,t-1}$	-0.0000	0.0051	-0.0011
	(0.0000)	(0.0054)	(0.0027)
$Constant$	-1.9594	-18.1408^{**}	-4.2099^{**}
	(1.7546)	(5.7960)	(1.3574)
Time dummies	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes
Number of banks	276	601	2,541
Number of observations	2,393	8,418	26,885
Pseudo R^2	0.13	0.28	0.15

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3). See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

include the regional loan growth and the regional deposit growth[93] in the lagged vector of

[93]The regional deposit growth can be seen as a proxy for the regional saving rate.

explanatory variables $\boldsymbol{z_{i,t-1}}$ in (3).[94] The regional loan growth is defined as the relative change in loans summed over all banks in a federal state. The regional deposit growth is defined accordingly with respect to the deposits instead of loans. As is shown in Table A17, our baseline results are confirmed. The coefficients associated with the regional growth rates are economically small and mostly insignificant, suggesting that regional trends do not seem to matter for the critical events of banks, at least at the level of federal states.

To summarize, we have checked whether or not our findings are sensitive to different estimation techniques, more conservative assumptions/definitions of variables as well as alternative/additional variables, and we show that the main results remain unchanged.

[94] The results remain qualitatively the same if we augment $\boldsymbol{z_{i,t-1}}$ by either the regional loan growth or the regional deposit growth.

Table A17: RE logit estimation: specification including the regional loan growth and the regional deposit growth – different banking groups (no subsequent critical events)

Explanatory variables	Other commercial banks	Savings banks	Credit cooperatives
$log(LTD_{i,t-1})$	-0.0998	3.4611***	0.4469***
	(0.0810)	(0.7339)	(0.1229)
$log(LTIBL_{i,t-1})$	-0.0231	0.1257	-0.4279***
	(0.0598)	(0.5048)	(0.1214)
$ROA_{i,t-1}$	-0.1246***	-1.9798***	-0.2397*
	(0.0346)	(0.4311)	(0.0950)
$log(CR_{i,t-1})$	-0.2914	-1.2533	-1.6727***
	(0.2238)	(1.0251)	(0.2936)
$log(LLR_{i,t-1})$	-0.0017	0.8550**	0.9665***
	(0.0154)	(0.2969)	(0.0864)
$log(AdminR_{i,t-1})$	0.5315**	0.0267	1.1270***
	(0.1636)	(1.0413)	(0.2829)
$log(Liquid_{i,t-1})$	-0.1236	0.7838**	0.3033**
	(0.0940)	(0.2768)	(0.1034)
$log(Total\ Assets_{i,t-1})$	-0.0413	-0.2627	0.1733**
	(0.0912)	(0.1594)	(0.0563)
$Z-Score_{i,t-1}$	0.0002	-0.0178	-0.0000
	(0.0001)	(0.0100)	(0.0002)
$RegLoangr_{i,t-1}$	-0.0604	-0.0068	0.0029
	(0.0316)	(0.0282)	(0.0114)
$RegDepositsgr_{i,t-1}$	0.0102	-0.0051	-0.0248
	(0.0272)	(0.0388)	(0.0138)
$Constant$	-1.3839	-18.4078**	-3.7696**
	(1.7298)	(5.8256)	(1.3833)
Time dummies	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes
Number of banks	279	601	2,541
Number of observations	2,407	8,418	26,885
Pseudo R^2	0.13	0.29	0.15

Notes: The dependent variable is a dummy y_{it} that takes on the value one if bank i experiences financial distress in period t for the first time after being financially sound for at least one year, and zero if it is financially healthy in t. The table reports the estimated coefficients and standard errors (in parentheses) using the random effects logit model (3). See Appendix A.2 for the exact definition of the explanatory variables. Dummy variables are included ("Yes"), not included ("No"). Estimated dummy coefficients are not reported. Symbols *(**,***) denote statistical significance at the 10% (5%, 1%) level.

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