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**Working Paper**

## Borrowers under water! Rare disasters, regional banks, and recovery lending

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## Borrowers Under Water! Rare Disasters, Regional Banks, and Recovery Lending

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# Borrowers Under Water!

## Rare Disasters, Regional Banks, and Recovery Lending\*

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### Abstract

We show that local banks provide corporate recovery lending to firms affected by adverse regional macro shocks. Banks that reside in counties unaffected by the natural disaster that we specify as macro shock increase lending to firms inside affected counties by 3%. Firms domiciled in flooded counties, in turn, increase corporate borrowing by 16% if they are connected to banks in unaffected counties. We find no indication that recovery lending entails excessive risk-taking or rent-seeking. However, within the group of shock-exposed banks, those without access to geographically more diversified interbank markets exhibit more credit risk and less equity capital.

*Keywords: disaster risk, credit demand, natural disaster, relationship lenders*

*JEL Classification: G21, G29, O16, Q54*

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## 1. Introduction

Small- and medium-sized enterprises (SME) generate approximately half of the gross domestic product (GDP) in industrialized economies, such as Germany and the United States (Kobe, 2012). Yet, many SME are opaque compared to public firms and generate geographically less diversified cash flows. These features impose higher hurdles on SME to access external funding and increase their exposure to rare, yet impactful, local disaster risks. To the best of our knowledge, we are the first to identify simultaneously if (i) local lenders bolster local macro shocks, (ii) whether SME do rely on local banks to finance the recovery from such shocks, and (iii) whether the price to pay for any potential corporate recovery is an impaired resilience of regional financial systems.

We answer two specific questions that are closely intertwined, but have been considered in isolation up to now. Do local banks mitigate the fallout from realized disaster risk by means of *recovery lending*? And does such lending compromise the stability and performance of local banking systems? To identify *recovery lending*, we exploit the plausibly exogenous variation of firms’ exposure to economic damage due to the flooding of the river Elbe in Germany in May 2013. The flood resulted from a combination of heavy rainfall, wet soil conditions, and a large hydraulic load in the river system (Schröter et al., 2015; Thieken, 2016). This economically significant shock affected the counties (“Kreise”) around the river Elbe and its tributaries most harshly. The total damage amounted to 6 billion Euros (BMI, 2013) and triggered 180,000 insurance cases worth approximately 2 billion Euros (GDV, 2013). Figure 1 shows the geographical dispersion of damage in terms of the share of activated flood insurance contracts for nine categories after June 2013.

– Figure 1 around here –

This spatial distribution of disaster shocks paired with the fact that German SME rely mostly on small savings and cooperative banks permits the sharp isolation of *recovery lending*. These banks operate either de jure or de facto only locally. Therefore, we can separate loan responses by banks that are exposed directly to the disaster from lending changes of banks that are only indirectly exposed because they hold credit portfolios with many borrowers located in flooded counties.

We hypothesize that local banks are pertinent for any post-flood (re-)allocation of financial funds for two main reasons. First, insurance markets for disaster risk are generally incomplete, as shown for the United States by Froot (2001). In the case of the Elbe flood, only one-third of the flooding damages were insured (GDV, 2013). Second, the destruction of collateral during natural disasters implies an increase in information asymmetry. Relationship lenders with private information about local SME are therefore particularly important because they are better able and more willing to provide (additional) credit (Degryse and van Cayseele, 2000; Elsas, 2005; Behr et al., 2013). This factor is crucial because Cortés (2014) shows that those SME that depend on relationships with local banks drive the economic recovery in terms of improved job retention and creation patterns after a natural disaster.

Our unique setting gives rise to three important innovations compared to most prior studies that are confined to banks’ responses to natural disasters. The first is our identification strategy. We exploit that banks are exposed to disaster shocks based not only on their own location but also that of their corporate customers. Banks are considered to be exposed to the disaster if and only if a critical share of their customers are located in counties directly affected by significant flooding damage. By matching customer locations and bank identities, we isolate the exogenous natural disaster shock faced by local banks emanating from their loan exposure to firms in affected counties. Consequently, our main test disregards banks in flooded counties (henceforth: affected counties) and compares banks in unaffected counties that provided credit to corporate borrowers in affected counties (henceforth: exposed banks) with unexposed banks that primarily banked with local customers.

Second, on top of isolating *recovery lending* as the main response of banks to local macro shocks, we test if *recovery lending* has undesirable side effects, such as increased risk-taking by local emergency lenders or rent-extraction from captured borrowers. To test for a potential undermining of regional banking system stability, we begin by estimating differential risk-taking responses of exposed banks. Next, we shed light on the importance of having access to larger internal capital markets if local banks are part of geographically more diversified banking groups that are also active in unaffected counties. These results bear important ramifications for the discussion on how to design resilient regional financial systems, for example whether many small local lenders are more vulnerable to regional macro shocks compared to larger and geographically more diversified multimarket banks.

Third, most studies that relate natural disasters to bank behavior focus on mortgage lending to households (Cortés, 2014; Chavaz, 2016; Berrospide et al., 2016; Cortés and Strahan, 2017), but disregard both corporate lending as well as the borrowing responses of these firms. In contrast, we gauge how disaster shocks affect credit provisioning responses of local lenders and we document the existence of *emergency borrowing*. To this end we match approximately 1.1 million firms with approximately 2,000 banks that operate in all German counties. Following Popov and Rocholl (2018), Huber (2018), and Dwenger et al. (2018), we observe granular bank-firm relationships as opposed to aggregate (mortgage) lending to counties from Creditreform data, a non-profit rating agency. Thereby we can test if firms that reside in affected counties but are connected to banks domiciled in unaffected counties (henceforth: treated firms) borrow more. This angle complements studies on the direct effects of natural catastrophes on firm behavior (Noth and Rehbein, 2018).

We find that exposed banks in unaffected counties lend significantly more after 2013. This *recovery lending* effect amounts to an increase of 3% relative to unexposed banks. Against the backdrop of average pre-flood loan growth of approximately 5%, this magnitude is economically meaningful. This differential lending hike is driven by unsecured, non-mortgage lending. Regional banks finance their demand shock response by activating local savings. Wholesale funding, by contrast, exhibits no significantly different role in financing the lending expansion of exposed lenders in unaffected counties. We find little evidence that *recovery lending* entails riskier banking as such. Neither proxies for solvency nor credit risk among exposed

banks exhibit significantly different responses relative to unexposed banks. Likewise, we find no evidence that *recovery lenders* exploit flooded corporate borrowers, as net interest income does not differ significantly. However, we also show that within the group of exposed local banks that extend *recovery lending*, those without access to geographically more diversified banking group networks incur more credit risk and deplete capital by more compared to exposed banks that are part of spatially more diversified banking groups. Thus, the resilience of regional banking systems is strengthened if banking groups are active in geographically more diversified markets. This finding complements studies that stress the importance of cross-market re-allocation of funding on banking group internal capital markets to transmit policy and to bolster both domestic and international liquidity shocks (Campello, 2002; Cremers et al., 2011; Cetorelli and Goldberg, 2012). We add to these studies by demonstrating that the presence of regionally diversified banking groups enhances the ability of local group members to mitigate regional macro shocks.

Next, we trace the recipients of this differential lending expansion by exposed banks in unaffected counties. We find that corporate borrowing of treated firms in affected counties is significantly higher than that of untreated firms and overcompensates for the adverse borrowing conditions after 2013, resulting in an overall 16% increase in treated firms' credit. Consequently, firms with existing ties to banks in counties that were themselves not directly affected by the flood enjoyed *recovery lending*. Hence, local banks are important to mitigate disaster risks and aid the recovery of disaster-struck SME.

Our paper relates to a growing literature analyzing the relationship between lending and disaster shocks. The paper closest to ours in this regard is Cortés and Strahan (2017), who also identify disaster responses, comparing lending responses in non-shocked localities of multimarket banks with and without a connection to disaster-ridden markets. We complement their work in three distinct ways. First, we investigate how the spatial composition of corporate borrower portfolios influences post-shock corporate, rather than household, mortgage lending. Second, we directly take the perspective of firms in affected counties and test explicitly for corporate *emergency borrowing*. Thereby, we demonstrate that additional lending actually arrives in the affected counties rather than being routed to other investment opportunities, commensurate with a “flight-to-safety” pattern. Finally, we provide evidence of the absence of adverse performance and stability features of local banking markets due to *recovery lending*. In sum, our results suggest that small, local banks fulfill an important role in the economic recovery from natural disasters.

Whereas Cortés and Strahan (2017) and Chavaz (2016) find lending hikes in response to natural disasters, such a *recovery lending* response is anything but clear. Garmaise and Moskowitz (2009) document, for example, lower credit provision for Californian properties exposed to earthquake risk. They attribute this pattern to the imperfections in the disaster risk insurance markets, which also prevailed in Germany prior to the flood. Sawada and Shimizutani (2008) show that the destruction of collateral in the wake of the Kobe earthquake caused tighter credit constraints among households with less real estate wealth prior to the disaster, resulting in reduced post-disaster consumption. It remains an empirical question whether such wealth constraints apply also to corporate *recovery lending*, which we can answer in our study of SME

instead of household lending. In doing so, we complement the evidence in Berg and Schrader (2012) on credit supply contractions by a single micro credit provider to SME in Ecuador that were subject to volcanic eruptions. Relevant to our study, they also show that longer relationships mitigate this average tightening of credit constraints. Finally, our study relates to the insight in Schüwer et al. (2018) that banks that were hit by Hurricane Katrina in 2005 substituted customer lending with government securities. They argue that this asset swap helped to stabilize those banks. We test more explicitly for bank risk proxies and potential rent-seeking at the expense of captured SME. In addition, we shed light on the importance that small, local banks have access to larger and geographically more diversified intra-group markets to provide respond to regional macro shocks by extending *recovery lending*.

## 2. Data: sources, combination, and culling

*Firm-level data.* We obtain German firm-level data from Bureau van Dijk’s Dafne and Amadeus databases. The former contains the name of the bank (or banks) with which each firm maintains a (Hausbank) relationship (Dwenger et al., 2018). The information on firm-bank relationships are collected by the German credit rating agency Creditreform from firm surveys and financial statements (see, e.g., Engel and Midden-dorf, 2009; Breuer et al., 2017; Popov and Rocholl, 2018; Huber, 2018; Dwenger et al., 2018, who also use the same source to gauge bank-firm relationships). Based on annual vintages of the Dafne database, we construct a time-series of bank-firm relationships for more than one million firms between 2011 and 2015. This sample also includes the postal code of each firm, to which we match flood damage data obtained from the German Insurance Association (GDV, 2013, see Figure 1). We augment these bank-firm relationship data with firm-specific, annual financial accounts data from Amadeus. Because SME generally lack access to more complex financial markets, they rely mostly on banks for their financing needs. This renders the presence of SME in the data important to isolate any potential corporate *recovery lending*. The median firm in the sample has seven employees and assets of approximately 350,000 EUR, which, according to the definition of the European Commission (2003), denotes a micro firm.

*Bank-level data.* We collect data for small savings and cooperative banks, which are the major players in local markets and account for approximately one-third of the aggregate total banking assets in Germany (German Council of Economic Advisors, 2014). These banks pursue local relationship-based strategies, particularly aimed at SME. Therefore, the banks generate and possess more private information about their customers than do larger, nationally active banks (Behr et al., 2013). Information asymmetries to assess the structural ability of borrowers to repay their debts after a random disaster shock are therefore lower. These banks permit the clearest identification of lending responses to local disaster shocks, and we refer to them henceforth as local banks. We combine the firm information with bank data and define bank-firm relationships from a string-based match of bank names and firm names from observable relationships (Popov and Rocholl, 2018; Huber, 2018; Dwenger et al., 2018). The databases contain annual financial account

information and provide the locations of the banks’ headquarters. Thereby, we identify which banks are located in affected counties themselves.<sup>1</sup>

*Natural disaster data.* To gauge the damage inflicted by the Elbe flood of 2013, we use data on claims filed for insured properties that were damaged by the flood between May 25 and June 15, 2013. The GDV aggregates economic value destroyed relative to what is covered by insurance contracts by county (“Kreis”) for confidentiality reasons. We observe nine damage categories, which represent the percentage of insurance contracts for which a claim was filed by customers. Lower categories indicate less damage relative to asset values covered by insurance contracts.<sup>2</sup> The GDV collects this information from all 460 of its members, which include all major German insurance providers. The data also inform the risk calculation models of insurance companies, and regional aggregates are reported regularly (GDV, 2013).

*Culling.* After combining valid firm, bank, and disaster data for the period 2011-2015, we clean the data in four steps. First, we collapse the sample on the bank level and keep only relationships with local banks to ensure a correct mapping of the regional damage data, which leaves  $N = 13,662$  observations for  $K = 1,472$  banks. Second, we sample only non-missing observations for the six bank variables that we define in Subsection 3.1 and specify in the baseline regression ( $N=13,474$ ;  $K=1,4509$ ). Third, to consider a comparison of symmetric pre- and post-shock periods, we further restrict the sample to observations between 2011 and 2015 and exclude the year of the flood (2013) itself from our main analysis because we want to unveil a more persistent *recovery lending* effect instead of instantaneous accounting adjustments due to the flood ( $N=5,307$ ;  $K=1,373$ ). Last, we consider only banks that existed for at least one year before 2013 and at least one year after 2013, thereby reducing the sample to 4,064 observations for 1,076 banks.

### 3. Specification and identification

#### 3.1. Estimation of banks’ responses

To test whether lending differs significantly between exposed and unexposed banks in unaffected counties before and after 2013, we estimate a difference-in-difference regression:

$$\ln(\text{Loans})_{it} = \beta_1(\text{Exposed}_i \times \text{Post}_t) + \beta_2\text{Post}_t + \alpha_i + \alpha_t + \sum_{k=1}^K \gamma_k C_{kit-1} + \epsilon_{it}. \quad (1)$$

The dependent variable  $\ln(\text{Loans})$  is the natural logarithm of gross loans (Loans) for bank  $i$  in year  $t$ . Exposed is a dummy variable that identifies banks that lent primarily to firms located in affected counties. Subsection 3.2 details how we identify banks’ exposures. The Post indicator is equal to 0 for the years 2011 and 2012 and 1 for 2014 and 2015. The coefficient of interest is  $\beta_1$ : the treatment effect of the flood on

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<sup>1</sup>We used Bankscope until it was discontinued as of accounting year 2014 and the successor BvD product Orbis Bank Focus thereafter. The two data sources coincide almost perfectly in the jointly available 2013 vintage of financial accounts.

<sup>2</sup>Activation rates range from  $\leq 0.04\%$  in Category 1 to 10%–15% in Category 9. See Figure 1 for a detailed definition.

exposed banks. To gauge unobservable bank traits, we specify bank fixed effects  $\alpha_i$ , which also absorbs the single term Exposed. To capture business cycle effects, we specify year fixed effects  $\alpha_t$ .

– Table 1 around here –

All variables are defined in Table 1, and Table 2 presents descriptive statistics for the bank sample in the pre- and post-flood periods. The first panel of Table 2 shows that approximately 36% of German banks are exposed to the flood through their connections to borrowers headquartered in affected counties in 2013.

– Table 2 around here –

The second panel of Table 2 shows the five bank-specific control variables, which enter Equation (1) in first lags. First, we use the natural logarithm of banks' total assets ( $\text{Size}=\ln(\text{Total Assets})$ ) to differentiate small from large banks. Second, the ratio of banks' total equity to total assets (Capital Adequacy) controls for bank capitalization. Thereby, we gauge differences in banks' abilities to buffer insolvency shocks in their credit portfolio. Third, Liquidity is the ratio of banks' cash holdings to total assets and captures different abilities to buffer short-term shocks. Fourth, we measure local bank profitability with net return on annual average assets (RoA). More profitable banks should be more able to absorb shocks (e.g., Gropp and Heider, 2010). Finally, we specify the share of securities relative to total assets to control for potentially different business models of banks (Securities). The average bank is small, with total assets of 1.4 billion USD, and it exhibits an equity ratio of 8.5%. The average bank in the sample holds 1.8% cash relative to total assets. Profitability is low during our sample period, amounting to 3 basis points on average. Security portfolios account for only one-quarter of banks' total assets, which corroborates the importance of lending business to local banks.

The third panel of Table 2 features further dependent variables to gauge banks' responses to disaster risk beyond corporate lending. We use Mortgage Loans and Customer Loans to investigate alternative channels of recovery lending. Total Deposits, their two sub-categories (Customer Deposits and Interbank Deposits), and any securitized funding (Wholesale Funding) help to detect differential flood effects on banks' liability structures. To test for systematic changes in loan quality, we regress flood exposure on impaired (or non-performing) loans over total assets (Impaired Loans). The performance variables used to gauge banks' risk-return profiles are the Z-score and the ratio of net interest income over expenses (Net Interest Income). The former is the inverse distance to default and is equal to the natural logarithm of the sum of the return on assets (RoA) and the capital ratio divided by the standard deviation of RoA. The latter gauges the relative importance of interest-bearing activities of the bank.

### 3.2. Identification through banks in unaffected counties

Our identification strategy isolates banks' corporate *recovery lending* responses by comparing banks exposed to the disaster via the location of their firm customers to those that were not exposed. Importantly,

we do so only within unaffected counties and exclude banks that reside in affected counties. Thereby, we avoid confounding loan supply and credit demand responses. To identify which banks are exposed to this disaster-induced shock, we measure, per bank, how many borrowers are located in affected counties.

For each bank, we take the weighted average of flood damage categories across all firms  $j = 1, \dots, M$  that report a relationship with the bank. Each firm contributes to each bank’s disaster exposure the damage category of the county  $r$  where the firm is located. We define the demand shock exposure of bank  $i$  to the flood as the (size-weighted) flood damage to the bank’s average firm-customer  $j$ , given the firm’s county  $r$ , where  $M$  is the total number of firms connected to bank  $i$  as of 2013:<sup>3</sup>

$$\text{Exposure}_i = \frac{\sum_{j=1}^M \left( \frac{\text{Assets}_j}{\text{Mean Assets}_M} \times \text{Claim Ratio Category}_r \right)}{M}. \quad (2)$$

We define banks as exposed (unexposed) if their exposure value is above (below) the median measured across all banks. In contrast to Cortés (2014) or Schüwer et al. (2018), we discard banks that are located in affected counties themselves. Figure 2 (a) illustrates how we isolate disaster shocks faced by exposed banks (depicted by solid circles) that are located in unaffected counties but are exposed to sufficiently many firms that reside in affected counties (depicted by solid squares). Our identification hinges on comparing these banks with unexposed banks in unaffected counties (depicted by transparent circles), which bank mostly with firms that have not been put under water by the flooding of the river Elbe in 2013.

– Figure 2 around here –

We focus on banks that are not directly exposed in isolation because they offer the cleanest identification of changes in lending due to disaster shocks transmitted only through banks’ credit portfolios. To ensure that our exposure measure is valid, the local banks that we compare must not exhibit significantly different lending patterns before the flood of 2013. Table 3 shows the first and second moments of our variables measured in average percent change for exposed and unexposed banks for the 2011-2012 period.

– Table 3 around here –

The rightmost column presents the normalized differences (Imbens and Wooldridge, 2009; Lambert et al., 2017). A normalized difference larger than 0.25 indicates that the differences in the trends between both groups of banks are significant. The descriptive statistics illustrate that the variables fulfill the parallel trends assumption. Moreover, local banks should not have differed in terms of other observable bank traits that might confound the effect of the disaster shock that we seek to identify. To that end, we specify bank

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<sup>3</sup>This approach captures actual relationships in the year of the flood so as to obtain a precise measure of banks’ flood exposures. Exposure varies minimally between 2011 and 2013. The results are insensitive to alternative weighting schemes.

fixed effects to ensure that level-differences in bank characteristics do not bias our results.<sup>4</sup>

In sum, we identify the differential *recovery lending* effect based on the within-county variation between exposed banks that catered credit to corporations in affected counties versus unexposed banks with credit portfolios of local, non-flooded customers.

#### 4. Banks' responses to the flood

##### 4.1. *Recovery lending: headline results*

We estimate Equation (1) with OLS and clustered standard errors at the bank level. Table 4 shows the results for the main sample of local banks residing in unaffected counties in the two years before and after the flooding of the river Elbe in 2013. There are 390 exposed banks in unaffected counties, compared to a total of 1,076 unexposed banks in these counties, i.e., the market on the left in Figure 2.

The estimated coefficient  $\beta_1$  is positive and significant at the 1% level in Column (1) of Table 4. Exposed banks increased their lending after the Elbe flood relative to unexposed local banks. The economic magnitude of this effect is relevant: exposed banks domiciled in unaffected counties increased their lending by roughly 3%  $((\exp(0.0288) - 1) \times 100 = 2.92)$  compared with unexposed banks in 2014 and 2015. This positive *recovery lending* effect corroborates the role played by local banks in coping with the fallout from disaster risk documented for developing economies in (e.g., Berg and Schrader, 2012) and the United States (e.g., Cortés and Strahan, 2017).

– Table 4 around here –

This *recovery lending* effect contrasts, however, with the negative effects reported for more specialized (mortgage) lending in Japan (Sawada and Shimizutani, 2008) and the United States (Garmaise and Moskowitz, 2009). A potential reason for this difference is that overall corporate lending rather than residential mortgage lending is driving our result. Therefore, we specify the natural logarithm of mortgage lending as the dependent variable in Column (2). The interaction term between the post-flooding indicator and loans that are secured by real estate is not statistically significant. The result that local banks' mortgage lending does not respond significantly to the disaster shock may indicate that the value of corporate credit depends much more on (tacit) information that the bank possesses about the productivity of the firm and its management. By contrast, mortgage loan values depend more directly on tangible collateral that has been destroyed during the disaster.

Column (3) further isolates corporate *recovery lending* by showing that the baseline effect is driven by customer lending. The interaction term is significantly positive and of a very similar magnitude to the

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<sup>4</sup>Figure OA1 in the Online Appendix shows that exposed banks do not engage in significantly more new firm relationships after 2013 compared to unexposed banks. Importantly, exposed banks are less likely to terminate existing firm relationships after 2013. It is therefore unlikely that the positive average treatment effect on the average loan volume documented here – the intensive margin – is confounded by a contraction along the extensive margin by exposed banks towards treated firms.

baseline specification. Banks seem to have expanded credit in categories associated with non-land collateral requirements. In times when the quick provision of credit is important to firms – such as after a natural disaster – local banks with private information about borrowers’ structural ability to operate their business resort to the provision of (unsecured) lending.

The existence of *recovery lending* begs the question of how local banks finance such additional lending. One possibility is that local banks are best equipped to attract local savers to fund shocked, yet structurally sound, corporate borrowers in nearby markets. Retail savers may be reluctant to directly fund solvent but opaque borrowers in neighboring affected counties. But they might be happy to entrust their local relationship lender to screen those borrowers on their behalf. Alternatively, observed lending expansions might actually result from intra-group treasury management. Local savings and cooperative banks are part of internal capital markets to the extent that head institutions – either central cooperative banks or so-called Landesbanken – can and do channel funds between local entities (Cremers et al., 2011).

To identify the sources of *recovery lending*, we specify in Column (4) of Table 4 the logarithm of total deposits, separated into interbank deposits in Column (5) and customer deposits in Column (6). For both customer and interbank deposits we find a positive differential effect between exposed and unexposed banks within unaffected counties. Together with the direct terms of the post-flood indicator, our results indicate a significant contraction of interbank deposits for all banks in unaffected counties as opposed to an increase in local customer deposits. This result is consistent with the findings reported by Cortés and Strahan (2017) that multimarket banks re-allocate funding to shocked localities, i.e., reduce interbank funding to unaffected regions. The significant increase in local customer funding documented in Column (6) corroborates the notion that lenders with local relationships in unaffected counties succeed in activating local savings that can subsequently be routed to corporations in adjacent markets in addition to centrally managed internal capital market re-allocations. Below, we further scrutinize these initial indications that exposed banks not only increase lending in general but also route it to firms that were directly hit by the disaster.

In Column (7) we test whether exposed banks in unaffected counties rely, after the flood, on capital markets as an alternative to satisfy the additional credit demand from their corporate loan customers in affected counties. The dependent variable is the logarithm of wholesale funding, defined as any securitized borrowing. Exposed banks in unaffected counties do not expand their reliance on capital market funding.

When we turn to the control variables, we find that the effects of Size and Securities are identical across lending specifications. Larger banks with lending-oriented balance sheets exhibit larger gross loan volumes. Capitalization, liquidity ratios, and profitability differences across banks in unaffected counties are not significant. In the funding regressions depicted in Columns (4) through (7), bank size correlates significantly positive with all forms of re-financing volumes. There is some evidence that banks with relatively larger security shares relative to total assets tend to rely more on wholesale funding. The remaining covariates are not significant. We continue to specify the control variables but do not report results.

*Robustness of bank-level results.* Section OA1 of the Online Appendix provides a detailed discussion of various robustness checks, which we only summarize here. A first set of tests concerns the possibility that exposed banks cut their relationships to customers in affected counties. Whereas the available data only provides a fairly noisy measure of new and terminated customer relationships,<sup>5</sup> we test if the number of new relationships and the number of terminated customer relationships differs significantly between exposed and unexposed banks. This is not the case.

Next, we challenge the validity of the shock definition. The headline results do not hinge on the choice of the threshold used to define exposed banks. Also randomly assigning disaster-induced shocks to banks confirm that our results are not spurious.<sup>6</sup> Neither the inclusion of banks that are located in affected counties nor the identification of exposed banks based solely on their location in affected counties alters the results.

A third set of tests scrutinizes the comparability of banks. The headline results also hold for a matched sample of banks based on the five observable bank traits in Table 2. We could not reject the specification of a pre-disaster exposure indicator, as in Cortés and Strahan (2017).<sup>7</sup> But the results from the matched sample paired with insignificant pre-event trends in observables (see Table 3) provide strong indications that the main results are not driven by systematic differences pertaining to observable pre-crisis characteristics.

A fourth set of tests concerns measurement and specification errors. We saturate the baseline regression with county×time fixed effects to control for unobservable county-level dynamics. The exclusion of time-varying (bank) controls tests whether the results hinge on a particular choice of covariates (Gormley and Matsa, 2016). We also include the crisis year of 2013 as an additional post-disaster year, collapse the sample to control for autocorrelation concerns (Bertrand et al., 2004), estimate a single cross-section of differences in covariates, and specify a continuous indicator of disaster risk to explain lending changes (Khwaja and Mian, 2008). The main results hold in all of these tests.

#### 4.2. Risk and return implications of recovery lending

The documented *recovery lending* effect raises the question of whether the expansion of lending entails some cost, such as increased risk-taking or rent-extraction from disaster-captured SME. We test in Table 5 if the corresponding indicators differed between exposed and unexposed banks.

– Table 5 about here –

*Liquidity buffers.* In Column (1), we test if *recovery lending* reduces liquidity buffers of local banks. The significantly negative Post term in Table 5 confirms that the asset share of cash and reserves held with the

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<sup>5</sup>After all customers might just no longer demand credit rather than the bank denying it.

<sup>6</sup>We estimate 1,000 times an according placebo regression with randomly assigned treatments and find that the  $\beta_1$  coefficient is significant at the 5% level in only 6.3% of the simulations. Ideally, we would have obtained falsely significant results in not more than 5% of all simulations, but this result is still very close to that threshold. Overall, it therefore corroborates that our main result is very unlikely due to spurious correlation.

<sup>7</sup> However, we can show that our  $\beta_1$  coefficient remains positive and significant when we introduce a pre-disaster dummy, as in Cortés and Strahan (2017) in our regression.

central bank declines among all local banks in unaffected counties. Exposed banks in unaffected counties reduce their liquidity buffer even further in the years 2014 and 2015 compared to their local peers without a large share of flooded corporate credit customers. Hence, *recovery lending* reduced the liquidity buffers also in unaffected counties. This result corroborates the importance of liquidity regulation beyond insuring against sudden deposit outflows. In addition to that function, liquidity buffers appear to be useful to absorb local macro shocks to facilitate the provision of corporate credit.

*Credit risk.* To gauge changes in credit risk, we specify the ratio of impaired loans relative to gross loans, which is available for a subsample, as the dependent variable in Column (2). The effect of flood damage exposure on impaired loans is not statistically significant.<sup>8</sup> Perhaps local banks are the “connoisseurs” of local SME and possess superior information about the general viability of their customers’ business models. Therefore, the practice to continue lending after a disaster shock reflects their ability to select those firms that pursue fundamentally sound business models. These firms may eventually return to their pre-flood growth paths. Thus, banks’ that appear to be financing firms’ recovery from the flood do not appear to mechanistically have to incur systematically more credit risk.

*Capital adequacy.* Thus far, the results suggest that additional lending in response to disaster-demand from flooded customers is funded by an increase in interbank and customer deposits and a reduction in liquid assets. However, it remains unclear whether total balance sheets expanded or contracted. A potential concern from a financial stability perspective is that banks expanded their balance sheets with recovery loans without adjusting their equity capital. Therefore, we specify in Column (3) the ratio of total equity to total assets as the dependent variable. Strikingly, we find that unexposed banks increased their capital adequacy after the shock. Exposed banks exhibit an additional build-up of equity relative to assets. Thus, banks’ *recovery lending* responses did not undermine the resilience of local banks.

*Insolvency risk.* In Column (4), we test if the default risk of exposed banks in unaffected counties responded to the shock. We specify the Z-score as the dependent variable. Higher values indicate more stable banks. The Z-scores of exposed and unexposed banks are not significantly different from each other after the Elbe flood of 2013. This result confirms the preceding indication that exposed local banks manage to provide more credit without increasing risk.

*Rent extraction.* A potentially “dark side” to the thus far benevolent interpretation of local banks’ roles in providing *recovery lending* returns to Rajan (1992). Locked-in borrowers may suffer from rent extraction. Whereas interest rates charged on loans and offered on deposits are not directly available, we test in Column (5) if the net interest margins charged by banks providing *recovery lending* are higher. The insignificant interaction term suggests that local bankers are unlikely to skim rents from disaster-struck SME.

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<sup>8</sup>Because it may take time until credit risks materialize on banks’ balance sheets, we expand the sample and include impaired loans up and until 2016. The effect remains insignificant.

#### 4.3. Regional banking system resilience and intra-group markets

The results obtained so far assign an important role to local banks to buffer regional macro shocks. And the absence of drastically deteriorating balance sheets of exposed relative to unexposed banks bodes well for the resilience of regional banking systems comprised of small, local lenders. Yet the documented depletion of liquidity buffers raises the question, which types of regional banking systems are most able to cope with such local macro shocks in terms of providing *recovery lending*?

From a financial stability perspective it is a priori unclear why a financial system that features many relatively small local lenders with relationship expertise of local customers is optimal to fulfill such a function. Alternatively, a few, large multimarket bank holding groups with deep internal capital markets and geographically more diversified credit portfolios may be better suited to absorb regional shocks by re-allocating locally collected deposits to regions with increased need for credit, both within (Cremers et al., 2011) and across national borders (Cetorelli and Goldberg, 2012).

We tackle the question, which type of regional banking system is more resilient by exploiting a feature of German savings banks used before by Puri et al. (2011). All local savings and local cooperative banks in our sample are part of banking groups that are headed by two central banks in the case of cooperative banks and seven Landesbanken in the case of the savings bank sector as of 2013. These head organizations act as clearing houses, they intermediate intra-group liquidity, provide capital market access, and conduct wholesale and investment banking activities. Puri et al. (2011) exploit this setting to investigate the retail responses of local savings banks conditional on differential financial market shocks experienced by their respective Landesbank during the crisis of 2007/2008. We, in turn, use the geographic scope of activities of those head organizations to classify local banks into those with and without access to large, diversified intra-group markets (IGM) to collect deposit and originate credit.

Figure OA3 in the Online Appendix visualizes the regional markets of each German Landesbank as of 2013. The left panel shows that two Landesbanken are confined to a single federal state, namely Bayern LB in Bavaria and Saar LB in the Saarland. The right panel reproduces the damage intensities to demonstrate that exposed banks connected to Bayern LB faced local macro shocks that affected virtually all members of the banking group. These local banks therefore had no access to diversified IGM and we specify an according indicator variable equal to one for local banks connected to Bayern LB and Saar LB.

In contrast, other local banks exposed to the flood belonged to banking groups that also comprised members in unaffected counties. Consider, for example, local savings banks in the state of Sachsen. The right panel of Figure OA3 shows that the counties bordering the Czech Republic in the South-East were hit the hardest by the flood. The left panel of Figure OA3 indicates at the same time in yellow color that exposed local banks in Sachsen belonged to the banking group headed by Landesbank Baden-Württemberg (LBBW). The regional market of LBBW comprises also numerous counties that were completely unaffected by the natural catastrophe, for example in the state of Rhineland-Palatinate located in midwestern Germany. Exposed local banks in Sachsen therefore had access to geographically more diversified intra-group markets

and we code the No access IGM indicator variable to zero.<sup>9</sup>

With this categorization at hand, we estimate the following equation for the sample of exposed banks.

$$Y_{it} = \alpha_1(\text{No access IGM}_i \times \text{Post}_t) + \alpha_2\text{Post}_t + \alpha_i + \alpha_t + \sum_{k=1}^K \sigma_k C_{kit-1} + \epsilon_{it}. \quad (3)$$

First, we specify  $\ln(\text{Loans})$  as the dependent variable  $Y$  to test if banks exposed to local macro shocks with access to geographically more diversified intra-group markets provide more *recovery lending* compared to exposed banks without access. Table 6 presents the corresponding results. Column (1) shows that access to intra-group markets was no pre-requisite for local lenders in Germany to buffer against the macro shock represented by the flooding of the river Elbe in 2013. Whereas Table 4 shows that exposed banks lend more to firms in affected counties compared to unexposed banks, we do not find evidence of a significant differential effect of having access to larger intra-group markets within the sample of exposed banks. Thus, small local banks that are part of banking groups of different geographical scope seem to be equally able to cushion macro shocks of the size investigated here.

– Table 6 about here –

One important feature of larger intra-group banking markets is the ability to re-allocate financial funds within the group in response to different credit demand and deposit supply. Therefore, we specify next  $\ln(\text{Interbank Loans})$  and  $\ln(\text{Interbank Deposits})$  in Columns (2) and (3), respectively. Thereby, we test more directly if local banks with access to IGM do use their “Hinterland” in the banking group to re-allocate funding to affected counties. These interaction terms are not statistically different between local banks with and without access to intra-group markets that comprise a geographically more diverse portfolio of counties. We also find no evidence that customer deposits, a local source of funding as opposed to interbank markets at the group level, are attracted more by banks without access to intra-group markets. Taken together, these results suggest that both types of exposed banks – with and without access to an intra-group markets – are equally able to fund additional *recovery lending*, presumably by reducing liquidity buffers at the level of the local bank. As such, large internal capital markets appear to be of lesser importance in our setting regarding their role to provide re-financing sources to local banks.

A third line of tests concerns the possibility that local banks without access to larger and more diversified intra-group markets may incur additional risks by operating on geographically more confined markets. To this end we specify the share of impaired loans relative to total loans to detect differential implications for the resilience of local banks with and without IGM access. In contrast to the absence of differential effects on observable bank risk between exposed and unexposed banks reported in Table 5, Column (5) in Table 6

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<sup>9</sup>Local cooperative banks are defined to have access to IGM because all exposed ones belong either to DZ Bank or to WGZ Bank, which both provide a connection to unaffected counties.

reveals that within the group of exposed local banks no access to intra-group markets implies that local banks incur more credit risk. This result therefore indicates that regional banking systems that are geographically more diversified are more resilient to risks emerging from local macro shocks conditional on local member banks of the group being exposed to such macro shocks.

Column (6) generalizes this inference by also including unexposed local banks in the sample. As shown before, the differential effect between exposed and unexposed banks on the share of non-performing loans remains statistically not discernible from zero. But the triple interaction term corroborates the indication that having no access to intra-group markets is associated with higher credit risk conditional on being a local banks with substantial corporate customer credit exposure towards affected counties. This interpretation is further supported by Table OA3 in the Online Appendix. It shows estimation results for the differential effect of No access IGM on the four risk proxies specified in Table 5. Local banks without IGM access exhibit lower capitalization compared to disaster-exposed banks with access to a “Hinterland”.

## 5. Firms’ responses to lending adjustments

### 5.1. Specification

Results for banks’ responses to the flooding of the river Elbe strongly suggest a corporate loan supply expansion by local banks induced by the demand shock experienced by borrowers put under water. However, from observing banks’ responses alone, we cannot firmly conclude that it is indeed *recovery lending* directed towards stressed firms. Any lending expansion may in fact be routed to non-stressed customers in unaffected counties. To answer the question of who actually receives the additional lending, we therefore analyze firms’ responses. We specify the following regression to explain observed corporate borrowing in affected counties:

$$\ln(\text{Credit})_{jt} = b_1(\text{Treated}_j \times \text{Post}_t) + b_2\text{Post}_t + a_j + a_t + \sum_{k=1}^K \lambda_k C_{kjt-1} + \epsilon_{jt}. \quad (4)$$

The dependent variable is the natural logarithm of firm  $j$ ’s sum of total short-term loans and long-term debt in year  $t$ . Mimicking bank-level regressions, we compare the two years preceding the disaster (2011–2012) with the two years afterwards (2014–2015) by setting the Post indicator to 0 and 1, respectively. Treated indicates if a firm is connected to an exposed bank in an unaffected county. In the baseline specification, firms are treated if they have a relationship to at least one such local intermediary with a weighted average flood damage score based on their credit portfolio above the median (see Figure 2 (b) for an illustration).

We estimate Equation (4) first for a sample of firms with headquarters in affected counties that have a connection to an exposed bank after 2013. Albeit being a subordinate concern given the discussion in the Online Appendix around Figure OA1, this requirement avoids potential biases due to also including in the sample firms with which banks terminated credit relationships because of the flood of 2013. At the same time, firms in this sample may have selected themselves into banking relationships with intermediaries outside their home county because of the flood. We ensure below that our results also hold when we include only firms with identical banking relationships since 2011 until the end of our sample period.

Firm-level control variables are lagged by one year and comprise the natural logarithm of total assets (Size<sup>f</sup>), the Liquidity Ratio (the ratio of firms' cash and cash equivalents over short-term liabilities), the Solvency Ratio (the ratio of the sum of net profits (after tax) and depreciations over total liabilities), and the Current Ratio (the ratio of firms' current assets over current liabilities). We keep only firms with non-missing observations for these traits and require that we have one observation per firm before and after 2013. This procedure leaves a sample of 40,796 observations for 11,965 firms. Descriptive statistics are depicted in the bottom panel of Table 2. The bottom panel of Table 3 corroborates the validity of our identification approach, as all the observable firm traits do not exhibit statistically different developments prior to the flood of 2013. As noted before, this fact is insensitive to winsorizing the data.

## 5.2. Results on emergency borrowing by firms

All firm-level results provided in Table 7 (except the last column) refer to a sample of firms that are headquartered in affected counties. If the increase in bank loans documented above is indeed *recovery lending* directed towards stressed borrowers under water, we should observe a positive interaction effect on corporate borrowing for flooded firms that are connected to banks outside their flooded home market, i.e., the treatment group of firms.

– Table 7 about here –

*All banks.* To explore the effect on treated firms, we start with the sample in the first column of Table 7 that comprises firms in affected counties with relationships to banks inside and outside affected counties. This sample has 40,796 observations for 11,965 firms. The difference-in-difference coefficient is significantly positive, which shows that, relative to firms with no such relationships, corporate borrowers with a relationship with an exposed bank expanded their borrowing in 2014 and 2015 compared to the pre-disaster period. In economic terms, the estimated coefficient implies that treated firms increase their borrowing by roughly 61% ( $(\exp(0.4768) - 1) \times 100 = 61.09$ ) compared to untreated firms prior to 2013. Consistent with Noth and Rehbein (2018), the effect of the flood on the corporate debt of untreated firms inside affected counties is significantly negative and large, namely, approximately -46%. Therefore, the total effect on treated firms due to the flood is approximately 16%.

*Out-of-county banking.* As shown in the bottom panel of the table, we imposed no restrictions on the firms sampled in Column (1) regarding the number and composition of their bank relationship(s). This approach implies that some firms might maintain ties not only to an exposed outside bank but also to one or more banks that are domiciled in the affected counties themselves. In this setting, it is difficult to identify if observed changes in credit are driven only by *recovery lending* from out-of-county – or outside – banks that are exposed to the shock through their customer credit portfolios or reflect, in part, adjustments by banks that were flooded themselves. To mitigate this type of bias, we identify in Column (2) firms that exclusively maintain ties to banks outside affected counties by coding the additional dummy variable Triple equal to 1

for firms with connections to outside banks. The regression results show a significantly larger increase in firms' credit if they were connected to exposed out-of-county banks indicated by the triple interaction effect  $\text{Treated} \times \text{Post} \times \text{Triple}$ . The triple interaction effect shows that credit for treated firms relative to firms with connections to an unexposed outside bank increases after 2013 by around 92%. The insignificant estimates of the  $\text{Post}$  and  $\text{Treated} \times \text{Post}$  coefficients imply that untreated firms inside affected counties and exposed firms that are only connected to banks inside the affected counties do not increase their borrowing. As for the full sample, the negative direct term gauging the post-flood period indicates a reduction in corporate debt levels after the flood. Overall, the firm-level perspective corroborates the bank-level conclusions that local intermediaries act as *recovery lenders* that are pivotal to bolstering local macro shocks.

*Single bank relationships.* In the sample of Column (2), some firms might still maintain multiple banking relationships with both exposed and unexposed outside banks. Therefore, we sample only the 1,364 firms with connections to outside banks and specify in Column (3) the indicator variable  $\text{Triple}$  to equal to 1 for firms with a single bank relationship. Thereby, we control for potential within-firm substitution that might bias the estimate of *recovery lending*. This specification further sharpens the test for *recovery lending* because those firms that rely on one exclusive provider of financial funds should respond most sensitively after a local macro shock to such backstop lenders. In line with this notion, we estimate a triple interaction effect that is almost five times as large as the effect for firms connected to multiple banks outside affected regions. Hence, the main effect of increasing credit for treated firms is predominantly due to firms with single bank relationships.

*SME.* In Column (4), we further differentiate large firms and SME within the sample of those firms that report a single bank relationship. Large firms may resort to capital markets to raise any additionally required funding to buffer and recover from the shock. We therefore specify the indicator variable  $\text{Triple}$  equal to 1 for those firms that are defined as a SME in the Amadeus database. Conditional on having just one bank relationship, all treated firms exhibit a significant increase in their borrowing, but this effect is significantly mitigated for SME. As an alternative, we sample in the first two columns of Table OA4 in the Online Appendix only SME with single bank relationships and estimate a simple difference-in-difference effect within this sub-sample. Those results confirm that on balance small firms that rely on just one bank relationship receive relatively more credit from outside banks compared to other small firms without such bank relationships.

*Unaffected counties.* Column (5) presents a falsification exercise to challenge our previous findings. We test for a differential credit uptake by single-relationship firms (as in Column (4)) that are connected to exposed banks, but reside in unaffected counties. If *recovery lending* is indeed a response by banks in unaffected counties that are only indirectly exposed in response to credit demand hikes from shocked corporate borrowers in flooded counties, we should not see any differential borrowing by firms in unaffected counties. The

estimated difference-in-difference coefficient is insignificant. Hence, the increase in credit by exposed banks appears not to have been granted as extra credit to firms in unaffected counties.

*Robustness of firm-level results.* Section OA2 in the Online Appendix provides robustness tests for the firm-level regressions that mimic those conducted at the bank level. Overall, the main findings on emergency borrowing are insensitive to the definition of (un)affected counties, are unlikely biased by confounding effects, remain intact if we use the reduced sample of single bank relationship SME only, hold up after a matching exercise of treated and untreated firms, hold for firms with relationships with both exposed and unexposed banks, and hold in a sample of firms with unchanged bank-relationships throughout 2011-2014.

## 6. Conclusion

We investigate the role of local banks to absorb regional macro shocks in the form of natural disasters. Specifically, we isolate a corporate *recovery lending* channel by considering both the perspective of banks as the provider of financial funds and the borrowing behavior of disaster-struck firms. Our results highlight three main findings.

Using the flooding of the river Elbe and its adjacent tributaries in 2013 as an exogenous shock, our first main finding is a statistically significant *recovery lending* effect. Local banks that are domiciled in unaffected counties but are exposed to disaster-ridden firms in affected counties lend 3% more in the post-flood period compared with unexposed local banks. Against the backdrop of an average loan growth rate of 5% prior to 2013, this effect is economically significant. Importantly, this expansion in lending is not associated with higher insolvency risk, higher loan impairment rates, or with rent-skimming from (disaster-)captured, small firms. Instead, we show that shocked banks are better capitalized, albeit exhibiting reduced liquidity buffers.

However, a second key finding pertains to significant differences in the resilience towards regional macro shocks within the group of banks that are exposed to local macro shocks. Those that are embedded in banking groups with more diversified intra-group markets to collect deposits and originate loans are better able to withstand these adverse conditions. We show that exposed banks with access to geographically more diversified intra-group markets provide *recovery lending* without additional risk-taking.

Third, we find that firms in flooded counties that have ties to out-of-county *recovery lenders* in unaffected counties benefit from these relationships in terms of increased borrowing. Firms without these ties, in turn, exhibit declining credit after the flood, corroborating earlier results on the direct effects of the flood on firms' leverage. Thus, the lending hike by local banks in non-flooded counties seems indeed to be used to cater to the additional credit demand of firms directly hit by the shock.

In sum, our results suggest that local lenders are important in developed financial systems to provide *recovery lending* especially to smaller firms that have been struck by local macro shocks. At the same time, more diversified networks of local banks are better suited to provide this buffering function of local macroeconomic shocks compared to relatively isolated and geographically clustered regional banking systems.

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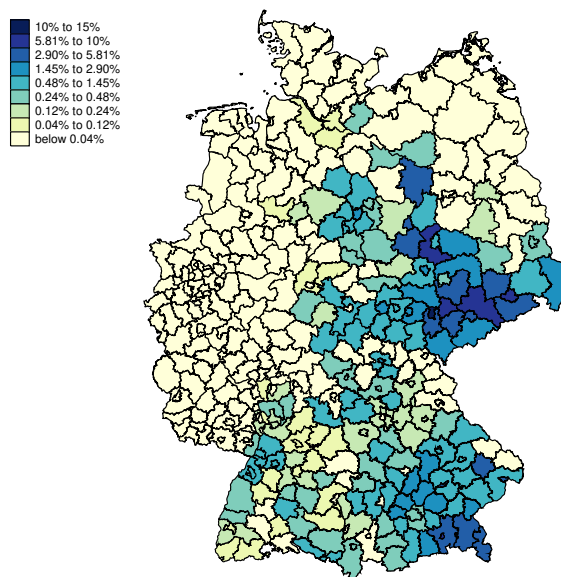
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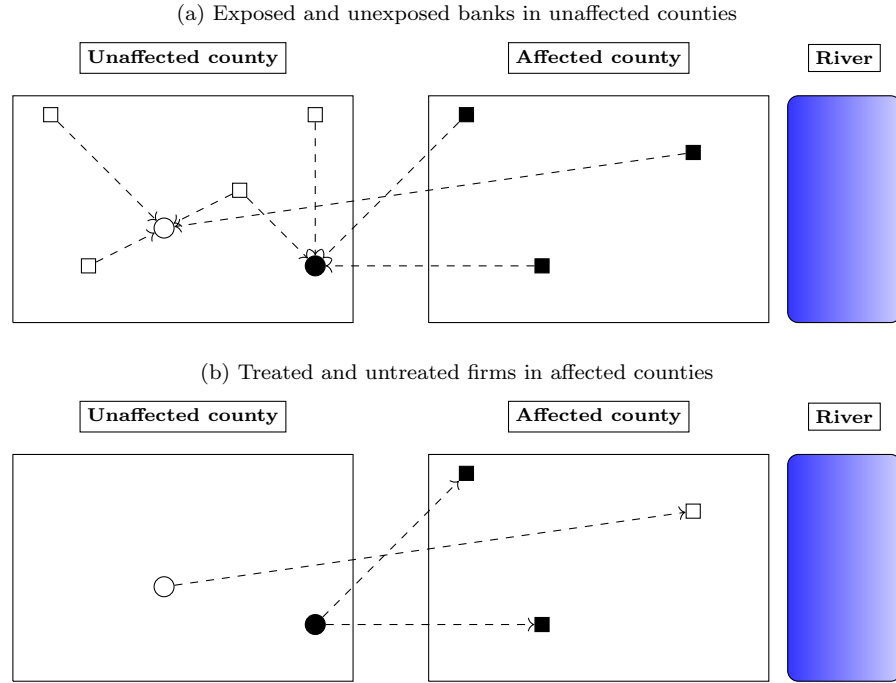
## Figures and Tables

Figure 1: Affected German counties by damage category



This figure shows the distribution of the damage sustained due to flooding in Germany from May 25 through June 15 2013, by county. Flooding damage is reported as the percentage of flood insurance contracts activated during the period, divided into nine categories, from 0% to 15%. The baseline threshold to define counties and the firms that are headquartered in them as affected is category 5. The data are obtained from the German Association of Insurers (GDV).

Figure 2: Identification of (un)affected counties, (un)exposed banks, and (un)treated firms



This figure shows banks (circles) and firms (rectangles) in affected and unaffected counties. In Subfigure (a), black rectangles indicate firms in affected counties, and white rectangles indicate firms in unaffected counties. The dashed arrows connect firms to banks with which they maintain a relationship. The classification of exposed (black circles) and unexposed (white circles) banks depends on their exposure to firms in affected and unaffected counties, irrespective of their own location. Subfigure (b) shows the same exposed (black circle) and unexposed (white circles) banks outside the affected counties as before. The dashed arrows connect banks to firms with which they maintain a relationship. We categorize a firm in an affected county as treated if it is connected to an exposed bank in an unaffected county. Hence, black rectangles indicate treated firms in affected counties, and white rectangles indicate untreated firms in affected counties.

Table 1: Variable definitions

	Definition
<b>Banks</b>	
Exposure	The weighted average of flood damage categories across all firms on the bank level.
Exposed	Dummy variable (median split of Exposure) indicating whether a bank is exposed to the flood through its firms.
Post	Dummy variable that is one for the years 2014-2015 and zero for 2011-2012.
Loans	Gross loans in billion USD. Includes Residential Mortgage Loans (Mortgage) + Other Mortgage Loans + Other Consumer/ Retail Loans + Corporate & Commercial Loans (Commercial) + Other Loans (Other) + Reserve against possible losses on impaired or non-performing loans.
Total Assets	Total assets in billion USD.
Size	The natural logarithm of Total assets.
Capital Adequacy	Share of Equity on Total Assets. Equity: Common equity + Non-controlling interest + Securities revaluation reserves + Foreign exchange revaluation reserves + Other revaluation reserves
Liquidity	Share of Cash on Total Assets. Cash: Cash and non-interest-earning balances with central banks.
Securities	Share of Securities on Total Assets. Securities: Reverse repos and cash collateral + Trading securities + Derivatives + Available for sale securities + Held to maturity securities + At-equity investments + Other securities.
RoA	Net Income over Average Total Assets.
Mortgage Loans	Loans secured by a land charge (usually residential property).
Customer Loans	All Loans and leases that do not fall into any other category. In practice: All loans not secured by residential property collateral.
Total Deposits	Total deposits in billion USD. Includes customer and bank deposits.
Interbank Deposits	The sum of all deposits from other banks in billion USD.
Interbank Loans	The sum of all loans to other banks in billion USD.
Customer Deposits	The sum of all customer deposits in billion USD.
Wholesale Funding	Wholesale funding in billion USD. Includes the sum of long-term funding, trading liabilities and derivatives.
Impaired Loans	Reserve against possible losses on impaired or non-performing loans as a share of Gross Loans.
Z-score	Distance to default measure. Z-score is defined as $\ln(\text{RoA} + (\text{Equity}/\text{Total Assets})/\text{sd}(\text{RoA}))$ .
Net Interest Income	Net interest income or expense (net position) over Total Assets.
<b>Firms</b>	
Credit	Total short-term loans and long-term debt in million USD.
Treated	Dummy variable that indicates whether a firm is connected to an exposed bank.
Post	Dummy variable that is one for the years 2014-2015 and zero for 2011-2012.
No access IGM	Dummy variable that is one for local savings banks associated with Bayern LB and Saar LB. The dummy variable is zero for all cooperative banks and for all savings banks residing in federal states other than Bavaria and Saarland.
Total Assets <sup>f</sup>	Total assets in million USD.
Size <sup>f</sup>	The natural logarithm of Total Assets <sup>f</sup> .
Liquidity Ratio	The ratio of firms' cash and cash equivalents over short term liabilities.
Solvency Ratio	The ratio of the sum of net profits (after tax) and depreciations over total liabilities.
Current Ratio	The ratio of firms' current assets over current liabilities.

Table 2: Descriptive statistics

	Mean	SD	Percentile	
			1st	99th
<b>Bank sample</b>				
<i>Treatment and main left-hand-side variable:</i>				
Exposure	1.841	1.055	1.000	4.357
Exposed	0.361	0.480	0.000	1.000
Loans	0.897	1.935	0.021	7.526
<i>Controls:</i>				
Total Assets	1.401	2.765	0.040	11.062
Capital Adequacy	0.085	0.020	0.045	0.147
Liquidity	0.018	0.009	0.000	0.045
RoA	0.003	0.002	0.000	0.010
Securities	0.265	0.117	0.043	0.593
<i>Alternative left-hand-side variable:</i>				
Mortgage Loans	0.407	0.886	0.000	3.542
Customer Loans	0.443	1.047	0.007	3.502
Total Deposits	1.232	2.359	0.037	9.655
Customer Deposits	1.026	1.957	0.030	8.445
Interbank Deposits	2.051	4.589	0.020	18.690
Wholesale Funding	0.351	2.198	0.010	4.870
Impaired Loans	0.037	0.037	0.000	0.134
Z-score	4.714	1.293	2.565	8.330
Net Interest Income	0.023	0.004	0.013	0.034
<b>Firm sample</b>				
<i>Treatment and main left-hand-side variable:</i>				
Treated	0.960	0.195	0.000	1.000
Credit	2.712	13.831	0.000	42.190
<i>Controls:</i>				
Total Assets <sup>f</sup>	9.674	33.949	0.033	127.685
Liquidity Ratio	0.040	0.095	0.001	0.550
Solvency Ratio	0.323	0.321	-0.625	0.936
Current Ratio	0.048	0.099	0.002	0.583

This table presents summary statistics for all the variables used in the analyses. The baseline bank-level sample comprises 4,064 observations for 1,076 banks. Due to missing information, we have only 4,058 observations for Mortgage Loans (1,076 banks), 2,459 observations for Impaired Loans (1,031 banks), and 3,810 observations for the Z-score (1,048 banks). Banks' balance sheet information comes from Bankscope for the period 2011-2014 and from Orbis for 2015. The firm sample comprises 40,796 observations for 11,965 firms (see Column (1) of Table 7). Detailed definitions of the variables are provided in Table 1.

Table 3: Pre-2013 statistics parallel trends for banks and firms

	Mean	SD	Mean	SD	ND
<b>Pre-2013 average changes</b>					
<i>Bank sample:</i>					
	Exposed		Unexposed		
D.Gross Loans	0.056	0.073	0.051	0.069	0.05
D.Size	0.032	0.067	0.030	0.067	0.03
D.Capital Adequacy	0.093	0.102	0.064	0.083	0.22
D.Liquidity	-0.181	0.345	-0.202	0.428	0.04
D.RoA	0.095	0.701	0.048	0.585	0.05
D.Securities	0.077	0.203	0.086	0.205	-0.03
D.Mortgage Loans	0.054	0.272	0.044	0.241	0.03
D.Customer Loans	0.074	0.109	0.071	0.104	0.02
D.Total Deposits	0.030	0.068	0.029	0.069	0.01
D.Customer Deposits	0.034	0.065	0.032	0.066	0.02
D.Interbank Deposits	0.039	0.297	0.034	0.214	0.02
D.Wholesale Funding	-0.099	0.315	-0.098	0.438	-0.00
D.Impaired Loans	-0.127	0.573	0.013	0.973	-0.12
D.Z-score	0.023	0.024	0.014	0.021	0.27
D.Net Interest Income	-0.027	0.101	-0.025	0.090	-0.01
<i>Firm sample:</i>					
	Treated		Untreated		
D.Credit	0.349	2.135	0.316	1.904	0.01
D.Total Assets <sup>f</sup>	0.073	0.287	0.090	0.312	-0.04
D.Liquidity Ratio	0.262	1.233	0.320	1.444	-0.03
D.Solvency Ratio	0.069	1.021	0.189	1.190	-0.08
D.Current Ratio	0.189	0.939	0.247	1.150	-0.04

This table presents average changes (in percent) and standard deviations for the period 2011-2012 for the major variables that are used in the analyses for (un)exposed banks and (un)treated firms. Detailed definitions of the variables are provided in Table 1. Normalized differences (Imbens and Wooldridge, 2009) are shown in the last column. A normalized difference larger than 0.25 indicates that the difference in the averages of both groups of banks is significant.

Table 4: Recovery lending by banks

	(1) ln(Loans)	(2) ln(Mortgage Loans)	(3) ln(Customer Loans)	(4) ln(Total Deposits)	(5) ln(Interbank Deposits)	(6) ln(Customer Deposits)	(7) ln(Wholesale Funding)
Post	0.0548*** (0.0077)	0.0576** (0.0226)	0.0735*** (0.0139)	0.0193*** (0.0069)	-0.1324*** (0.0196)	0.0500*** (0.0069)	-0.6210*** (0.0562)
Exposed×Post	0.0288*** (0.0062)	0.0096 (0.0238)	0.0246** (0.0115)	0.0142*** (0.0046)	0.0404** (0.0170)	0.0113** (0.0050)	-0.0447 (0.0559)
L.Size	0.6845*** (0.0518)	0.6903*** (0.1623)	0.6361*** (0.0629)	0.6856*** (0.0511)	1.1046*** (0.0986)	0.5806*** (0.0515)	0.9011*** (0.2452)
L.Capital Adequacy	-0.0192 (0.2603)	0.6259 (0.9141)	0.0764 (0.5096)	-0.5448** (0.2365)	-1.7011** (0.6669)	-0.2523 (0.2392)	-1.0088 (1.9194)
L.Liquidity	-0.5853* (0.3525)	0.3204 (1.0087)	0.6965 (0.7233)	-0.2780 (0.3320)	-1.3498 (0.8682)	0.1584 (0.3571)	-0.9916 (2.8294)
L.RoA	0.4885 (0.6707)	-1.4463 (3.9140)	-0.3669 (1.3157)	-0.3400 (0.7259)	-2.9917 (2.2003)	0.5659 (0.5931)	3.1125 (5.3878)
L.Securities	-0.3735*** (0.0503)	-0.5447*** (0.2275)	-0.4789*** (0.1001)	-0.0537 (0.0386)	0.1525 (0.1426)	-0.1230*** (0.0410)	1.1707*** (0.3849)
Within R2	0.67	0.13	0.52	0.61	0.20	0.64	0.30
Observations	4064	4058	4064	4064	4064	4064	4064
Banks	1076	1076	1076	1076	1076	1076	1076
Exposed Banks	390	390	390	390	390	390	390
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	5.90	4.87	5.24	6.30	4.37	6.11	1.56
SD	1.32	1.63	1.29	1.27	1.42	1.27	1.71

This table shows the regression results for Equation (1) with different dependent variables that are indicated in the column headers. Column (1) reports the results for the natural logarithm of Loans. Column (2) reports the results for the natural logarithm of Mortgage Loans. Six observations for mortgage loans are missing. Our results for the other categories remain unchanged if we further reduce the sample to 4,058 observations. Column (3) reports the results for the natural logarithm of loans to cooperates and households (excluding real estate); Customer Loans. The dependent variables in Columns (4), (5), and (6) are the natural logarithms of Total Deposits, Interbank Deposits, and Customer Deposits. The dependent variable in Column (7) is the natural logarithm of Wholesale Funding. Exposed is a dummy variable indicating whether a bank is exposed to the flood through its firms, i.e., whether it is above or below the median exposure of its firm damages. Post is a dummy equal to 0 for the years 2011-2012 and 1 for 2014-2015. Included control variables are: Size, as the natural logarithm of total assets; Capital Adequacy, as the ratio of equity to total assets; Liquidity, as the share of cash on total assets; RoA, as return on assets; Securities, as the share of total securities over total assets. All bank controls are lagged by one year (indicated by L.). We control for bank and year fixed effects. Clustered standard errors of the point estimates on the bank level are shown in parentheses. The last two rows show the mean and standard deviation of the dependent variable. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Bank liquidity and risk

	(1)	(2)	(3)	(4)	(5)
	Liquidity	Impaired Loans	Capital Adequacy	Z-score	Net Interest Income
Post	-0.0041*** (0.0006)	-0.0238*** (0.0053)	0.0078*** (0.0005)	0.2432*** (0.0494)	-0.0011*** (0.0002)
Exposed×Post	-0.0012*** (0.0005)	-0.0023 (0.0018)	0.0018*** (0.0004)	-0.0204 (0.0427)	0.0000 (0.0002)
Within R2	0.12	0.10	0.68	0.66	0.46
Observations	4064	2459	4064	3810	4064
Banks	1076	1031	1076	1048	1076
Exposed Banks	390	377	390	376	390
Bank controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Mean	0.02	0.04	0.09	4.71	0.02
SD	0.01	0.04	0.02	1.29	0.00

This table shows regression results for Equation (1) with different dependent variables that are indicated in the column headers. Column (1) reports the results to explain Liquidity. Column (2) presents the estimates with impaired loans as a share of gross loans as the dependent variable. Column (3) reports the results for Capital Adequacy. Column (4) presents the results for the Z-score, defined as  $\ln(1 + RoA + (Equity/TotalAssets))/sd(RoA)$ . For negative values of  $RoA + (Equity/TotalAssets)/sd(RoA)$ , we set the Z-score to zero. The Z-score is a distance to default measure. Higher values indicate less risk. In Column (5), we specify the banks' Net Interest Income, defined as the difference between interest income and interest expense, over total assets as the dependent variable. Exposed is a dummy variable indicating whether a bank is exposed to the flood through its firms, i.e., whether it is above or below the median exposure of its firm damages. Post is a dummy equal to 0 for the years 2011-2012 and 1 for 2014-2015. Control variables (includes but not shown for brevity) are: Size, as the natural logarithm of total assets; Capital Adequacy, as the ratio of equity to total assets; Liquidity, as the share of cash on total assets; RoA, as return on assets; Securities, as the share of total securities over total assets. All bank controls are lagged by one year (indicated by L.). The results for Liquidity, Capital Adequacy, and the Z-score remain the same when we exclude (lagged) Liquidity, Capital Adequacy, and RoA as independent variables. We control for bank and year fixed effects. Clustered standard errors of the point estimates on the bank level are shown in parentheses. The last two rows show the mean and standard deviation of the dependent variable. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Lending, funding, and risk without access to geographically diversified intra-group markets

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Loans)	ln(Interbank Loans)	ln(Interbank Deposits)	ln(Customer Deposits)	Impaired Loans	Impaired Loans
Post×No access IGM	−0.0125 (0.0149)	0.1480 (0.1394)	−0.0841 (0.0541)	−0.0033 (0.0113)	0.0089*** (0.0024)	0.0000 (0.0021)
Exposed×Post						−0.0030 (0.0019)
Exposed×Post×No access IGM						0.0077** (0.0033)
Within R2	0.76	0.13	0.16	0.79	0.08	0.10
Observations	868	868	868	868	868	2459
Banks	377	377	377	377	377	1031
Exposed Banks	377	377	377	377	377	377
No access IGM Banks	29	29	29	29	29	49
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls and interaction terms components	Yes	Yes	Yes	Yes	Yes	Yes

This table shows regression results for Equation (3) with different dependent variables that are indicated in the column headers. The sample in the first five columns considers exposed banks only. In Columns (1) to (5) we interact Post with a dummy variable No access IGM, where the latter abbreviates intra-group markets. This dummy variable is equal to one for local savings banks associated with Bayern LB and Saar LB because the regional markets of both Landesbanken coincide with only one federal state and are thus not as diversified as regional markets of Landesbanken comprising multiple federal states. The dummy variable is zero for all cooperative banks since all banks belong to one of the two central institutions (DZ Bank or WGZ Bank) and thereby are connected to other federal states. The dummy variable is also zero for all savings banks residing in federal states other than Bavaria and Saarland, since all other regional markets of Landesbanken extend to other federal states. In the last column we also consider all unexposed banks and introduce the respective interaction terms with Post and No access IGM. Column (1) reports the results to explain the natural logarithm of Loans. Column (2) reports the results for the natural logarithm of Interbank Loans. Column (3) presents the results for the natural logarithm of Interbank Deposits. In Column (4), we specify the natural logarithm of Customer Deposits as the dependent variable. In Columns (5) and (6) we specify Impaired Loans as the dependent variable. Exposed is a dummy variable indicating whether a bank is exposed to the flood through its firms, i.e., whether it is above or below the median exposure of its firm damages. Post is a dummy equal to 0 for the years 2011-2012 and 1 for 2014-2015. Included control variables are: Size, as the natural logarithm of total assets; Capital Adequacy, as the ratio of equity to total assets; Liquidity, as the share of cash on total assets; RoA, as return on assets; Securities, as the share of total securities over total assets. All bank controls are lagged by one year (indicated by L.). We control for bank and year fixed effects. Clustered standard errors of the point estimates on the bank level are shown in parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Emergency borrowing by firms: triple-treatment and sub-sampling

	(1)	(2)	(3)	(4)	(5)
Triple treatment:	Baseline	Outside banks	Single bank Credit	SME	Falsification
Post	−0.6249*** (0.1995)	−0.0356 (0.3528)	−0.4900 (0.4040)	−2.1050*** (0.7721)	−0.2260*** (0.0414)
Treated × Post	0.4768** (0.2011)	−0.1153 (0.3542)	0.1942 (0.4256)	2.8408*** (0.9807)	−0.0106 (0.0644)
Post × Triple		−0.8968** (0.4242)	−0.7668 (0.4860)	0.9170 (0.8225)	
Treated × Post × Triple		0.9224** (0.4411)	1.0983** (0.5364)	−1.7535* (1.0452)	

Table 7: continued

	(1)	(2)	(3)	(4)	(5)
Triple treatment:	Baseline	Outside banks	Single bank ln(Credit)	SME	Falsification
L.Size <sup>f</sup>	0.8877*** (0.0797)	0.8878*** (0.0797)	0.8449*** (0.1807)	0.9775*** (0.2180)	0.9267*** (0.0497)
L.Liquidity Ratio	-0.3743 (0.8565)	-0.3662 (0.8559)	-3.1722 (2.3855)	0.1282 (2.6268)	-2.8530*** (0.7059)
L.Solvency Ratio	-1.6665*** (0.1744)	-1.6663*** (0.1744)	-1.2971*** (0.4174)	-1.4824*** (0.5060)	-1.7684*** (0.1082)
L.Current Ratio	0.7459 (0.6750)	0.7388 (0.6744)	3.2417 (2.1218)	0.5915 (2.4733)	3.0209*** (0.6327)
Within R2	0.02	0.02	0.02	0.04	0.02
Observations	40796	40796	5657	2966	70569
Firms	11965	11965	1677	906	21506
Treated firms	11490	11490	1364	723	6184
Triple-treated firms		1364	723	667	
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Mean	10.02	10.02	9.43	8.14	8.02
SD	5.77	5.77	5.98	6.10	5.86
Sample choices					
Firm counties are:	affected	affected	affected	affected	unaffected
Banks are located:	in- and outside	in- and outside	outside	outside	outside
Firm-bank relationships:	multiple	multiple	single	single	single
Firm size selection:	none	none	none	only SME	only SME

This table shows regression results for different samples of firms shown in the bottom panel. The dependent variable is the natural logarithm of firms' short and long term debt. Treated is a dummy variable for firms with a relationship to an exposed bank after 2013. Column (1) shows the differential *emergency borrowing* effect for all firms in affected counties with any type of bank relationship. Triple abbreviates three different indicator variables that distinguish sub-groups as follows. In Column (2), Triple is a dummy that differentiates firms connected only to banks outside affected counties. In Column (3), Triple is a dummy that differentiates within the preceding sample those with a single bank relationship. In Column (4) Triple is a dummy that differentiates within the preceding sample small- and medium-sized firms according to the Amadeus definition. Column (5) considers only small- and medium-sized firms with a single bank relationship in unaffected counties. Post is a dummy equal to 0 for the years 2011-2012 and 1 for 2014-2015. Control variables are included but not reported for brevity: Size<sup>f</sup>, as the natural logarithm of firms' total assets; Liquidity Ratio, as the ratio of firms' cash and cash equivalents over short-term liabilities; Solvency Ratio, as the ratio of the sum of net profits (after tax) and depreciations over total liabilities; Current Ratio, as the ratio of firms' current assets over current liabilities. All firm controls are lagged by one year (indicated by L.). We control for firm and year fixed effects. Clustered standard errors of the point estimates on the firm level are shown in parentheses. The last two rows show the mean and standard deviation of the dependent variable. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

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