Borrowers Under Water!

Rare Disasters, Regional Banks, and Recovery Lending*

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Abstract

We test if and how banks adjust their lending in response to disaster risk in the form of a natural catastrophe striking its customers: the 2013 Elbe flooding. The flood affected firms in East and South Germany and we identify shocked banks based on bank-firm relationships gathered for more than a million firms. Banks with relationships to flooded firms lend 13-23% more than banks without such customers compared to the pre-flooding period. This lending hike is associated with higher profitability and reduced risk. Our results suggest that local banks are an effective mechanism to mitigate rare disaster shocks faced especially by small and medium firms.

JEL classification: G21, G29, O16, Q54

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1 Introduction

Natural disasters have far-reaching socioeconomic implications. They can inflict casualties among the population (Cavallo et al., 2010); destroy the capital stock of entire regions (Odell and Weidenmier, 2004); depress investment employment, and consumption growth (Vigdor, 2008; Strobl, 2011); and slow down economic growth over the long term (Cavallo et al., 2013; McDermott et al., 2014). Considering these effects, we predict that regional financial intermediaries might have mitigating effects on disaster shocks, by adjusting their lending.

A rich literature investigates the responses of financial intermediaries to financial shocks,[1] yet the role of banks in response to rare disasters and subsequent credit demand shocks is not well understood. The few available studies of financial systems' responses to rare disaster shocks generally investigate the lending behavior of banks that have been affected themselves. However, such approaches cannot address two major empirical challenges that arise in these settings. First, it is necessary to separate observed lending responses that are due to changed demand patterns from shocked firms from lending adjustments that reflect the direct damage to the banks, as might be caused by earthquakes, (Sawada and Shimizutani, 2008), hurricanes (Lambert et al., 2015), or other natural disasters (Cortés and Strahan, 2015). Second, the actual economic damage inflicted by natural disasters, rather than the mere occurrence of such events must be taken into consideration.

To address both these issues, we adopt a novel identification strategy and test it in the context of the significant flooding of several German regions in late May and early June

[1] Bank capital or liquidity shocks imply a (sudden) contraction of credit supply in domestic (Puri et al., 2011; Chodorow-Reich, 2014) and foreign (Khwaja and Mian, 2008; De Haas and Van Horen, 2012, 2013; Schnabl, 2012) credit markets, which leads to tightening credit conditions that contribute to aggregate output recessions (Jermann and Quadrini, 2012). Most studies analyze syndicated loan markets though, without gauging lending to small and medium-sized firms.

2013. The flood was an economically significant shock, causing total damage of 6 billion Euros (BMI, 2013) and igniting 180,000 insurance cases worth about 2 billion Euros (GDV, 2013). Heavy and widespread rainfall caused the flooding, which hit the regions around the river Elbe and its tributaries most harshly, though it also led to flooding in other regions of Germany. Figure 1 illustrates the geographical dispersion of damages inflicted by the flood, as measured by the share of activated flood insurance contracts for nine categories after June 2013.

– Figure 1 around here –

Regional banks might have a pertinent role in terms of economic responses to and fallout from natural disasters for several reasons. Froot (2001) shows that re-insurance markets are incomplete due to the market power of few incumbent re-insurance companies. Therefore, the re-allocation of financial capital in the form of insurance claims alone becomes impaired. This is supported by the fact that only roughly one-third of the flooding damages were insured (GDV, 2013). Contrary to previous empirical work that relies mostly on observed or expected physical damage, we exploit novel data on actual insurance claims to explain the role of local lenders as they respond to disaster-related damages.

Second we note the significance of underinvestment. Rare disasters are an important theoretical mechanism to explain countercyclical equity premia and thus underinvestment.[2] Building on work by Rietz (1988) and Barro (2006), Gabaix (2012) introduces time-variant disaster risk to demonstrate that agents require large and persistent equity premia to insure against low-probability/high-impact events, such as natural disasters.[3] Gourio (2012) also

[2]The equity premium is the spread between equity returns and risk-free rates, compared with consumption-implied risk preferences. The historical U.S. equity premium is around 6% (Backus et al., 2011).

[3]Disaster risk considerations also help to explain additional asset pricing puzzles, such as excess volatil-

shows with a real business cycle model, that an increase in disaster risk endogenously determines countercyclical risk premia and depresses investment growth. Thus, equity premia hinder the efficient allocation of capital and risk sharing among agents, especially after a natural disaster struck.

Accordingly, we predict that local relationship banks are particularly well suited to mitigate the frictions arising from natural disasters. Larrain (2006) already has established lower output volatilities in countries with more credit, due to banks' superior abilities to pool and diversify shocks. To the extent that natural disasters constitute *ex ante* uncertainty shocks (Bloom, 2009), relationship banks that generate and possess private information about the productivity of firms might help smooth out delayed corporate investments. In turn, to the extent that disaster risks represent *ex post* temporary (consumption) shocks to firms (Franco and Philippon, 2007),[4] banks are better able than markets or insurances to cater to firms preferences for financial flexibility (Gorbenko and Strebulaev, 2010), for example with outright lending or additional credit commitments.[5] Furthermore, the destruction of collateral implies a steep increase in information asymmetries in the aftermath of natural disaster shocks. Close relationship lenders with private information about local firms may be both more able and more willing to provide them with much needed credit (Degryse and van Cayseele, 2000; Elsas, 2005; Berg and Schrader, 2012).

Alternatively, banks might respond to both the possibility and the occurrence of natural disasters by contracting credit supply. From an *ex ante* perspective alone, credit supply for Californian properties exposed to earthquake risk for example, is significantly lower than that for similar properties that are less exposed to disaster risk (Garmaise and Moskowitz,

ity, forward premium puzzles, co-movement of asset prices, and others (Farhi and Gabaix, 2016). The prominent role of disasters in explaining the equity premium is not uncontested though (Julliard and Ghosh, 2012).

[4]As opposed to permanent technology and preference shocks.

[5]Recent business cycle studies emphasize firm-specific shocks to explain aggregate investment and output dynamics (Khan and Thomas, 2008; Carvalho and Gabaix, 2013).

2009). The imperfections in the disaster risk insurance markets, paired with the non-zero likelihood of a massive destruction of collateral and thus loan value, can induce banks to provide less lending ex ante. The destroyed capital stocks of non-financial firms and resulting write-offs in loan portfolios ultimately would need to be buffered by equity, suggesting an increase in banks' default probabilities (Klomp, 2014). Gerali et al. (2010) show that the unexpected destruction of bank capital leads to a significant contraction of credit supply. Related micro-empirical evidence from an *ex post* perspective confirms this effect; for example Sawada and Shimizutani (2008) document heterogeneous consumption growth among households after the Kobe earthquake, due to tighter credit constraints among households with less real estate wealth prior to the disaster. Granular loan-level evidence by Berg and Schrader (2012) also shows that small and medium-sized firms (SME) in Ecuador that were subject to volcanic eruptions experienced significantly more frequent loan disapproval from an individual microfinance institution, though they also find that longer relationships can mitigate this average tightening effect of credit constraints. According to Lambert et al. (2015), banks that were hit by Hurricane Katrina in 2005 substituted customer lending with government securities. This asset swap helped stabilize those banks after 2005, but it also represented a loan supply contraction that might have hindered the recovery of non-financial firms. More recently, Cortés and Strahan (2015) investigate how U.S. multi-region banks react to shocks from a natural disaster and meet increased credit demand. They use mortgage lending data to differentiate between banks' core and peripheral markets, and find that banks reduce their lending in the latter type of markets, to expand lending in their core markets. This evidence indicates that financial intermediaries may be able to absorb the increased credit demand that arises after a natural disaster.

The challenge faced by these important studies is the difficulty of identifying whether observed lending in disaster-ridden regions declines due to banks' supply contraction or due to collapsing credit demand by non-financial firms when the sampled banks are located in shocked regions themselves (Sawada and Shimizutani, 2008; Klomp, 2014; Lambert et al., 2015; Cortés and Strahan, 2015). The only study that we are aware of that relies on observed bank-borrower data to circumvent the problems arising from such geographic allocation is based on a study of one single micro-credit provider in Ecuador (Berg and Schrader, 2012). Hence, results are not necessarily applicable to entire (more developed) financial systems.

To address exactly these issues, we identify directly exogenous *demand* shocks that affect all banks in a large economy with a well-developed banking system that funds SMEs. Rather than identifying shocked banks depending on whether they are located in disaster-struck areas or not, we gather data about the banks' customer portfolios, then define banks as shocked if and only if a critical share of their customers has been exposed to damages caused by the flooding of the river Elbe.

With this novel approach, we establish a clear identification of how disaster shocks affect lending. To identify exposure to increased demand for individual banks, due to the natural disaster, we match approximately 1.1 million firms with approximately 2,000 banks operating in all German regions. To define the bank-firm relationships, we (string) match banks' names, with which each firm maintains a payment service relationship as in (Popov and Rocholl, 2016). By exploiting the difference in locations between banks and firms, we can more clearly separate demand from supply effects and provide important insights into how an unexpected demand shock affects bank lending. Another advantage of our setting arises because Germany has many small savings and cooperative banks, which are more likely to have close relationships with their firm-customers, thus potentially enabling them to overcome the information asymmetries that arise from the effects of a natural disaster more easily.

– Figure 2 around here –

Official statistics bear testimony to the substantial impact of the Elbe flood on local economies. Figure 2 depicts the number of jobs lost due to insolvencies in regions affected and unaffected by the flood over time. Right after 2012, the two trends diverge, such that the number of jobs lost due to insolvencies in the affected regions increase relative to those in the unaffected regions. The effect of the Elbe flooding thus is measurable on the county level, which provides a first indication that individual firms were significantly affected by the flood.

We find that flood-affected savings and cooperative banks increased their lending significantly after 2013. This effect is economically significant: We estimate a differential lending effect of around 23%, relative to unaffected banks. This result is robust to propensity score matching with pre-2013 bank traits, pre- and post periods of symmetric duration, pre-dated placebo flooding, and confounds due to lending by banks that resided in the flooded regions themselves. This last test in particular corroborates the importance of identifying demand shocks faced by banks, by gauging real shock exposure through their firm relationships rather than their own exposure to actual, materialized, low probability/high-impact shocks. We do not find any indication of a flight to safety by banks, such as in the form of larger cash or government security holdings. Instead, the shocked banks increase not only their lending levels but also the share of lending relative to their total assets. This increase is driven by unsecured, non-mortgage lending, consistent with the idea that banks can plug the liquidity shortages of firms facing a sudden disaster shock. This documented *recovery lending* does not entail riskier banking; rather, our results suggest only a mild reduction in loan loss provisions, together with more profitability and less risk taking by banks overall.

These results thus indicate a positive effect of close bank-firm relationships. Local banks provide additional credit in times of crisis. Local lenders in turn may constitute an important element in the financial system to mitigate tail risks that hit the real economy.

2 Data

2.1 Firm-level data

We obtain German firm-level data from the Dafne and Amadeus databases, both provided by Bureau van Dijk. The former contains the name of the bank (or banks) with which each firm maintains a payment relationship (Popov and Rocholl, 2016).[6] We use annual vintages of the Dafne database to construct a time-series of bank-firm relationships for more than a million firms between 2003 and 2014. 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), as depicted in Figure 1. We augment these bank-firm relationship data with firm-specific, annual financial accounts data from Amadeus, which are available for approximately 1.1 million firms. Because SMEs generally lack access to external debt or capital markets, we expect credit demand shock to be greater for smaller firms. The median firm in the data set has seven employees and assets of about 350,000 €; that is, they are micro firms according to the definition of the European Union (EU).[7]

[6]Bank-firm payment relationship data originate from scans of the firms' letterheads. We do not observe credit relationships directly. The coverage of the database has increased significantly over the years, such that some 22,000 firms were included in 2003, but about 1.4 million firms appear in the database by 2014.

[7]Micro firms have less than 10 employees, less than €2 million in turnover, and/or less than €2 million in total assets (European Comission, 2003).

2.2 Bank-level data

Next, we combine firm and bank data from Bankscope, another Bureau van Dijk database, using bank-firm relationships that we identified using a string-based match of bank names. Bankscope contains annual financial account information and provides the location of the headquarters, so we can identify which banks were located in a flooded region and thereby separate supply and demand effects more clearly by excluding banks that were likely subject to flooding themselves.

Because we lack any other relationship information other than the banks' names in the Dafne database, we manually inspect many matches to ensure that the firm-level data are combined with the correct financial information about the banks from Bankscope. We match around 99% of all bank-firm relationships. Most of the remaining 1% are (large) international banks that are mostly connected to large German firms. We exclude these banks, because our focus is on SMEs and their local relationship lenders, predominantly regional savings and cooperative banks.

2.3 Natural disaster data

To gauge the damage inflicted by the Elbe flood of 2013, we use a novel data set provided by the German Insurance Association (GDV). The data contain claims filed for insurance properties that were damaged during the flood between May 25 and June 15, 2013. An important advantage of our data is that we observe directly the economic value destroyed, relative to what is covered by insurance contracts. Put differently, we analyze if and to what extent banks respond to the damage arising from allegedly incomplete risk coverage of catastrophe insurance, as highlighted by Froot (2001).

For confidentiality reasons, the data are aggregated by county ("Kreis"), into nine damage categories, which identify the percentage of insurance contracts for which a claim was filed by customers.[8] Lower categories indicate less damage relative to the asset values covered by insurance contracts.[9] The GDV collects this information from all its 460 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).

The regional aggregation for each of the nine damage categories implies that we assume constant insurance coverage within each county. The identification strategy therefore exploits between-county variation in relative damage intensities. We combine the insurance claim rates data with the geographical location of both the firms and banks. To isolate bank lending responses that are due to the demand shock inflicted by the flood, our identification hinges on those banks that have business with firms affected by the flood, but which reside themselves in a non-heavily flooded region.

3 Specification and identification

3.1 Specification

The combination of firm, bank, and insurance claim data with valid location information results in a sample of 913,529 firms, of which 172,494 are headquartered in counties that were flooded by the river Elbe in 2013. These firms have a combined 1.5 million relationships with 2,047 different banks.

[8] Thus, we do not observe the damage inflicted on individual banks or firms.

[9] The precise definition of the categories is provided in Figure 1. Variation in percentage of activated insurance contracts per county ranges from Category 1 ($\leq 0.04\%$) to Category 9 (10%–15%).

We clean our data in two steps. First, we match the bank-firm sample with the 2,047 banks and 18,408 observations featuring bank balance sheet characteristics that are available in Bankscope. We sample only non-missing observations for the four bank variables that we use in our baseline regression: the natural logarithm of gross loans, equity over assets, the natural logarithm of total assets, and cash over total assets. This matching process leaves us with a sample of 16,945 observations and 1,862 banks. Second, we require that banks have existed at least for one year before 2013 and at least for one year after 2012. This requirement leaves us with a final sample of 15,902 observations for 1,598 banks. To test if lending differs significantly between affected and unaffected banks, before and as of 2013, we estimate a difference-in-difference regression:

$$\ln\left(\text{Loans}\right)_{it} = \beta(\text{Affected}_i \times \text{Post}_t) + \alpha_i + \alpha_t \times \alpha_r + \sum_{k=1}^{K} \gamma_k C_{kit} + \epsilon_{it} \tag{1}$$

The dependent variable ln(Loans) is the natural logarithm of total gross loans for bank i in year t. Affected is a dummy variable that identifies banks that have been exposed to the flood. Subsection 3.2 is dedicated to a detailed description of how we identify banks affected by the flood. The Post dummy variable is equal to 0 for the years 2003-2012 and 1 for 2013 and 2014. The river Elbe flooded in the summer of 2013, so we assume that potential lending effects are already contained in banks' end-of-year balance sheets. The coefficient of interest is β, which reveals the treatment effect of banks exposed, through borrowers, to the flood. It indicates how much the volume of loans changes for the affected banks after 2012 compared with the period before relative to the change for the group of unaffected banks.

– Figure 3 around here –

As Figure 3 illustrates, prior to the flood, the log level of gross lending did not develop significantly differently across banks with and without client portfolio that were exposed to the shock in 2013. To further minimize concerns that we might estimate a biased treatment effect, due to confounding events, we also purge the specification of bank fixed effects α_i and interacted county-year fixed effects $\alpha_r \times \alpha_t$.[10] The former gauge unobservable bank traits; the latter control for region-specific demand shocks other than the flood, such as unobservable regional policies and business cycles.

– Table I around here –

A precise definition of all the variables that we use is provided in Table I and the descriptive statistics in Table II. The first panel of Table II shows that around 27% of German banks are affected by the flood through their exposure to borrowers that were in flooded regions in 2013. The separation between samples, with all banks in Panel (a) and regional savings and cooperatives in Panel (b), demonstrates that the vast majority of lenders in Germany are local savings and cooperative banks. We focus on these smaller, regional banks because they permit the clearest identification of lending responses to local demand shocks. Also, these local lenders maintain closer relationships with their regional customers, which reduces information asymmetries for assessing the borrowers' structural ability to repay their debts after a temporary, random disaster shock. Therefore, relationship banks should be more inclined to provide additional funds compared with arm's-length lenders or financial markets.

We also specify three bank-specific control variables in Equation (1). First, we use the natural logarithm of banks' total assets (size) to differentiate small from larger banks. Second, the ratio of banks' total equity to total assets (capital adequacy) controls for

[10]The combination of fixed effects makes single-year fixed effects redundant.

bank capitalization. In this way, we capture differences in the riskiness of banks and the distribution of abilities to buffer insolvency shocks in their credit portfolio. Third, liquidity is the ratio of banks' cash holdings to total assets, which we use to gauge differences in banks' abilities to buffer short-term shocks. The average bank is small, with total assets of \$15.7 billion, and it exhibits an equity ratio of 7.2%. The average savings and cooperative bank is even smaller, with assets of \$9 billion. On average, banks in our sample have 2.1% cash, relative to their total assets.

– Table II around here –

The second panel of Table II contains additional dependent variables to differentiate any potential lending effects in response to disaster risk. The lending share relative to total assets gauges whether any possible *recovery lending* also materializes, relative to the total size of the bank. To test for systematic changes in loan quality, we regress the flood treatment effect on loans, net any write-offs, loan loss reserves, and impaired (or non-performing) loans. The responses to realized disaster risk might include a flight to safety or alternative asset classes, so we also specify the asset shares of cash holdings, securities, and interbank lending. The asset composition of the average bank features a loan share of around 57%, with 26% securities.

The third panel shows descriptive statistics for the performance variables that gauge banks' risk-return profiles. The z-score is the inverse distance to default (Laeven and Levine, 2009). We take the natural logarithm of the sum of the return on assets (RoA) and the capital ratio divided by the standard deviation of RoA. We also specify RoA and return on equity (RoE) as direct proxies of profitability and the ratio of net interest income over expenses to gauge the relative importance of interest-bearing activities of the bank.

The bottom panel of Table II shows that the average bank is connected to around 740 firms with an average age of about 7 years. The average distance between banks and firms is 35 kilometers, which is fairly close, such that it facilitates (soft) information collection by banks and supports relationship banking (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010).

3.2 Identification

A key concern in explaining observed lending effects is the separation of credit demand and supply effects. The important innovation associated with our identification strategy is to mute concerns that observed lending effects are due to loan supply contractions of disaster-ridden banks, rather than the changing loan demands of firms in response to exogenous disaster risk. We argue that banks' connections to firms in affected areas isolate their exposure to demand shocks most accurately, rather than their own location.

To identify banks that are subject to a disaster-induced demand shock, we construct a measure of how many of its borrowers are located in flooded counties. In order to achieve this, we exploit the geographic variation of firms in each bank's portfolio and calculate the exposure of the bank to the flood event, according to the number of firms that indicate a payment link to that bank. For each bank, we take the weighted average of flood damage categories across all the firms that report a payment link with the bank. Depending on its location, each firm contributes the damage category of the county where it is located (Figure 1). The demand shock exposure of bank i to the flood thus is the (size-weighted) flood damage to the bank's average firm-customer j, given the firms' county r, where N is the total number of firms connected to bank i as of 2013:

$$\text{Exposure}_i = \frac{\sum_{j=1}^{N} \left(\frac{\text{Assets}_j}{\text{Mean Assets}_N} \times \text{Claim Ratio Category}_r \right)}{\text{N}} \tag{2}$$

We define banks as affected if their exposure value is 4 or higher and as unaffected if the exposure value is lower than 2.5. We choose these thresholds to ensure that we consider only significant economic damage, leading to insurance claims, as demand shocks and that we sample sufficiently many shocked firm and associated bank observations. Exposures between 2.5 and 4 represent buffer categories, so we omit these observations from the baseline specification:[11]

$$\text{Affected}_i = \begin{cases} 0 & \text{if Exposure}_i < 2.5 \\ 1 & \text{if Exposure}_i \geq 4 \end{cases} \tag{3}$$

Figure 4 illustrates how we isolate demand shocks faced by affected banks. The circles depict firms, whereas triangles depict banks. Both are located in counties r, indicated by larger squares. Each county is assigned categorical insurance claim data from Figure 1, which we indicate by $C = 1, ..., 9$. Firms' exposure to the flood is based on these values, which we depict with increasingly dark circles as the intensity of the disaster shock increases. Banks are not directly affected by the flood, contrary to Lambert et al. (2015) or Cortés and Strahan (2015). Instead, banks' flood exposures depend solely on the firms with which they conduct business, as indicated by the arrows. A bank is affected if the average exposure of its firms is $\geq$4 and unaffected if it is <2.5. Thus, affected banks can be located in heavily flooded regions, such as r=8 and r=6, but remain unaffected if most of their customers are located in non-heavily flooded regions, such as the unaffected bank depicted in region r=6.

[11] We show in Figure 6 that our main results are not driven by the exact definition of these thresholds.

Conversely, banks can be located in less severely flooded regions, such as those in the upper right-hand corner, r=1. Yet banks are still considered shocked if their average borrower is located in a heavily damaged county, as illustrated by the bank depicted as a solid black triangle. We also look at these banks in isolation, because they offer the cleanest identification of changes in lending due to demand shocks transmitted to the bank through its credit portfolio. Finally, banks in heavily flooded areas may remain unaffected if their firms are located outside the flood perimeter, such as the unaffected bank in the lower-left region.

– Figure 4 around here –

A potential concern regarding our identification strategy arises because local banking markets may be regionally delineated, either *de jure* or *de facto*. This trait has been exploited in German banking studies that consider the (cross-border) transmission of financial shocks (Puri et al., 2011), additional risk taking due to bailouts by regional insurance schemes (Dam and Koetter, 2012), or loan supply effects due to social ties between bankers and local politicians (Behn et al., 2013). Our approach to identify affected banks solely on the grounds of the location, and thus the disaster exposure of their customers, can isolate the causal effects of disaster risk on loan supply if and only if these banks also conduct business with firms outside their own county of residence. If banks always and only conduct business with firms in their respective county, our identification strategy would be moot and cast doubt on whether the results are driven by demand or supply effects.

– Figure 5 around here –

To this end, Figure 5 provides an example of the spatial distribution of firm customers of banks located in Munich. Counties closer to Munich logically host more Munich-based bank customers. However, the figure also clearly shows that these banks also conduct business with substantial numbers of clients outside their local market, including those close to the river Elbe. These effects may be driven by a few supra-regionally active banks headquartered in metropolitan areas like Munich, such as Hypo Vereinsbank.

– Table III around here –

In Table III, we thus specify the number of banks that we classify as unaffected, in the buffer zone, and affected, depending on their borrowers' exposure to the flood, together with information about the damage category of the county in which each bank is located. For example, the first cell of Table III shows that we classify 774 banks as unaffected that are located in counties in category 1. We define banks as outside the direct impact of the flood if they are located in any county with a category lower than 5. The number of banks outside the flood area, which are affected solely by their borrower relationships, then numbers 60 (i.e. the first four cells in the affected column: $2 + 3 + 3 + 52 = 60$). This bank treatment frequency is sufficient to obtain reasonable estimates, and the procedure mitigates concerns about supply effects. For example Raiffeisenbank Ronshausen Marksuhl, a very small bank located in a county near the city of Kassel, is located in a county of category 1, so it was very unlikely to be affected directly by the flood. But the majority of its business is conducted with firms residing one county closer to the Elbe. As a result, we classify this bank as affected (through the demand of its firm clients) in our analysis.

4 Main Results

We estimate Equation (1) with OLS and clustered standard errors at the bank-level. Table IV shows the main estimation results. In Column (1), we include all universal banks from the commercial, savings, and cooperative banking sectors. Moreover, we include banks that reside in flooded regions themselves. The estimated coefficient β is not significant. Thus, in a specification in which we pool banks that are affected with those that are exposed to the flooding only through their firm customers, we do not find a faster increase of gross loans compared with banks whose firm customer portfolios include mostly firms residing in unaffected counties after the disaster. The same is true for Column (2), in which we only include banks outside the affected regions but still sample nationally active, large banks together with small, local relationship lenders.

A potential explanation for the absence of results might be that arm's-length lenders behave systematically differently from relationship banks, thereby giving rise to insignificant lending responses. Berg and Schrader (2012) offer an additional insight that may be pertinent to our case: shocks in the form of volcanic eruptions induced higher rejection rates suggesting a loan supply contraction. Demand for credit, in turn, also increased after these disasters struck. Yet, they show that firms with relationships with the investigated micro lender continued to have identical credit access after the disaster. We therefore anticipate a positive *recovery lending* effect that should exist especially for banks focused on building a bank-firm relationship.

In Columns (3) and (4) of Table IV, we report a specification in which we consider only local savings and cooperative banks, both with and without local lenders that reside in flooded regions themselves. These banks are smaller than commercial banks, but account for approximately one-third of aggregate total assets in Germany, such that they are major players in most of Germany's regions (German Council of Economic Advisors, 2014). They pursue regional relationship-based strategies, particularly aiming at SMEs, and may therefore generate and possess more private information about their customers than do larger, nationally active banks (Elsas and Krahnen, 1998; Elsas, 2005; Behr et al., 2013). For these banks, we thus expect a *recovery lending* effect. The comparison with Columns (1) and (2) shows that this specification includes about 120 fewer banks, namely small commercial banks, the so-called "Big Five" (multi)national commercial banks, central savings banks (*Landesbanken*), and the head organizations of the cooperative banking sector.

The interaction term in Column (3) is significant at the 1% level and positive. Affected savings and cooperative banks increased their lending after the Elbe flood relative to the unaffected savings and cooperative banks. The economic magnitude of this effect is very relevant. Shocked savings and cooperative banks increased their lending by roughly 23% ($(\exp(0.21) - 1) \times 100 = 23.37$) compared with the group of unaffected banks in 2013 and 2014. This evidence of a substantial positive *recovery lending* effect by local banks in the savings and cooperative banking sector in turn suggests that bank lending has a prominent role in the recovery of firms after disaster risk materializes, not only in developing economies as in Berg and Schrader (2012), but also in developed financial systems like Germany's. This *recovery lending* effect is consistent with results reported by Cortés and Strahan (2015) for the U.S. financial system showing that banks in regions hit by natural disasters increase their lending to meet increased loan demand.[12]

– Table IV around here –

However, these results may still confound credit demand and supply responses to the disaster, because we included banks located in counties that were struck by the Elbe flood. Recall that this identification does not hinge on direct damage of the bank itself. Still, the estimated differential lending effect might only imperfectly separate credit demand from bank supply responses to the shock if local lenders primarily cater to local customers.

[12]Our baseline results remain intact for different lags of the bank control variables and for regressions without bank characteristics, see Table OA1 in the Online Appendix. We also find identical results when controlling for the industry concentration in banks' portfolios by means of a size-weighted Herfindahl Index across industry classifications of each banks' borrowers, see Table OA2.

To address this potential bias, in Column (4) we consider only savings and cooperative banks that are not located in severely flooded areas. The estimated differential lending effect is virtually identical in terms of its magnitude, significance, and direction of the effect: a differential increase in loans by about 23% after the flood compared with unaffected cooperative and savings banks. This result provides robust evidence for an economically significant *recovery lending* effect, in contrast with the negative effects reported for more specialized (mortgage) lending in Japan (Sawada and Shimizutani, 2008) and the United States (Garmaise and Moskowitz, 2009) or micro-credit lending in developing economies (Berg and Schrader, 2012).

Three explanations may help reconcile our findings with these previous studies. First, we identify the disaster treatment on the basis of firm customers', instead of the banks' locations. Thereby, we can identify the loan demand element instead of supply adjustments to disaster shocks more easily. Second, we consider overall lending to firms, rather than specialized mortgage lending to private customers. Thus, the value of the type of credit that we study depends much more on (tacit) information that the bank possesses about the productivity of the firm and its management, instead of tangible collateral that has been destroyed, as is the case for mortgage loans. Third, we analyze a large sample of universal banks in a well-developed financial system rather than a selected sample of banks.

Across all four specifications, the effects of size and capitalization, as measured by our control variables, are identical. Larger banks affected by the disaster exhibit larger gross loan volumes relative to the time before the flood, whereas better capitalized banks actually contract their lending. Liquidity as measured by cash holdings relative to total assets, is not statistically significantly related to the log-levels of gross loans for our preferred sample of local savings and cooperative banks. Therefore, we specify but do not the report results for the control variables hereafter.

5 Robustness

This section checks the robustness of our baseline results. We provide results for our preferred sample of local savings and cooperative banks that do not reside in the flooded regions themselves. All tables are available on request for the three alternative samples.

Matched sample Whereas the identification of a *recovery lending* effect through banks' firm-customer portfolios strengthens the case that we isolated demand responses to disaster risk, the descriptive data in Table II raise questions about the comparability of affected and unaffected banks. As Figure 3 demonstrates, lending prior to the flood developed not significantly differently between affected and unaffected banks.

But banks also differ in their other observable traits, such as size, capital adequacy, and liquidity. Descriptive statistics show significant level differences in control variables between affected and unaffected banks. Whereas the focal outcome variable, gross loans, does not exhibit any pre-crisis *trend* difference between affected and non-affected banks (see Figure 3), we nevertheless seek to ensure that our results are not driven by systematic differences pertaining to observable pre-crisis characteristics. For example, larger banks might have a larger portfolio of out-of-region borrowers, which might render them more likely to be categorized as affected. To mitigate spurious counterfactual concerns, we conduct propensity score matching based on size, capitalization, and liquidity buffers observed prior to the flood in 2012. We conduct this matching for the sample of all banks (Column (1) in Table 4), apply a 1:1 caliper match with a caliper width of 0.01 (Caliendo and Kopeinig, 2008), and identify propensity score matches for 326 affected banks.

Column (1) in Table V provides the results for savings and cooperative banks, that were outside the direct impact zone of the flooding. We drew this sample from the matched sample of 652 banks. This result corroborates the findings from the baseline regression, though with a slightly smaller point estimate for the *recovery lending* effect. Thus, concerns that we compare significantly different banks in terms of observable traits and falsely attribute any differential lending to their fundamentally different sizes, capitalization, and/or liquidity do not appear relevant.

– Table V about here –

Symmetric periods We also scrutinize our results with regard to a potential bias due to the longer pre-flooding period, compared with the post-flooding period. We impose symmetric pre- and post-shock sample periods and estimate Equation (1) by specifying only 2011 and 2012 as the base period. The results for not directly flooded savings and cooperative banks appear in Column (2) of Table V. The effect for the shorter base period remains statistically significant and positive. Whereas the magnitude of the *recovery lending* effect is smaller–namely, around half the size of the baseline regression (i.e. around 11%)–the qualitative result that local banks expand their post-disaster lending clearly is not driven by the longer base period.

Collapsed sample Another concern in difference-in-difference regressions is the potential presence of auto-correlation in the dependent variable (Bertrand et al., 2004). To mitigate that possibility, we included time-by-county fixed effects in our analysis. Alternatively, we remove the time-series component from the data by taking the means of both the dependent and explanatory variables for the pre- and post-disaster periods. The results from this cross-sectional estimation appear in Column (3) of Table V, showing that in this specification, the interaction term is still positive and significant indicating that our baseline results are not biased by auto-correlation.

Placebo event To ensure that the flood of 2013 actually imposed a disaster *recovery lending* effect on banks with many affected borrowers in their portfolio, we test whether a pre-crisis lending trend existed. To this end, we go beyond the graphical inspection of the observed lending outcome in Figure 3 and estimate a placebo regression, using 2005 as the placebo event period. If a confounding trend exists prior to the flood of 2013, it should reveal itself in terms of a significant difference-in-difference effect in such a regression. Column (4) of Table V shows the results, which demonstrate that our findings are driven by the 2013 event, instead of a general, long-term trend, because we find no significant effects for the interaction term.

Falsification of flooded banks To rule out the possibility that our identification is merely a proxy for banks directly affected by the flood, in Column (5) of Table V, we consider regression results in which we define banks as shocked if and only if they are located in a severely flooded region themselves (as in e.g., Lambert et al. (2015) or Cortés and Strahan (2015)). Each bank is classified as affected or unaffected according to the claim ratio category of the county where it is located. We classify banks as directly affected if they are located in a county that shows a claim rate category ≥ 5 and unaffected if the claim rate category is <5. We specify time-fixed effects instead of time$\times$region fixed effects because the affected indicator no longer varies on the bank-region level. This data structure implies that each bank in the same county has the same category C, and thus the same value for the affected variable.

For the sample of regional savings and cooperative banks, the interaction term is not statistically different from 0, therefore banks located in affected regions do not increase their lending significantly after 2013 compared with banks in unaffected regions. This result offers important evidence that credit supply adjustments by directly affected banks, as documented in prior literature, can differ quite starkly from the response of banks to *demand* shocks that their firm-customers, in particular SMEs, experience. Using bank-firm relationships to gauge banks' disaster risk exposures therefore appears to be strongly relevant.

Disaster threshold validity A final source of concern is the fairly heuristic definition of "disaster" exposure. Recall that we defined banks as exposed to the disaster shock if the asset-weighted average of the damage category associated with their observed customer portfolio is larger than or equal to 4. The control group comprises banks with a damage category average below 2.5. To ensure that the main results do not only hold for this specific identification of exposed and non-exposed banks, we estimated Equation (1) for varying ranges of affected and non-affected banks, respectively. Specifically, let

$$\text{Affected}_i = \begin{cases} 0 & \text{if Exposure}_i < \text{LB} \\ 1 & \text{if Exposure}_i \geq \text{UB}, \end{cases} \tag{4}$$

in which LB denotes the lower bound of average damage categories considered affected and UB is the upper bound of average damage categories considered unaffected.

Accordingly, UB ranges from 2.5 to 5 in order to define affected banks, with a fixed threshold of unaffected banks with an average damage category, that is lower than 2.5, as we show in Figure 6 Panel (a).[13] Upwards of an exposure of 4, we document significantly positive interaction terms, as reported in the baseline. Point estimates before that threshold are insignificant, as we might have expected given that the separation of affected and

[13]The number of observations is too low for thresholds above 5 to permit reasonable estimates.

unaffected banks decreases (see also Table II).

– Figure 6 around here –

Conversely, we let the LB range from 1.5 to 4 while holding the threshold for affected banks fixed at values ≥ 4.[14] Figure 6 Panel (b) depicts the associated estimates of the interaction coefficient, with confidence bands pertaining to a certainty level of 5%. Across almost the entire range of thresholds, these point estimates are positive. However, when both groups become increasingly equal (beyond 3.5), the point estimates turn insignificant.

These threshold permutations for classifying both affected and unaffected banks are in line with our expectations: As unaffected and affected banks move farther away from each other in terms of their exposure to the flood, the estimated *recovery lending* effect becomes larger and statistically significant. Thus, the main effect is robust to variations in the precise definition of the disaster thresholds used to identify shocked and non-shocked banks.

6 Mechanisms and channels of *recovery lending*

6.1 Loan portfolio components

Banks affected by the 2013 Elbe flooding due to their firm relationships increase their lending in subsequent years. To better understand the mechanism behind this *recovery lending* effect, we investigate the effects across three different loan categories: real estate loans, public loans, and other loans. The latter category is the residual of gross total loans

[14]The number of observations is too low for thresholds below 1.5 to permit reasonable estimates.

after subtracting the former two categories, according to the Bankscope definition. They comprise all other loans to non-financial institutions.

– Table VI around here –

The first Column of Table VI provides the baseline results for savings banks and cooperative banks that do not reside in affected regions for the sample of banks for which we have complete data about all three sub-categories of gross loans. To compare the effect of the flood across loan categories, we include only observations for which all loan categories are available. Therefore, the sample is somewhat smaller than the baseline in Column (4) of Table 4, and the point estimate of the *recovery lending* effect is smaller, yet it remains significant and economically important.

The interaction term for the real estate loans specification in Column (2) of Table V is insignificant. The finding that affected banks do not expand their real estate loan business after 2013 is important. It shows that the baseline *recovery lending* result does not necessarily contradict Garmaise and Moskowitz's (2009) finding that banks significantly reduced their real estate lending in the aftermath of the 1994 Northridge earthquake. The documented aggregated increase in *recovery lending* in Germany thus appears to be driven by other loan categories, not investigated in their setting. The insignificant result for German real estate lending even may suggest that insurance markets for real estate work better in Germany than in the United States. A more likely explanation though is that we simply cannot estimate effects with sufficient precision due to the use of annual data, which hinders the identification of the short-term effects that Garmaise and Moskowitz (2009) investigate.

Column (3) of Table V shows that banks significantly reduce their lending to public entities by 36%. This large effect could indicate crowding-out effects of the public disaster assistance that followed the 2013 Elbe flooding, directed to borrowers that were channeled through local governments in affected regions. In counties that were particularly hard hit by the flood, federal financial assistance might have addressed most of the needs of local municipalities, public utilities, and other government customers of banks, such that they demanded less credit from the private sector. Detailed data on federal support schemes are unavailable, such that we cannot offer an explicit test of this explanation, but our "brute force" approach that uses county-by-year fixed effects helps mitigate concerns that such effects systematically contaminate the significantly negative coefficient of public lending.

Finally, Column (4) of Table V shows that the baseline *recovery lending* effect is driven by the other loans category. This effect is significantly positive and virtually identical in magnitude to that reported for the baseline specification. According to the variable documentation of Bureau van Dijk, this credit category comprises loans without land property pledged as collateral – precisely the loan category consistent with a *recovery lending* motive for local lenders. Banks seem to have expanded credit in categories associated with lighter collateral requirements. In times when the quick provision of credit is important to firms – as after an event like a flood or another natural disaster – local lenders with private information about borrowers' structural ability to operate their business resort to the provision of (unsecured) lending.

6.2 Funding components

Next, we ask whether banks related to flooded loan customers raised more funding to finance additional lending. To this end, we specify in Table VII the natural logarithm of four different types of bank liabilities as the dependent variable.

– Table VII around here –

Column (1) shows that total deposits do not respond significantly at affected banks. At face value, this result suggest that depositors are not footloose and did not respond with runs to this disaster shock (Diamond and Dybvig, 1983). But when we separate total into customer and interbank deposits, the absence of a joint effect is put into perspective. Affected banks attract more customer deposits, but loose interbank deposits.

The increase in customer deposits shown in Column (2) might reflect two narratives.[15] First, German savers may consider insured deposits particularly save to store liquidity in times of increased uncertainty due to the realization of a tail risk. Second, whereas insured retail depositors maybe considered unsophisticated savers that are less interest-rate sensitive compared to institutional providers of bank funding, Schlueter et al. (2015) show that deposit outflows decline significantly in response to contractual incentives, such as staggered interest payments. Alas, we can not test formally if affected banks have attracted additional retail funding by offering higher prices given the absence of pricing data. But we will therefore consider below an indirect pricing proxy on loans and deposits, namely net interest income.

Note that the magnitude of the increase in retail deposits in response to the Elbe flood is just around a tenth of the size estimated for the increase in lending. Therefore, attracted retail deposits alone do not explain the expansion of *recovery lending*. In addition, the results in Column (3) shows that the increase in retail deposits is almost exactly offset by

[15]Unfortunately, customer deposits cannot be further distinguished into household versus corporate deposits. Note that total deposits also contain money-market funding, which is however negligible for this sample of local savings and cooperative banks.

the contraction of interbank deposit supply. Potentially, counterparties in the interbank market respond to increased (perceived) risk of affected banks by rationing credit (see, for example, Cocco et al., 2009, on the existence of relationship lending in the Portuguese interbank market). Alternatively, for these regional savings and cooperative banks, the contraction might also indicate a reallocation of financial funds by central head institutions (*Landesbanken*) away from the indirectly affected banks specified here towards those located in directly shocked regions in the vein of Cremers et al. (2011).

Finally, Column (4) accounts for the argument put forward in Huang and Ratnovski (2011) that wholesale funding might be cheaper, but also more risky because of lumpy withdrawals if wholesale lenders and capital markets loose faith in the solvency or the liquidity of the bank. Therefore, we specify the natural logarithm of wholesale funding as a dependent variable. The according coefficient is insignificant, which is consistent with the very limited role played by this source of funding for small, regional banks.

6.3 Asset composition

The documented *recovery lending* effect raises the question, whether the differential expansion of (unsecured) lending results from a reallocation of banks' assets, for instance divesting securities in exchange for more lending? Therefore, we investigate if the relative share of firm credit became more important for affected banks. This point is important to understand for policy makers, in that an alternative explanation might be that local banks increase their loans to some extent, but expand their safe asset holdings (e.g., cash or government securities), even more.

We specify the relative asset shares of different asset categories to shed light on a key question: Do affected banks significantly change their asset *composition* in response to the

Elbe flooding of 2013? Table VIII demonstrates that banks not only increase their gross loans in Column (1) but also increase the share of net loans (gross loans minus reserves) by around nine percentage points more than unaffected banks relative to the period before 2013 (Column (2)). Column (3) reveals that this relative increase in net loans is associated with a small, statistically significant decrease in loan loss reserves compared with those of the unaffected banks for the sample of banks that are not located in a heavily flooded county. A potential explanation for this result is that local banks lend more recklessly in dire times and take consciously higher credit risks with low loan loss reserves. Alternatively, especially these "connoisseurs" of local SMEs might possess superior information about the general viability of their customers' business models and therefore continue lending with relatively low provisions,because they anticipate with some confidence that these firms will return to their pre-flood growth paths once they have recovered from the massive disaster shock they have experienced.

– Table VIII around here –

This narrative is hard to test explicitly without detailed credit data the bank-firm level. However, the results in Column (7) offer some circumstantial evidence. For some banks, we can identify the number of "impaired loans" on which repayment is past due by at least 90 days. These loans decrease among the affected banks by 3.1 percentage points compared with unaffected banks after the flood. This result is interesting; *a priori* we might expect that repayment ability would decrease among the flood-affected firms. But an alternative hypothesis, supported by our evidence, is that banks engage in refinancing with firms more frequently if they know those firms have suffered flooding, which then decreases the impaired loans after the flood, compared with the level for banks with less exposure to the flooded firms.

We find no support for the supposition that local banks exhibit a flight to safety. Column (4) of Table VIII shows that the positive aggregate effects documented in the baseline regression is not driven by interbank loans, as might have been the case if local savings banks preferred to lend to their respective head institutions instead of to their SME customers. Likewise, we do not find any evidence in Column (5) that banks increase their securities following the flood, such as risk-free German Bonds. Column (6) also rejects the idea that banks fund their post-flood loans by reducing cash reserves. For all three asset category shares, the flood interaction is statistically not different from 0.

6.4 Risk and return implications

The significant reduction of impaired loans in response to the flood already offers an important indication that *recovery lending* is not associated by default with more reckless banking, but it is important to recognize that this information is only available for a small subsample. Therefore, we investigate more explicitly whether the extra provision of credit by affected banks is associated with any differences in their risk-return profiles.

– Table IX around here –

In Column (1) of Table IX, we specify the Z-score (Laeven and Levine, 2009) as the dependent variable in Equation (1).The Z-score of affected banks is significantly larger than the Z-score of unaffected banks after the Elbe flooding of 2013. A higher Z-score means that banks are more stable; this result confirms the preceding indication that affected local banks manage to provide relatively more credit while simultaneously reducing their overall risk. From an economic perspective, the increase is large, in that affected banks increase their stability by around 15%. Columns (2) and (3) of Table IX show that the increase of Z-scores is not driven by higher equity ratios (Column (2)). Instead, it originates from higher returns on assets, which increase by 0.3 percentage points. This relative increase in the profitability of the affected banks is corroborated in Column (4), which uses the return on equity as the dependent variable.

A potential explanation that contradicts the largely benevolent interpretation of local banks roles in providing *recovery lending* goes back to Rajan (1992): Locked-in borrowers may suffer from rent extraction by banks. Therefore, in Columns (5) through (7) of Table IX, we offer results for the net interest margin and its components in response to the flood. These results provide little evidence of rent skimming by malicious local bankers. The effect on interest expenses is barely significant, but the effects on the net interest margin, and concurrently the scaled interest income, are not. The increase in the profitability of affected banks thus does not seem driven by the exploitation of the (temporary) market power of local lenders dealing with disaster-struck SMEs.

6.5 Disaster learning, government banks, and relationship lenders

The Elbe flood of 2002 In 2002, many of the affected regions adjacent to the Elbe river were subjected to another flood, referred to as The Great Flood, or *Jahrhunderthochwasser*. The damage amounted to 11 billion Euros in Germany, and more than 100 people lost their lives. This earlier flood is potentially pertinent to our analysis; recall that the major economic reason banks in general, and local lenders in particular, might have an important role to play in the aftermath of realized tail risks stems from the failure of re-insurance markets and the formation of myopic expectations about low-probabilty/high-impact events, such as natural disasters.

But if firms learn from the occurrence of such tail events, they should have adapted their insurance coverage and their own disaster risk provisioning in terms of equity. In that case, we should not find a significant lending response by banks affected through their firm-customer portfolio to firms that experienced both the 2002 and the 2013 flood. To test this notion, we augment Equation (1) with another dummy variable, $Affected2002$, in Column (1) of Table X. It identifies banks affected by the 2002 Elbe flooding, adhering to the same identification scheme applied to the 2013 Elbe flood, but using damage data from 2002 obtained from GDV (2013).

– Table X around here –

Column (1) of Table X shows the results for a regression in which we specify dual interaction terms between each affected dummy variable (floods of 2002 and 2013) and the post-flood period, as well as their triple interaction term. The baseline effect for the 2013 flood remains intact, but we find neither a significant lending response towards the 2002 flooding nor a significant learning effect from the triple interaction term. This result suggests the limited scope for learning from tail events. Instead, SMEs appear to have shorter lived memories and remain somewhat ignorant of the possible occurrence of such disastrous events in the longer run, which would be consistent with theories of bounded rationality to explain the insufficient consideration of risk, see Gennaioli and Shleifer (2010, 2012).

Government versus private banks Our sample of local savings and cooperative banks might camouflage important differences that arise due to government ownership of savings banks. Especially in times when national interests dominate economic considerations, politicians might compel savings banks to support firms struck by a natural catastrophe.[16]

[16] Behn et al. (2013) note the political influence on savings banks' lending decisions. Anecdotally, many observers attributed the crisis management by then-chancellor Gerhard Schröder during the 2002 flood as the turing point in the run-up to the federal parliament election later that year. After trailing the

Therefore, in Column (2), we report the interaction of an indicator for savings banks with the post-flood period dummy and also include the resulting triple interaction term. The baseline interaction effect of the 2013 flood indicator and the post-flood period remains statistically significant and positive, however the triple interaction effect is insignificant. Thus, the increase in lending by affected banks is not statistically different across savings and privately owned cooperative banks. This result suggests that a bank's relationship lending status may be more important during recovery from disasters than its formal ownership, as savings and cooperative banks can both act as relationship lenders.

Bank-borrower relationships We test this notion of relationship lending more formally. Banks might be better able to buffer shocks if they maintain intensive relations with borrowers, such that they acquire hard and soft information about their borrowers. This additional soft information may enable banks to distinguish between temporary liquidity problems and solvency issues of their clients. To learn whether some special features of relationship banking are at work in our analysis, we investigate the interaction of baseline effects with three variables: the pre-crisis average of the number of banks' firms over total assets, the pre-crisis average borrower relationship length (in years) per bank, and the pre-crisis average distance between banks and borrower (in kilometers) per bank. We transform these three continuously distributed variables into dummies for interaction, such that they are 1 if the bank is above the 75th percentile of the distribution or 0 if it falls below the 25th percentile.

The first relationship proxy captures the notion formalized, for example, by Hauswald and Marquez (2006), namely, that larger customer pools enhance the quality of private information gathered by the banks. The more agents the bank can screen, the more

conservative party in the polls prior to the flood, his social-democratic party eventually secured a landslide victory after massive media attention focused on Schröder's handling of the Great Flood.

private information it can generate. Therefore, we scale the number of firms with which a bank maintains relationships by total assets and interact this proxy for information quality with the shock indicator and the post-flood period indicator. The result for the triple interaction term confirms that banks with relatively larger customer pools increased their lending after the flood by approximately the same magnitude as the baseline effect. This result supports the notion that a broader customer base enables banks to generate private information more easily, which in turn, aids the provision of *recovery lending* when tail risks materialize.

However, the results in Column (4) in Table X, which specify the average duration of the customer relationship, indicate a mild reduction of post-flood lending by those affected banks that serviced the portfolios with the oldest relationships. The results of Column (5) are in line with these findings, as the interaction effect of the average distance between affected banks and their firms yielded no statically significant relationship with gross lending. Longer and closer relationships might have allowed affected banks to more clearly identify firms considered unable to recover from the flood. Overall, the results gained from these three relationship indicators are mixed, possibly stemming from the fact that any indirect measure of bank-firm relationships is too noisy to have measurable effects in our sample.

7 Conclusion

We investigate whether banks expand their lending in the aftermath of materialized tail risks. To this end, we use the flooding of the river Elbe of 2013 and its adjacent tributaries as an exogenous disaster risk shock, then identify loan demand responses among more than a million German SMEs. In contrast with prior studies, we observe the inflicted economic damage, in the form of insurance claim rates, at a granular regional level. By matching SMEs with their banks, we can isolate which banks are exposed to the disaster shock solely through their firm-customer portfolios, as opposed to being flooded themselves. Thereby, we can separate the loan demand shocks of customers more clearly from the loan supply adjustments of banks that are shocked themselves.

The main outcome of our analysis is the identification of an economically and statistically significant *recovery lending* effect. In particular, local savings and cooperative banks that cater to disaster-ridden SMEs exhibit around 23% more lending after the flood compared with non-affected local banks before the event. This result is robust to matched sampling, placebo events, and falsification tests. We further document that the effect is driven by lending to non-financial firms rather than mortgage lending, which illustrates the importance of credit providers that are willing and able to act in times of stress. Furthermore, this expansion in lending is not associated with higher credit risk. Instead, our results show that shocked banks exhibit less risky, more profitable financial profiles.

A possible explanation for this seemingly contradictory result might relate to the ability of local relationship lenders to act on private information that they generate in their intensive relationships with local SMEs. We find some indication that local banks with relatively larger customer pools, and thus better abilities to generate tacit information, lend particularly more after the crisis. Conversely, we do not find any evidence that government-owned savings banks step in significantly more often as emergency lenders, or that firms exposed to earlier tail events adjusted their disaster risk provisioning.

These results suggest that banks in general, and local lenders in particular, fulfill an important function in developed financial systems, serving as providers of *recovery lending* to SMEs that have been struck by disaster. Clearly, such patterns raise a new question whether such lending is effective and efficient from a welfare perspective. Future research on the implications of such *recovery lending* for the performance of individual firms and aggregate productivity appears to be warranted.

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Figures and Tables

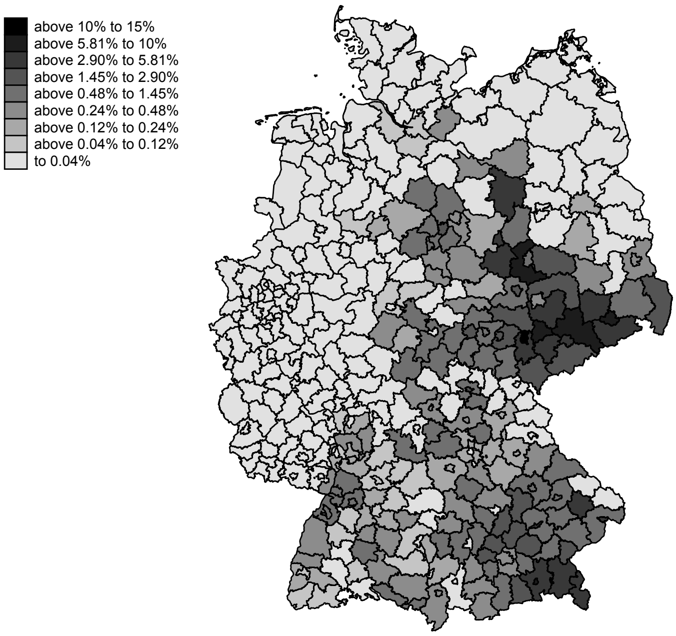


Figure 1: Affected German counties by damage categories

This figure shows the distribution of the damage sustained due to flooding in Germany from May 25 through June 15 2013, by county (Kreise). Flooding damage is reported as the percentage of flood insurance contracts activated during the period, divided into nine categories, from 0% to 15%. The data come from the German Association of Insurers.

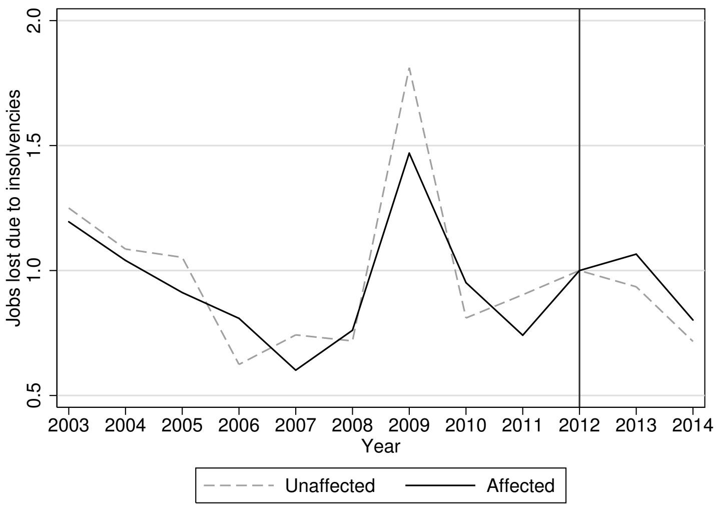


Figure 2: Jobs lost due to firm insolvencies by affected and non-affected regions

This figure plots the number of jobs lost due to insolvencies of German firms over time, relative to the year 2012. The solid line represents all counties affected by the flood (damage category < 2.5), and the dashed line indicates the unaffected counties (damage category ≥ 4). The data come from official German insolvency statistics.

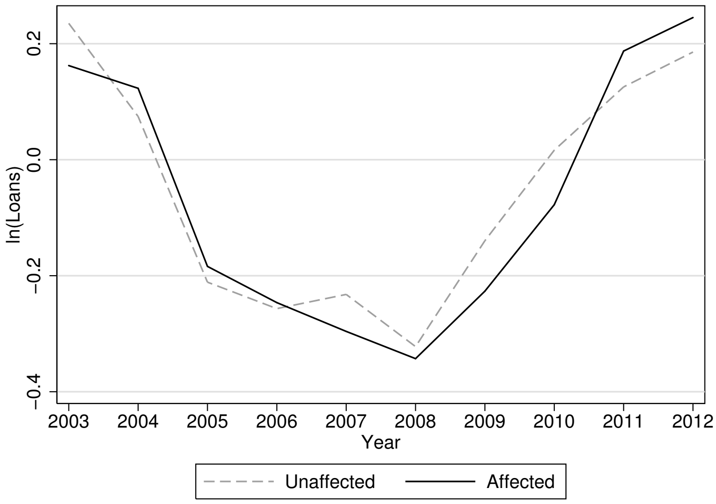


Figure 3: Parallel trend inspection

This figure plots the demeaned loan level of unaffected (dashed line) and affected (solid line) banks over time for the years before the flood, 2003-2012. Demeaning is done by subtracting the overall mean for each respective group from each particular year's mean value.

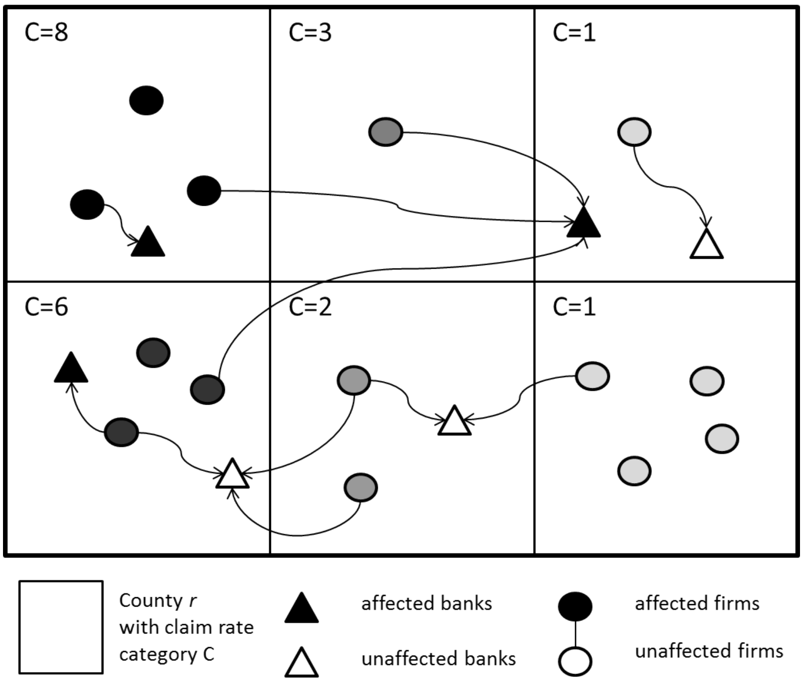


Figure 4: Identification of affected banks

This figure illustrates our identification of affected and unaffected banks. Each square displays an artificial county with firms (circles) and banks (triangles). The level of flooding affecting each firm is indicated by different shades of grey, such that darker colors indicate greater effects of the flood. Firms are affected when the county they are located is affected, such as $C = 8$. Banks can be affected in two ways: if they are located in an affected county ($C = 8$) or if they are located in an unaffected county, such as $C = 1$ but are connected (illustrated by arrows) to firms in affected counties (e.g., left most bank in $C = 1$). What matters for our identification is the bank's (weighted) mean of its firm connections. If this mean is ≥ 4, banks get classified as affected (black), whereas if it is < 2.5, they are classified as unaffected (white).

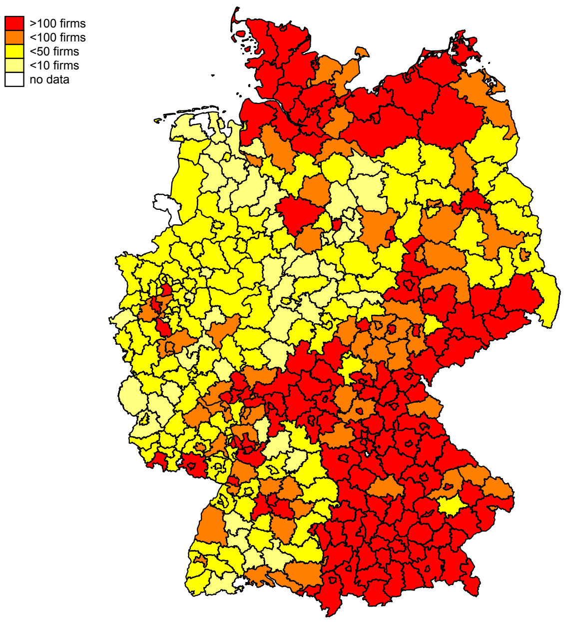
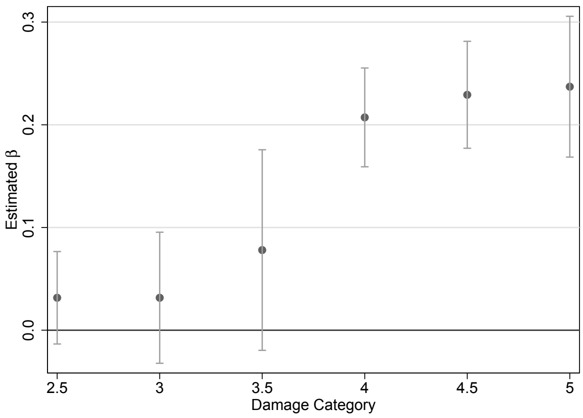


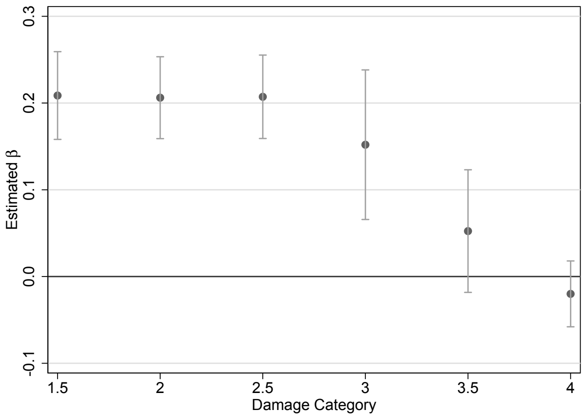
Figure 5: Number of firms connected to all Munich banks by region

This figure shows the number of firms connected to all banks located in Munich, by German counties. The data comes from the bank-firm connections that we drew from the Dafne database.

Figure 6: Varition of the tresholds for affected and unaffected banks



(a) $\hat{\beta}$s for affected thresholds 2.5-5



(b) $\hat{\beta}$s for unaffected thresholds 1.5-4

These figures display the estimated β coefficients ($\hat{\beta}$) from the baseline difference-in-difference estimation of changes in log of gross loans for savings and cooperative banks located in unaffected regions. Panel (a) shows the results when the threshold for unaffected banks is set to values lower than 2.5 and the upper thresholds varies according to the values displayed on the x-axis. If the affected threshold is >5, the number of affected banks is too low for reasonable estimates. In Panel (b) the threshold for affected banks is set to $\geq$ 4, and the thresholds for unaffected banks varies according to the values displayed on the x-axis. If the unaffected threshold is set to <1.5, the number of unaffected banks is too low for reasonable estimates.

Table I: Variable Definitions

Variable	Definition
Main Variables	
Affected2013	Dummy variable indicating whether a bank is affected by the flood through its firms. A value of 1 indicates that the average firm of any bank is exposed with a value of category 4 or higher, while a value of 0 indicates its average firm is exposed by anything less than 2.5
Gross 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. The vast majority of banks only report the following three sub-categories:
Public	Official: Loans and leases to corporate and commercial firms. In practice: Loans to public (local) authorities
Mortgage	Loans secured by a land charge (usually residential property)
Other	All Loans and leases which 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.
Bank deposits	The sum of all deposits from 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.
Size	Total assets in Billion USD.
Cap. Adequacy	% Share of equity on Total Assets. Includes 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
Assets - Share of TA	
Gross Loans	Share of Gross Loans on Total Assets.
Net Loans	Share of Net Loans on Total Assets. Net loans: Gross loans - Loan Loss Reserves
Loan Loss Reserves	Share of Loan Loss Reserves on Total Assets. LLR: Reserve against possible losses on impaired or non performing loans
Interbank Loans	Share of Interbank Loans on Total Assets. Interbank: Interest-earning balances with central banks and loans and advances to banks net of impairment value including loans pledged to banks as collateral
Securities	Share of Securities on Total Assets. Securities: Includes reverse repos and cash collateral + Trading securities + Derivatives + Available for sale securities + Held to maturity securities + At-equity investments + Other securities
Impaired Loans	Reserve against possible losses on impaired or non performing loans as a share of Gross Loans
Risk and Return	
Risk (Z-score)	Distance to default measure. Z-score is defined as ln(RoA + (Equity/Total Assets)/sd(RoA))
RoA (%)	Net Income/Average Total Asset in %
RoE (%)	Return on Equity in %.
Interest Expense	Includes Interest Expense on Customer Deposits+ Other Interest Expense + Preferred Dividends Paid & Declared
Interest Income	Includes Interest and Commissions received on loans, advances and leasing
Net Interest Income	Net interest income or expense (net position) in million USD
Relationship Indicators	
Affected2002	Dummy Variable indicating whether the bank was also affected by a similar flood in 2002 via its firms, analogous to the Affected2013 variable
Total Funding	Total Funding in Billion USD. Includes Total Deposits, Money Market and Short-term Funding+ Total Long Term Funding + Derivatives + Trading Liabilities
Number of firms	Number of firms who report a relationship with a particular bank
Avg. Age of firms (years)	Average age in years of the relationship between the bank and its firms
Avg. Distance to firms (km)	Average direct distance between the center of the zipcode of the bank and the center of the zipcode of the firms

Table II: Descriptive Statistics

	a) All Banks					b) Savings and Cooperatives				
				Percentile					Percentile	
	N	Mean	SD	1st	99th	N	Mean	SD	1st	99th
Main Variables										
Affected2013	12830	0.269	0.444	0.000	1.000	11749	0.283	0.451	0.000	1.000
Gross Loans (bil$)	15902	7.865	82.267	0.016	149.974	14296	4.955	31.861	0.019	131.988
Total Assets (bil$)	15902	15.681	141.763	0.038	328.830	14296	9.324	59.112	0.037	253.790
Public Loans (bil$)	10017	0.521	6.628	0.000	6.750	9415	0.216	2.265	0.000	3.282
Mortgage Loans (bil$)	10209	3.837	52.500	0.000	82.722	9506	2.531	14.587	0.000	78.960
Other Loans (bil$)	15895	4.916	52.338	0.006	100.191	14296	3.118	21.186	0.007	76.575
Cap. Adequacy	15902	0.072	0.039	0.021	0.173	14296	0.070	0.021	0.034	0.134
Liquidity	15902	0.022	0.027	0.000	0.063	14296	0.021	0.008	0.000	0.044
Assets - Share of TA										
Gross Loans	15902	0.574	0.151	0.085	0.877	14296	0.585	0.126	0.251	0.840
Net Loans	15902	0.572	0.150	0.083	0.869	14296	0.583	0.126	0.250	0.833
Loan Loss Reserves	3751	0.010	0.010	0.000	0.039	3317	0.010	0.010	0.000	0.036
Inter bank Loans	15889	0.126	0.112	0.003	0.648	14295	0.113	0.078	0.004	0.369
Securities	15863	0.258	0.126	0.003	0.625	14296	0.262	0.115	0.041	0.592
Impaired Loans	3588	0.039	0.035	0.000	0.147	3270	0.039	0.035	0.000	0.140
Risk and Return										
Risk(Z-score)	14720	3.937	0.953	1.517	6.417	13119	4.056	0.870	2.410	6.471
SD(RoA)	15902	0.002	0.008	0.000	0.019	14296	0.002	0.002	0.000	0.007
RoA	15889	0.003	0.005	-0.001	0.018	14284	0.003	0.003	0.000	0.012
RoE	15889	0.039	0.125	-0.023	0.220	14284	0.036	0.037	0.000	0.167
Interest Expense	15856	0.019	0.009	0.000	0.042	14251	0.019	0.007	0.000	0.033
Interest Income	15856	0.043	0.012	0.015	0.066	14251	0.043	0.008	0.026	0.059
Net Interest Income	15888	0.024	0.009	0.003	0.039	14283	0.024	0.005	0.013	0.036
Relationship Indicators										
Affected2002	13433	0.247	0.431	0.000	1.000	12336	0.239	0.427	0.000	1.000
Total Funding (bil$)	15902	13.813	127.643	0.033	287.130	14296	8.411	53.316	0.033	231.439
Number of firms per Bank	15900	746.150	3448.819	2.000	4824.000	14294	575.618	992.694	6.000	4404.000
Average Age of Relationship	15902	7.040	1.868	3.667	12.000	14296	7.104	1.853	4.063	12.000
Average Distance to firm	14718	35.425	66.146	0.000	319.980	11205	20.707	34.793	0.000	196.667

This table presents summary statistics for all the variables we use in our analyses. Banks' balance sheet information come from Bankscope. Information on the number, age, and distance of the banks' firms are taken from the match of firms in the Dafne database with banks from Bankscope. Average distance to firms is calculated as the average direct distance from the center of the zipcode of the bank and the center of the zipcode of the firms. public, mortgage, and other are the three main subgroups of gross loans. Gross loans, commercial, mortgage, size and total deposits are reported in billions of U.S. dollars. Shares are reported as shares of total assets. Detailed definitions of the variables are provided in Table I. We provide descriptive statistics by affected and unaffected banks (pre-/post) in the online appendix.

Table III: Comparison of banks affected through their firms versus by their own location

		Exposure			
		Unaffected	Buffer	Affected	Total
	1	774	44	2	820
	2	137	15	3	155
Category	3	15	124	3	142
of	4	10	105	52	167
Bank	5	1	11	188	200
County	6	0	1	57	58
	7	0	0	37	37
	8	0	0	14	14
	9	0	0	2	2
	Total	937	300	358	1595

This cross table displays the (non-)overlap between banks in directly affected counties (banks' location) and banks' exposure to the flood through their firms. The vertical columns display the damage category of banks in their respective county. The horizontal rows display the categories of the affected variable assigned to the bank, according to its firm connection from Equation (3). The cells then refer to the number of banks with each respective combination of damage category assigned according to their own location versus due to the category assigned from the exposure through their firms.

Table IV: *Recovery lending* by banks with disaster-struck borrowers after the flood

	(1)	(2)	(3)	(4)
	All Banks		Savings and Cooperatives	
	ln(Loans)	ln(Loans)	ln(Loans)	ln(Loans)
Affected2013×Post	-0.0842	-0.1535	0.2076***	0.2058***
	(0.1332)	(0.1335)	(0.0242)	(0.0231)
Size	0.9626***	0.9659***	0.9579***	0.9680***
	(0.0473)	(0.0480)	(0.0183)	(0.0163)
Cap. Adequacy	-1.2318**	-1.2930**	1.4216***	1.3395***
	(0.5187)	(0.5229)	(0.3237)	(0.3736)
Liquidity	-1.3854**	-1.3764**	0.3315	0.3990
	(0.5940)	(0.5938)	(0.2500)	(0.2859)
Observations	12830	9885	11749	8867
Banks	1295	996	1169	876
Affected Banks	358	60	342	49
Within R2	0.6869	0.6929	0.8009	0.8310
Banks flooded themselves?	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes
Time × Region FE	Yes	Yes	Yes	Yes

This table shows regression results for Equation (1). The dependent variable in all four columns is the natural logarithm of banks' gross loans (ln(Loans)). Column (1) reports the effect for all banks in the sample. Column (2) reports effects only for banks located in non-heavily flooded regions. Column (3) reports the effects for savings and cooperative banks. Column (4) reports the effects for savings and cooperative banks located in non-heavily flooded regions. Affected is a dummy variable indicating, whether a bank is affected by the flood through its firms, according to the definition in Equation (3); a value of 1 indicates that the average firm of any bank is affected in category 4 or higher, whereas a value of 0 indicates that its average firm is affected by anything lower than category 2.5. Post is a dummy equal to 0 for the years 2003-2012 and 1 for 2013-2014. Included control variables are size, capital adequacy, and liquidity. Size is the natural logarithm of total assets. Capital adequacy is the ratio of equity to total assets. Liquidity is the share of cash on total assets. We control for bank and region×year fixed effects. Clustered standard errors on the bank level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table V: Robustness and falsification tests for the *recovery lending* effect

	(1)	(2)	(3)	(4)	(5)
	Matched Sample ln(Loans)	Symmetric Periods ln(Loans)	Collapsed Sample ln(Loans)	Placebo Event ln(Loans)	Falsification ln(Loans)
Affected2013×Post	0.1726***	0.1040*	0.2232***	0.1381	-0.0025
	(0.0326)	(0.0570)	(0.0253)	(0.1115)	(0.0068)
Size	0.9219***	0.9085***	0.9860***	0.9625***	0.9785***
	(0.0600)	(0.0302)	(0.0136)	(0.0207)	(0.0169)
Cap. Adequacy	1.5719**	1.1143***	0.7605*	1.7538***	1.3745***
	(0.6564)	(0.3295)	(0.4580)	(0.2934)	(0.2496)
Liquidity	1.3760**	-0.0377	1.3281**	0.1830	0.4740**
	(0.6129)	(0.2862)	(0.6424)	(0.2755)	(0.2264)
Observations	3691	3450	1752	6515	14296
Banks	364	876	876	876	1419
Affected Banks	48	49	49	49	301
Within R2	0.6508	0.6561	0.8629	0.8223	0.8039
Banks flooded themselves?	No	No	No	No	No
Bank FE	Yes	Yes	Yes	Yes	Yes
Time × Region FE	Yes	Yes	Yes	Yes	No
Controls	Yes	Yes	Yes	Yes	Yes

This table shows the regression results for Equation (1). The dependent variable in all four columns is the natural logarithm of banks' gross loans (ln(Loans)). This sample only includes not directly flooded savings and cooperative banks. Column (1) reports the results based on a matched sample, based on a 1:1 caliper match, using size, capital adequacy, and liquidity as the matching parameters (caliper width of 0.01). Column (2) reports the effects for equal pre- and post-flood periods. The pre-flood period thus includes 2011 and 2012, while 2013 and 2014 constitute the post-flood period. Column (3) reports the effects for the collapsed data sample (Bertrand et al., 2004). Column (4) displays the placebo difference-in-difference estimation of changes in gross loans, placing the placebo event in 2005. In this regression, Post is a dummy variable equal to 0 from 2003-2004 and 1 from 2005-2012. Column (5) displays the results of a supply effect falsification test, using the banks' direct location as a measure of being affected. The affected dummy is equal to 1 if they are located in a county classified category 5 or higher and unaffected if they are assigned to a category lower than 5. Affected is a dummy variable indicating, whether a bank is affected by the flood through its firms, according to the definition in Equation (3); a value of 1 indicates that the average firm of any bank is affected in category 4 or higher, whereas a value of 0 indicates that its average firm is affected by anything lower than category 2.5. Post is a dummy equal to 0 for the years 2003-2012 and 1 for 2013-2014. Included control variables are size, capital adequacy, and liquidity. Size is the natural logarithm of total assets. Capital adequacy is the ratio of equity to total assets. Liquidity is the share of cash on total assets. We control for bank and region×year fixed effects. Clustered standard errors on the bank level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table VI: Growth of gross loan components

	(1) Gross Loans	(2) Real Estate Loans	(3) Public Loans	(4) Other Loans
Affected2013×Post	0.0929***	0.0492	-0.4608***	0.1972**
	(0.0130)	(0.1638)	(0.0873)	(0.0835)
Observations	5772	5772	5772	5772
Banks	863	863	863	863
Affected Banks	48	48	48	48
Within R2	0.8648	0.1653	0.0960	0.6212
Banks flooded themselves?	No	No	No	No
Bank FE	Yes	Yes	Yes	Yes
Time × Region FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

This table shows the regression results for Equation (1), using different (sub-)categories of loans as the dependent variable. All dependent variables are expressed in natural logs. This sample only includes not directly flooded savings and cooperative banks. Column (1) reports the results for gross loans, using the sample for which the three main sub-categories are available. Column (2) reports the results for real estate loans, which are secured by a land charge (usually residential property). Column (3) reports the results for loans made to public institutions. Column (4) reports the results for all other loans to non-financial firms, not covered by other categories. Affected is a dummy variable indicating, whether a bank is affected by the flood through its firms, according to the definition in Equation (3); a value of 1 indicates that the average firm of any bank is affected in category 4 or higher, whereas a value of 0 indicates that its average firm is affected by anything lower than category 2.5. Post is a dummy equal to 0 for the years 2003-2012 and 1 for 2013-2014. Included control variables are size, capital adequacy, and liquidity. Size is the natural logarithm of total assets. Capital adequacy is the ratio of equity to total assets. Liquidity is the share of cash on total assets. We control for bank and region×year fixed effects. Clustered standard errors on the bank level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table VII: Growth of funding components

	(1) Total Deposits	(2) Customer Deposits	(3) Bank Deposits	(4) Wholesale Funding
Affected2013×Post	0.0009	0.0294**	-0.2674***	-0.4566
	(0.0017)	(0.0124)	(0.0974)	(0.2825)
Observations	8867	8867	8867	8867
Banks	876	876	876	876
Affected Banks	48	48	48	48
Within R2	0.9826	0.8755	0.5083	0.0259
Banks flooded themselves?	No	No	No	No
Bank FE	Yes	Yes	Yes	Yes
Time × Region FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

This table shows the regression results for Equation (1), using different (sub-)categories of bank funding as the dependent variable. All dependent variables are expressed in natural logs. This sample only includes not directly flooded savings and cooperative banks. Column (1) reports the results for total deposits, using the sample for which the three main sub-categories are available. Column (2) reports the results for customer loans. Column (3) reports the results for deposits from other banks. Column (4) reports the results whole funding which comprises long term funding, derivatives and trading liabilities. Affected is a dummy variable indicating, whether a bank is affected by the flood through its firms, according to the definition in Equation (3); a value of 1 indicates that the average firm of any bank is affected in category 4 or higher, whereas a value of 0 indicates that its average firm is affected by anything lower than category 2.5. Post is a dummy equal to 0 for the years 2003-2012 and 1 for 2013-2014. Included control variables are size, capital adequacy, and liquidity. Size is the natural logarithm of total assets. Capital adequacy is the ratio of equity to total assets. Liquidity is the share of cash on total assets. We control for bank and region×year fixed effects. Clustered standard errors on the bank level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table VIII: Asset composition effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Gross Loans	Net Loans	Loan Loss	Interbank	Securities	Liquidity	Impaired loans
			Share of Total Assets				Share of Gross Loans
Affected2013×Post	0.0868***	0.0850***	-0.0028	-0.0209	-0.0601	0.0080	-0.0313***
	(0.0084)	(0.0075)	(0.0025)	(0.0596)	(0.0631)	(0.0088)	(0.0091)
Observations	8867	8867	2078	8866	8867	8867	2047
Banks	876	876	809	876	876	876	802
Affected Banks	49	49	42	49	49	49	42
Adj. R2	0.8991	0.9008	0.0314	0.7020	0.8206	0.6189	0.3854
Within R2	0.0411	0.0435	0.0143	0.0040	0.0312	0.0103	0.0274
Banks flooded themselves?	No	No	No	No	No	No	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time × Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows the regression results for Equation (1). All dependent variables are reported as ratios. This sample only includes not directly flooded savings and cooperative banks. Columns (1)-(6) report shares of total assets. Column (7) reports the share of gross loans. Column (1) presents the estimates for the share of gross loans, Column (2) for net loans, Column (3) for loan loss reserves, Column (4) for interbank loans, Column (5) for securities, Column (6) for Liquidity (cash), and Column (7) presents the estimates with impaired loans as a share of gross loans as the dependent variable. Affected is a dummy variable indicating, whether a bank is affected by the flood through its firms, according to the definition in Equation (3); a value of 1 indicates that the average firm of any bank is affected in category 4 or higher, whereas a value of 0 indicates that its average firm is affected by anything lower than category 2.5. Post is a dummy equal to 0 for the years 2003-2012 and 1 for 2013-2014. Included control variables are size, capital adequacy, and liquidity. Size is the natural logarithm of total assets. Capital adequacy is the ratio of equity to total assets. Liquidity is the share of cash on total assets. We control for bank and region×year fixed effects. Clustered standard errors on the bank level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table IX: Risk and return effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Z-score	Capital Adequacy	Return on Assets	Return on Equity	Interest Expense	Interest Income over Assets	Net Interest Income
Affected2013×Post	0.1368**	0.0008	0.0026***	0.0472***	-0.0020*	-0.0008	0.0012
	(0.0672)	(0.0034)	(0.0007)	(0.0144)	(0.0011)	(0.0009)	(0.0013)
Observations	8257	8867	8864	8864	8847	8847	8863
Banks	802	876	876	876	876	876	876
Affected Banks	41	49	49	49	49	49	49
Adj. R2	0.9826	0.8775	0.3264	0.2723	0.8673	0.8292	0.7768
Within R2	0.0241	0.0467	0.0078	0.0010	0.0045	0.0152	0.0455
Banks flooded themselves?	No	No	No	No	No	No	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time× Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows the regression results for Equation (1). All columns have different dependent variables. This sample here only includes not directly flooded savings and cooperative banks. Column (1) 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, such that higher values indicate decreased riskiness (Laeven and Levine, 2009). Column (2) provides the estimates for capital adequacy, defined as total equity over total assets. Column (3) presents the results for return on assets, whereas Column (4) refers to the return on equity. Columns (5) and (6) show the results of banks' interest expenses and income over total assets, respectively. In Column (7), we use the banks' net interest income (interest income - interest expense) over total assets as the dependent variable. Affected is a dummy variable indicating, whether a bank is affected by the flood through its firms, according to the definition in Equation (3); a value of 1 indicates that the average firm of any bank is affected in category 4 or higher, whereas a value of 0 indicates that its average firm is affected by anything lower than category 2.5. Post is a dummy equal to 0 for the years 2003-2012 and 1 for 2013-2014. Included control variables are size, capital adequacy, and liquidity. Size is the natural logarithm of total assets. Capital adequacy is the ratio of equity to total assets. Liquidity is the share of cash on total assets. We control for bank and region×year fixed effects. Clustered standard errors on the bank level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table X: Relationship lending as an amplifier of recovery banking

	(1)	(2)	(3)	(4)	(5)
	ln(Loans)	ln(Loans)	ln(Loans)	ln(Loans)	ln(Loans)
Affected2013×Post	0.1792***	0.2172***	0.1564***	0.2304***	0.2171***
	(0.0328)	(0.0274)	(0.0430)	(0.0386)	(0.0467)
Affected2013×Affected2002×Post	-0.0158				
	(0.0650)				
Affected2013×Savings× Post		-0.0402			
		(0.0328)			
Affected2013×firms/TA×Post			0.1544**		
			(0.0625)		
Affected2013×AvgRelLength×Post				-0.0907***	
				(0.0325)	
Affected2013×AvgRelDistance×Post					-0.0550
					(0.0463)
Affected2002×Post	-0.0072				
	(0.0472)				
Savings×Post		0.0214***			
		(0.0079)			
firms/TA×Post			-0.0078		
			(0.0083)		
AvgRelLength×Post				0.0190*	
				(0.0097)	
AvgRelDistance×Post					-0.0106
					(0.0105)
Observations	7478	8867	8867	8867	6904
Banks	809	876	876	876	699
Affected Banks	49	49	49	49	49
Bank in Triple Interaction	16	24	24	26	13
Adj. R2	0.9984	0.9985	0.9985	0.9985	0.9987
Within R2	0.8486	0.8318	0.8318	0.8315	0.8617
Banks flooded themselves?	No	No	No	No	No
Bank FE	Yes	Yes	Yes	Yes	Yes
Time×Region FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

This table shows the regression results for Equation (1). The sample includes only savings and cooperative banks not directly affected by the flood. The dependent variable in all four columns is the natural logarithm of banks' gross loans (ln(Loans)). This table shows variants of the baseline regression with triple interactions using different indicators for relationship banks. The first interaction is a triple interaction with a dummy for banks that were also affected through their firms by the 2002 flood. We present these results in Column (1). In Column (2), we present a triple interaction with a dummy that identifies savings banks. The third triple-interaction indicator in Column (3) is a dummy based on the average number of firms over a bank's total assets in the pre-flood years. The dummy (TA/firms) is equal to 0 if the bank is below the 75th percentile of this distribution and 1 if it is above the 75th percentile. Column (4) reports the results for a dummy based on the average age of the relationship each bank has with its customers in the pre-flood years. The dummy (AvgRelLength) is equal to 0 if the bank is below the 75th percentile of this distribution and 1 if it is above the 75th percentile. Column (5) reports the results for a dummy based on the average distance of each bank to its customers in the pre-flood years. The distance is based on the linear distance between the zipcodes of the banks and firms respectively. The dummy (AvgRelDistance) is equal to 1 if the bank is above the 75th percentile of this distribution and equal to 0 if it is below the 75th percentile. Affected is a dummy variable indicating, whether a bank is affected by the flood through its firms, according to the definition in Equation (3); a value of 1 indicates that the average firm of any bank is affected in category 4 or higher, whereas a value of 0 indicates that its average firm is affected by anything lower than category 2.5. Post is a dummy equal to 0 for the years 2003-2012 and 1 for 2013-2014. Included control variables are size, capital adequacy, and liquidity. Size is the natural logarithm of total assets. Capital adequacy is the ratio of equity to total assets. Liquidity is the share of cash on total assets. We control for bank and region×year fixed effects. Clustered standard errors on the bank level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Online appendix

Table OA1: *Recovery lending* by banks with disaster-struck borrowers after the flood: lagged controls and w/o controls

	Lagged control variables				W/o control variables			
	(1)	(2)	(3)	(4)	(5)	(5)	(7)	(8)
	All Banks		Savings and Cooperatives		All Banks		Savings and Cooperatives	
	ln(Loans)	ln(Loans)	ln(Loans)	ln(Loans)	ln(Loans)	ln(Loans)	ln(Loans)	ln(Loans)
Affected2013×Post	0.0131	-0.0576	0.3259**	0.3261**	-0.1019	-0.2048	0.3300*	0.3300*
	(0.1043)	(0.0991)	(0.1369)	(0.1347)	(0.2378)	(0.2480)	(0.1961)	(0.1949)
L.Size	0.7857***	0.7913***	0.7775***	0.7926***				
	(0.0383)	(0.0386)	(0.0222)	(0.0184)				
L.Cap. Adequacy	-1.1589	-1.1797	1.1116***	1.1057**				
	(0.7651)	(0.7878)	(0.3960)	(0.4513)				
L.Liquidity	-2.3306**	-2.3537**	0.2023	0.1623				
	(0.9156)	(0.9316)	(0.2822)	(0.3239)				
Observations	11509	8872	10562	7981	12830	9885	11749	8867
Banks	1295	996	1169	876	1295	996	1169	876
Affected Banks	358	60	342	49	358	60	342	49
Within R2	0.5044	0.5119	0.5154	0.5401	0.0002	0.0008	0.0016	0.0019
Banks flooded themselves?	Yes	No	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time × Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows regression results for Equation (1). The dependent variable in all four columns is the natural logarithm of banks' gross loans (ln(Loans)). Column (1) reports the effect for all banks in the sample. Column (2) reports effects only for banks located in non-heavily flooded regions. Column (3) reports the effects for savings and cooperative banks. Column (4) reports the effects for savings and cooperative banks located in non-heavily flooded regions. Affected is a dummy variable indicating, whether a bank is affected by the flood through its firms, according to the definition in Equation (3); a value of 1 indicates that the average firm of any bank is affected in category 4 or higher, whereas a value of 0 indicates that its average firm is affected by anything lower than category 2.5. Post is a dummy equal to 0 for the years 2003-2012 and 1 for 2013-2014. Included control variables are size, capital adequacy, and liquidity. Size is the natural logarithm of total assets. Capital adequacy is the ratio of equity to total assets. Liquidity is the share of cash on total assets. "L." indicates that a variable is lagged by one year. We control for bank and region×year fixed effects. Clustered standard errors on the bank level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA2: *Recovery lending* by banks with disaster-struck borrowers after the flood: controlling for the banks' industry concentration

	(1)	(2)	(3)	(4)
	All Banks		Savings and Cooperatives	
	ln(Loans)	ln(Loans)	ln(Loans)	ln(Loans)
Affected2013×Post	-0.3631	-0.3610	0.1903***	0.1923***
	(0.2252)	(0.2212)	(0.0241)	(0.0258)
Size	0.9564***	0.9610***	0.9647***	0.9733***
	(0.0758)	(0.0782)	(0.0188)	(0.0162)
Cap. Adequacy	-1.4416**	-1.4885**	1.5028***	1.5113***
	(0.6455)	(0.6411)	(0.3019)	(0.3437)
Liquidity	-1.0683	-1.0518	0.1928	0.3309
	(0.8524)	(0.8416)	(0.2892)	(0.3182)
HHI	0.0021	-0.0050	0.0071	-0.0005
	(0.0255)	(0.0315)	(0.0095)	(0.0114)
Observations	9190	7044	8438	6334
Banks	1244	959	1126	847
Affected Banks	358	60	342	49
Within R2	0.6293	0.6312	0.8460	0.8721
Banks flooded themselves?	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes
Time × Region FE	Yes	Yes	Yes	Yes

This table shows regression results for Equation (1). The dependent variable in all four columns is the natural logarithm of banks' gross loans (ln(Loans)). Column (1) reports the effect for all banks in the sample. Column (2) reports effects only for banks located in non-heavily flooded regions. Column (3) reports the effects for savings and cooperative banks. Column (4) reports the effects for savings and cooperative banks located in non-heavily flooded regions. Affected is a dummy variable indicating, whether a bank is affected by the flood through its firms, according to the definition in Equation (3); a value of 1 indicates that the average firm of any bank is affected in category 4 or higher, whereas a value of 0 indicates that its average firm is affected by anything lower than category 2.5. Post is a dummy equal to 0 for the years 2003-2012 and 1 for 2013-2014. Included control variables are size, capital adequacy, and liquidity. Size is the natural logarithm of total assets. Capital adequacy is the ratio of equity to total assets. Liquidity is the share of cash on total assets. HHI is a size-weighted Herfindahl Index on the bank level that considers the industry classifications of the banks' borrowers. We control for bank and region×year fixed effects. Clustered standard errors on the bank level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.