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Flooded through the Back Door: The Role of Capital in Local Shock Spillovers

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Flooded through the back door: The role of bank capital in local shock spillovers*

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Abstract

This paper demonstrates that low bank capital carries a negative externality because it amplifies local shock spillovers. We exploit a natural disaster that is transmitted to firms in non-disaster areas via their banks. Firms connected to a strongly disaster-exposed bank with lowest-quartile capitalization significantly reduce total borrowing by 4.8 %, employment by 2.7% and tangible assets by 7.5% compared to similar firms connected to a well-capitalized bank. These findings translate to negative regional effects on GDP and unemployment. Banks also particularly reduce their exposure to this-time-unaffected but in general disaster-prone areas following a disaster.

JEL classification: G21, G29, E44, E24
Keywords: natural disaster, real effects, shock transmission, bank capital

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1 Introduction

Higher levels of bank capital help to prevent bank failure and as a result can make the financial system more stable. This paper demonstrates that bank capital is also key in preventing real economic spillovers from one region to another. Using a natural disaster as a shock to the real economy, we show that the disaster spreads through low-capital banks to non-disaster affected firms, causing a significant decline in firms' real outcomes and translating to negative effects on aggregate regional GDP. The results indicate that there are previously disregarded positive externalities of higher bank capital, even if the stability of a given bank or the financial system as a whole is not threatened, because better capitalized banks do not transfer shocks to out of region, non-shocked firms.

The paper proceeds in two steps to demonstrate that the disaster spills over to out-of-region firms, which are exposed to it exclusively through their banks. Exploiting significant flooding of German regions in June of 2013, we identify firms in disaster areas and use their bank connections to identify the disaster exposure of banks. This step has been similarly used by Koetter et al. (2019), who show at the bank level that German banks increase their lending in the aftermath of flooding into the disaster region. They also demonstrate that firms in the disaster region benefit from this additional lending. Starting from there, this paper then identifies firms in *non-flooded* areas which are connected to disaster-exposed banks and compares them to firms which are located in the same region, but do not have a connection to a disaster-exposed bank. This approach is designed to isolate the effect of a reduction in bank funding for firms, as banks reduce lending in non-flooded areas to provide loans to flood-affected firms.

On average, banks' lending shifts from non-disaster regions into disaster regions entails a reduction in borrowing by 2.4%, employment by 2.1% and tangible assets by 4.5% for firms with a connection to a strongly exposed bank. However, this negative lending shift is exclusively driven by low-capital banks. After splitting banks into capitalization quartiles, only firms connected to strongly exposed low-capital banks experience a significant decrease in borrowing by 4.8%, employment by 2.7% and tangible assets by 7.5%. Firms connected to disaster exposed banks with sufficient capital are unaffected by the indirect disaster exposure. We show that the effects of this local shock amplification stemming from low levels of bank capital also affects aggregate regional GDP. Thus, even if an increase in bank capital causes lending reductions in normal times and is thus costly for firms (Gropp et al., 2019), better bank capitalization can prevent lending reductions after frequent small shocks to the real economy. The occurrence of firm-level real effects also strongly suggests that better capitalized banks do not jump in to replace reduced lending from less capitalized banks. This may be due to the fact that bank-firm relationships tend to be relatively stable and getting loans from other banks might be associated with high switching costs and information asymmetries.

Additional results demonstrate that firms located in regions with higher ex-ante disaster risk (but outside of the 2013 disaster regions) also suffer disproportionately large real effects. This finding is independent from the level of bank capital held by indirectly disaster-affected firms' banks. It suggests that banks shift lending away from disaster-risk after a natural disaster, to the detriment of firms in high-disaster risk regions. We suggest that this can be most easily explained by banks' need to re-balance their portfolio with regard to disaster risk, following an increase in lending into disaster regions. This finding further underscores the idea that banks' lending increase to natural disaster regions, which has been shown frequently in the literature (Cortés and Strahan, 2017), implies lending reductions and as a result real effects through a variety of channels, two of which we uncover in this paper.

Understanding the role of bank-capital in *local* shock spillovers is crucial. While global financial crises are rare, sudden changes to a regional economy are frequent. In Germany, each year, about 12% of counties experience a decline in GDP, even if omitting the crisis years of 2007, 2008 and 2009. For about 1% of regions, this negative shock to GDP is comparable in size to the shock of the financial crisis to the overall German economy

(-5.6% GDP in 2009).[1] This back-of-the-envelope calculation implies that every year, about 5 German counties experience a negative event that has similar economic effects as the financial crisis. As a result, understanding banks' lending reallocation patterns following local shocks is extremely important.

This paper contributes to the large discussion about the importance of bank capital for real firm outcomes. A number of studies have shown that low bank capital levels can amplify lending shocks. Most of these studies have focused on the effect of bank capital for banks' lending behavior, especially during financial crises. However, fewer studies have focused on the importance of bank capital for real, firm-level outcomes.[2] Gan (2007) shows that higher lenders' capital ratios are associated with higher investment rates of the borrowing firm. Kapan and Minoiu (2013) show that banks with higher capital ratios were able to more effectively maintain lending supply following the financial crisis of 2008 and as a result, firms borrowing from low-capital banks performed significantly worse. This paper expands the literature by highlighting the importance of bank capital to prevent local shocks from spilling over into different regions. Since one might expect that other banks can replace lending reductions in normal times, this finding is far from obvious and demonstrates that low bank capital poses an amplification risk even in normal times.

In addition to demonstrating the amplification effect of low bank capital levels, this paper also contributes to the literature on the real effects of bank lending reductions to firms (Chodorow-Reich, 2014; Huber, 2018).[3] The first contribution to this literature is

[1]Source: Statistisches Bundesamt and own calculations. Specifically, 12% of year-on-year changes in GDP are negative on the county level and 1% are a 5% decline or more. Frequently this is not due to a declining trend, but rather to unexpected regional developments.

[2]For the importance of bank capital on loan supply also refer to: Jayaratne and Morgan (2000), Kishan and Opiela (2000), Gambacorta and Mistrulli (2004), Meh and Moran (2010). For the importance of firm capital buffers also see: Chatelain et al. (2003). This literature is also closely related to the literature on bank-capital regulation. While the literature on the bank-level (and systemic) effects of bank capital regulation is large (e.g., Admati (2016); Dagher et al. (2016)), only a few study examine the real effects of bank capital regulation (Gropp et al., 2019; Jiménez et al., 2017a).

[3]The list of papers on the real effects of credit market frictions is long and growing. Peek and Rosengren (2000) show that Japanese credit market frictions had an effect on U.S. real activity. Gan (2007) shows reductions in investment and firm valuation for firms exposed via their banks to the land market collapse in Japan. Chava and Purnanandam (2011) show that during the Russian crisis, firms that relied on bank financing suffered real consequences. Almeida et al. (2012) show that firms whose

methodological. Most prior studies rely on banks' exposure to financial market frictions, such as the exposure to the financial crisis. One major caveat here is that bank choice may not be completely orthogonal to the banks' exposure to risky international financial markets. We argue that the credit supply shock arising from a natural disaster is better in this regard, because it is unexpected, especially for firms that are not directly located within the disaster regions. Our identification relies on the assumption that bank customers are unaware of their banks' disaster exposure prior to the flood. Given that there is some evidence that even insurance markets often fail to correctly price disaster risk (Froot, 2001), it seems unlikely that bank customers correctly price their banks' disaster risk. Additionally, the firms' bank choice must not be correlated with other factors that might be affected by flooding. We perform a number of additional checks to rule out these potential confounding factors without any change to the results.

Another contribution relates to the type of shock studied. There is ample evidence that financial shocks cross international borders (Popov and Udell, 2012; Puri et al., 2011; Schnabl, 2012). There is also growing within-country evidence that shocks can propagate to other national regions via integrated financial systems (Ben-David et al., 2017; Gilje et al., 2016; Chakraborty et al., 2018). We contribute to this literature by investigating real effects of a shock stemming from higher local credit *demand* elsewhere, instead of credit supply frictions arising in financial markets. We show that higher demand can be a driver of local shock spillovers and bank capital plays an important role in preventing them. Interpreting a natural disaster in a developed country as a demand shock is strongly supported by the literature, as both Chavaz (2016) and Cortés and Strahan (2017) document for the United States that banks reallocate funds towards mortgage loans in disaster-affected areas, while decreasing their lending to non-affected areas and

debt was maturing during the financial crisis cut their investment. Using bank-firm data from Italy, Cingano et al. (2016) estimate that the collapse of the interbank market decreased firm-level investment by 20%. Popov and Rocholl (2018) show that firms connected to German savings banks with exposure to U.S. mortgage markets performed worse than otherwise similar firms. Using firm-bank level data from Eastern Europe and Central Asia, Ongena et al. (2015) show that firms connected to internationally active banks suffer more during a financial shock. Berg (2018) provides evidence of negative real effects with rejected loan application data. Acharya et al. (2018) provide evidence that the European sovereign debt crisis had real, firm-level effects. Gropp et al. (2019) show that higher capital requirements cause credit reductions and subsequent negative real effects in firms.

(Koetter et al., 2019) demonstrate this demand effect specifically for the disaster used in this paper.[4]

2 The 2013 flood, insurance and government aid

Widespread flooding caused significant damages and loss of lives in Central Europe in June 2013 (Thieken, 2016). The flooding was caused by two main factors: pre-saturated soil levels combined with heavy rainfalls from May 30th to June 2nd (Schröter et al., 2015). Heavy flooding followed in many regions of Austria and in the following weeks in South-East Germany and the Czech Republic, causing many levee breaches and widespread flooding. Germany was mostly flooded in the areas around the Danube and Elbe river and their tributaries, which is why the event in Germany is often called “The Elbe Flood”. Despite its river-specific name, the 2013 flood event had a significant spatial distribution throughout Germany (see figure 1) and affected many major metropolitan areas, including major damage to the cities of Dresden, Passau, Halle (Saale) and Magdeburg.[5]

The 2013 flood was the biggest flood in Germany in terms of water discharge in the river network since 1954. In terms of economic damage, it was slightly smaller than the flooding of 2002, possibly because of flood protection measures instituted afterwards (Thieken, 2016). While initial reports indicated that the 2013 flooding exceeded the 2002 event in terms of damages, final estimates report the two events are similar in terms of the final economic damage: around 6-8 billion Euros for the 2013 flood and 11 billion for the 2002 flood. Of the 6-8 billion in damages, only 2 billion was insured (GDV, 2013), despite the 2002 flooding. This is in line with the idea that flood insurance costs rise

[4]The demand shock interpretation can be explained by the fact that bank lending is a good complement to insurance payouts and government aid for firms in the case of a natural disaster, in order to finance necessary rebuilding efforts. The unfulfilled loan demand in the aftermath of disasters in developing countries (Choudhary and Jain, 2017; Berg and Schrader, 2012) indicates that insurance and government aid may be crucial factors for banks to actually fulfill the increased loan demand in disaster regions, as such payments might serve as excellent down-payments or collateral for new loans. See section 2 for details regarding the specific flood and the subsequent government aid payments.

[5]Some of these damages were permanent. For example the ice hockey stadium in Halle (Saale) was flooded and has not been rebuilt to this date.

after the flood, as insurance companies adjust the rates after tail risks materialize. This is supported by the fact that insurance coverage is still low even after the 2013 flood (Thieken, 2016). In addition to low insurance coverage, the speed of insurance payments, especially during a large event can be slow. While the German Association of Insurers claims that payments can be made as quickly as two weeks after the damage is reported (GDV, 2013), in practice insurers' resources are often insufficient to accommodate so many contemporaneous claims.[6] As a result, going to a bank for flood relief and rebuilding efforts can be faster, especially when there is an option of drawing down on existing credit lines.

– Figure 1 around here –

Floods of this magnitude have several direct and indirect effects on firms in the flood area, with many difficult to estimate. Direct effects include damage to buildings and machines, but also turnover losses during the flood and during the rebuilding/repair effort. Indirect effects include health effects and interruptions of supply chains due to destroyed infrastructure. Thieken (2016) conducted a business survey following the flood, and found that the most frequent problem for businesses was in fact the loss of turnover, while the most significant in terms of economic damage was destroyed buildings and equipment. Considering the average total assets in our dataset of 14 million Euros, losses to firms were significant: on average surveyed firms reported around 1 million Euros in damages.

To recover the losses, uninsured firms could apply for flood relief from the German federal and state government. Even though the overall government fund was larger than the final damages, affected firms could claim a maximum of 80% of current asset value. For firms, rebuilding most often involves buying new equipment, which is more expensive than the

[6] Usually insurance claims that pass a certain amount will not be accepted on good faith, but the insurance company will send an expert to estimate the damage. Only after that assessment has taken place, the insurer will make a payment. Since such people are in limited supply, delays in the aftermath of disaster may be inevitable. There are no hard numbers on how long a "typical" insured person has to wait for insurance payments following a flood. Anecdotal evidence suggests that it is paid out within a few months, not a few weeks.

current value of the previous equipment. Further, only direct damages were reimbursed; indirect damages, such as losses from lost turnover, interrupted supply chains or employee productivity reduction were not reimbursed (BMI, 2013b). For all these reasons, it is thus likely that firms had to complement government aid by borrowing from banks in order to finance rebuilding efforts. Systematic evidence that banks indeed provided additional lending to disaster areas to the benefit of firms following the 2013 flood is provided by Koetter et al. (2019), who show that lending by banks and borrowing by firms increases in the disaster regions following the 2013 flood.

Flood prevention measures were taken after the 2002 flooding, however there is no indication that the 2013 flood was anticipated. Even during the flood, there was uncertainty about the extent to which water levels would rise. However, the 2002 flood may have increased the efficiency and especially the speed, with which aid relief was delivered following the 2013 flooding (BMI, 2013a). Both flood prevention measures and increased aid efficiency may have led to an overestimation of actual damages overall (Thieken, 2016), but there is no evidence that this effect was region or even firm specific. Live flood monitoring was also only expanded significantly after 2013, muting concerns that the 2002 flood caused the 2013 flood to be anticipated. Furthermore, there is no evidence that banks learned from the 2002 flood (Noth and Rehbein, 2019).

Taken together, the facts about the 2013 flood indicate that it was a significant and unexpected event for firms, which required firms to increase borrowing from banks. The expected government aid payments are likely to have served as good collateral or down-payments for financing rebuilding efforts. As a result, we hypothesize that banks who lent to - government supported - disaster areas reduced lending in other areas, resulting in potential negative real outcomes for firms located in non-disaster areas. It is important to highlight that while the flood event was certainly significant, the resulting loan shifts should be small in financial system terms. Total loans to non-financial corporations in Germany are roughly 800 billion Euros over the flood period. So, if roughly a third of the German financial system had to buffer the uninsured 4 billion in damages, this would still constitute just over 1% of total lending, hardly a large-scale shock in financial terms. This papers' results are particularly striking in this light, as banks propagate not only large financial shocks, but also small local shocks to "innocent" firm clients. This is important as local shocks can have multiple causes and occur much more frequently than large-scale financial crises.

3 Data

German firm-level data stems from the Dafne and Amadeus databases, both provided by Bureau van Dijk.[7] The former contains the name of the bank (or banks) with which each firm maintains a payment relationship (Popov and Rocholl, 2018).[8] Annual vintages of the Dafne database are used to construct a time-series of firm-bank relationships for more than a million firms between 2003 and 2014. We augment these firm-bank relationship data with firm-specific, annual financial accounts data from Amadeus.[9] The firm-level data is combined with bank-level data from Bankscope, another Bureau van Dijk database, using firm-bank relationships identified using a string-based match of bank names. Bankscope contains annual financial account information for the banks.[10]

To gauge the damage inflicted by the Elbe flood of 2013, we use a data set provided by the German Insurance Association (GDV). The data contains claims filed for insurance properties that were damaged during the flood between May 25 and June 15, 2013, as a

[7]The construction of the firm-bank level data largely follows Koetter et al. (2019), although they collapse the data to the bank level, while our data is on the firm level, which requires some additional cleaning.

[8]Firm-bank payment relationship data originate from scans of the firms' letterheads. We do not observe credit relationships directly. We also cannot identify branch-level information in the data. However, most banks in Germany are small, independent savings and cooperative banks with few or no branches. Additionally the identification strategy does not rely on the banks' (or branches) direct location. 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.

[9]Bureau van Dijk takes this information for German firms from the "Bundesanzeiger", where firms can report their balance sheet information. This reporting became more rigorously enforced starting in 2008.

[10]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 firm-bank relationships.

proportion of total insurance contracts, aggregated by county ("Kreis"), into nine damage categories.[11] Lower categories indicate less damage relative to the asset values covered by insurance contracts.[12] The GDV collects this information from all its 460 members, which include all major German insurance providers. The data also informs the risk calculation models of insurance companies and regional aggregates are reported regularly (GDV, 2013). We merge this flood level data with firms via their postal code.

The combination of the three datasets yields a firm-level dataset with information on each of the firms' banks, as well as the regional flood exposure of each firm based on the data from the German Insurance Association. We conduct a number of cleaning steps with the merged dataset. First, we drop firms and banks, for which no valid postal code can be matched and drop all inactive firms.[13] We also require firms to have reported at least their total assets, because otherwise the reporting accuracy might be questionable. We also drop all observations before 2008, because reporting of balance sheet information was not well enforced prior to that time. As a result, firms in the data before 2008 may have self-selected into the data (Popov and Rocholl, 2018). Because firms are often not reporting for all years[14] we require firms to be in the dataset at least one year before the flood of 2013 and one year after. Additionally, we require that the lags of the control variables be non-missing, and drop all observations where this is not the case. Finally, we drop financial firms from the dataset, in order to ensure that our results are not driven by banks and other financial institutions. The resulting dataset contains observations for roughly 115,000 firms for the period 2009-2014.

[11] Thus, we do not observe the damage inflicted on individual banks or firms. Also we do not have information on plants. As a result, we implicitly assume that the firms' location, i.e. the headquarter, is the same as its plant location. Considering that we examine mainly SMEs which are usually single-plant firms, this assumption appears to be reasonable.

[12] 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%).

[13] Because we cannot observe the reason that firms drop from the dataset, or become inactive, we choose not to investigate this as an outcome variable.

[14] Despite mandatory reporting this still occurs quite often. It is not clear whether this is a failure of firms to report because of a lack of enforcement or whether this is due to the information acquisition process by Bureau van Dijk.

4 Identification

The goal of this paper is to compare firms, which are outside of the direct disaster area, yet conduct business with a bank that has sufficient exposure to the disaster, to firms outside of the disaster area that do not have a relationship with a disaster-exposed bank. The underlying idea is that disaster-exposed banks reduce lending to non-disaster firms, especially if they have little capital. We illustrate graphically in figure 2, how we identify such firms. We first identify flood-affected and unaffected firms, based on their county, assigning them a value between 1 and 9 according to the insurance data (GDV, 2013) (equation 1). A firm in the most heavily flooded county is assigned a 9 and non-flooded counties receive a 1. Next, we identify the banks' exposure to the flood by averaging these category numbers of the banks' firm customers, weighted by the relative firm size (equation 2). This is illustrated in the figure by the dotted arrows. Next, we identify indirectly affected firms, by identifying their banks' exposure to flood and averaging if the firm has multiple banks. This is illustrated by the dashed arrows in the figure. This indirect disaster exposure measure serves as a continuous treatment indicator intended to compare indirectly affected and unaffected firms.[15] We identify firms without such an indirect exposure (illustrated by the blank squares) and compare indirectly affected with non-indirectly affected firms. Because we use county×year fixed effects, this comparison is strictly within region. The estimated comparison is illustrated by the smaller black frame within the unaffected region. In essence this illustrated comparison is the focus: Firms located in unaffected regions with varying levels of indirect exposure to the flood because of their banks.[16]

[15] In a previous version of the paper, we categorized firms into affected and unaffected groups.

[16] As an example, the data includes Contra Sicherheitsrevision GmbH, which is a small firm (15 employees) specializing in security and risk assessment for (large) companies and individuals. Its customers include insurance companies and many firms transporting valuables across Europe (tobacco, jewelry, cash). It is located in northern Brandenburg, far away from flooded regions. However, it maintains a relationship with Sparkasse Celle, which is a savings bank located much closer to the flooded areas. This bank maintains sufficient customer relationships to flooded areas to be exposed to the flood. It is unknown, why the firm maintains a relationship with this rather distant savings bank, although an internet search suggests its founder might have lived there. Nevertheless, concerning the 2013 flood, it is only connected to the region via its bank, not through any other discernible connection.

Such an *indirect* effect, as Cortés and Strahan (2017) suggest, stems from banks that shift lending from outside the disaster region into the disaster region. We exploit this *indirect* effect as an exogenous funding shock to firms, in order to investigate the real effects of small, local shocks on the real economy.

– Figure 2 around here –

4.1 Directly and indirectly affected firms

In order to identify the *indirect* effect of the natural disaster via its banks, we first identify *directly* affected firms. This is necessary for two reasons: First, the intended comparison is strictly between indirectly and not indirectly affected firms, which requires that directly affected firms be excluded. Second, the banks' disaster exposure is based on its firms' direct disaster exposure. We define *directly* affected and unaffected firms, according to their location in the flood affected counties. Specifically, firms located in counties which are ranked as category 4 or larger are classified as affected, while those that are in the lowest category (1) are classified as unaffected.[17] Since we mainly investigate firms in *directly unaffected* counties the exact threshold choice of the *directly affected* firms only matters slightly.

$$\text{DirAffected}_i = \begin{cases} 0 & \text{if claim ratio category}_{r_j} = 1 \\ 1 & \text{if claim ratio category}_{r_j} \geq 4 \end{cases} \tag{1}$$

In order to understand the indirect effect of a bank-level lending shift on firms, we estimate bank exposure to the disaster. In order to do so, we follow the identification employed by Koetter et al. (2019), which creates a measure of the banks' flood exposure, by examining the exposure of its associated firms. Each bank is assigned an individual flood exposure

[17]For an overview of the categories, refer to figure 1.

value, based on the proximity of its firm customers to the flood. Banks with more customers located closer to disaster regions will likely reallocate more funds toward the affected regions because their customer base is located there. This way of calculating the banks' flood exposure is similar to the method used in Cortés and Strahan (2017) and Chavaz (2016), although they use exposure to mortgage credit instead of firm customers. Specifically, the exposure measure is constructed by calculating the weighted average of the damage categories of each bank's firms, where the weight is the relative size of the firm, compared to all other firms the bank reports a payment relationship with. The damage categories for each firm are based on the firms' location in any of the nine damage categories reported, as shown in figure 1. Equation 2 demonstrates how the bank-specific exposure measure is constructed.

$$\text{exposure}_i = \sum_{j \in N_i} \left(\frac{\text{assets}_{j,N}}{\text{total assets}_{N_i}} \times \text{claim ratio category}_{r_j} \right) \tag{2}$$

Where N_i are the firms j of bank i located in region r_j. $ClaimRatioCategory_{r_j}$ is a value between 1-9 based on the firms' location in the counties as shown in figure 1.[18] Because firm-bank connections vary slightly over time, we use pre-disaster exposure in the year 2012 for the analysis. Because any firm can report payment relationships with multiple banks (although the majority only reports one), in order to construct the firms' exposure to the *indirect* effect of the flood, we then average the exposure of all of the firm's banks, where AvgExposure_j is the average exposure of all banks i working with firm j. This yields a firm-specific *indirect* exposure of the firm's average bank to the flood. Higher levels indicate that the firms' banks have many (large) customers in the disaster area, to which they extend credit (Koetter et al., 2019).

[18]Note that because there is geographical variation in the banks' customers, the banks' exposure to the flood is bank-specific as opposed to county specific.

4.2 Estimation

Using this classification of indirectly exposed firms, we estimate a difference-in-difference regression with continuous treatment. Equation 3 provides the estimation equation, where Y_{it} are real outcome variables of firm j. Post is a dummy for the period after the disaster, i.e. it is 0 for t = 2009-2012 and 1 for t = 2013-2014. α_j are firm fixed effects, while $\alpha_r \times \alpha_t$ are county-time fixed effects. C_{kit-1} are firm-specific lagged control variables, specifically: cash, size (total assets), debt (current liabilities), capital ratio (common equity/total assets).[19]

$$\ln \mathrm{Y}_{jt} = \beta(\text{indirect disaster exposure}_j \times \text{post}_t) + \alpha_j + \alpha_r \times \alpha_t \; + \sum_{k=1}^{K} \gamma_k C_{kjt-1} + \epsilon_{jt} \quad (3)$$

We initially choose three key dependent variables[20] – Y_{jt} – in order to estimate the impact on the firms' real performance. First, we investigate the amount of total borrowing by the firm. Detailed analysis of lending patterns by banks with flood affected customers has been done on the bank level in (Koetter et al., 2019). Since they use a very similar approach to measure changes in bank lending for the same flood event and data, we choose to stay exclusively on the firm level to avoid unnecessary repetition. As a result, we investigate whether indirectly affected firms' total borrowing decreases, which would be consistent with the results in Koetter et al. (2019). However the data does not allow separating (specific) bank loans from other loans taken by the firm and for many (small) firms loans must not be reported separately from total liabilities. As a result we use firms' total liabilities to investigate firms' overall borrowing, since it certainly captures all loans taken by the firm.

Next, we investigate firms' two main input factors: labor and capital. The second de-

[19] The exact definition of the control variables can be found in table OA1. All variables are winsorized at the 5% level.

[20] We additionally test other variables that are related to firm health. The results can be found in table OA2.

pendent variable is thus the number of employees of the firm (in logs). It is a key measure of firm performance and traditionally highly important from a policy perspective (Chodorow-Reich, 2014; Popov and Rocholl, 2018). In addition to employment, firms can also reduce their capital input if they are faced with a funding reduction from banks. We specifically test tangible fixed assets as a proxy for the firms' capital input.

Crucially, in these estimations we am able to control for firm and county×year fixed effects, because the classification into affected and unaffected categories is not only region-, but indeed firm- specific. This is particularly important for two reasons. First it removes the possibility of governmental aid biasing the estimates. With county×year fixed effects, the only assumption needed is that government aid was orthogonal to firm specific characteristics, i.e. that no firm was given preferential treatment over another firm. According to the flood aid plan of the German government this is indeed true, because all firms were reimbursed as a fraction of their actual damages (BMI, 2013a). Additionally county×time fixed effects control for regional demand and trade. Firms may of course not only have been exposed to the disaster via their banks but also via decreased demand from their customers or decreased supply from their suppliers. However, these kinds of exposures should be similar for firms in any unaffected region and independent of their banks' flood exposure, through which the affected variable is constructed. This enables a clear identification of the *indirect* shock.[21]

– Figure 3 around here –

This described identification requires some firms exist outside the direct flood impact which still have exposure to banks affected by the flood via their firm customers. To confirm that this is indeed the case, we show the distribution of *indirectly* affected firms outside of directly affected regions in figure 3. Panel (a) displays the mean of AvgExposure_j per region, while Panel (b) displays the maximum values. Directly affected areas are dis-

[21] To the extent that firms' bank choice may not be orthogonal to the firms flood exposure, for example because a firm might choose a bank in a region where it has many suppliers / customers, we conduct several robustness tests, by controlling for the bank-firm distance and sector×time fixed effects.

played in white, independent of the indirect exposure. The figure demonstrates that firms' exposure to flood-affected banks is diversely distributed around Germany, although regions close to the flood tend to have more indirect flood-exposure. This is to be expected and a crucial reason why county×year fixed effects are important. Panel (b) further demonstrates that there are at least some *indirectly* affected firms in most regions. This increases confidence in the fact that the identification indeed captures firms' indirect flood-exposure via its banks, and not some unobserved other (regional) correlation and demonstrates that there are at least some firms for which this paper's identification can be exploited in most regions.

– Table 1 around here –

Descriptive statistics for all the variables used in the analysis of the paper can be found in table 1. Detailed variable definitions are provided in table OA1 in the online appendix.

4.3 Importance of bank capital in disaster shock transmission

While there is some evidence that low-capital banks are more likely to transmit financial shocks to firms (Gan, 2007; Jiménez et al., 2017b), not much attention has been paid toward the fact if bank capital affects local shock spillovers. However, the same mechanisms that cause a general reduction in lending during financial crisis might amplify regional spillovers. For smaller shocks, banks can reduce lending in certain regions if they lack sufficient capital. This spillover effect should be significantly affected by the banks ability to buffer even smaller shocks to its balance sheet with equity. Concretely, two factors may cause lower capital banks to amplify regional spillovers: first, banks with lower capital ratios might have more trouble refinancing loans on the interbank market, as they are perceived as more risky. We term this mechanism the *risk channel*. Second, in the case of a loan demand shock, banks near the margin of mandatory capital requirements may not be able to raise liabilities to finance new loans without violating capital regulations.

We term this the *regulatory channel.* A key part of this paper is to contribute to the understanding of whether bank capital is important for the transmission and amplification of unexpected local shocks and to get some idea about the channels through which it might work. We thus add triple-interaction effects to our difference-in-difference analysis and estimate Equation 4 in the following way:

$$
\begin{aligned}
\ln \mathrm{Y}_{jt} = {} & \beta_1(\text{indirect disaster exposure}_j \times \text{post}_t) \\
& + \beta_2(\text{indirect disaster exposure}_j \times \text{post}_t \times \text{bank capital}_j) \\
& + \beta_3(\text{bank capital}_j \times \text{post}_t) + \alpha_j + \alpha_r \times \alpha_t \; + \sum_{k=1}^{K} \gamma_k C_{kjt-1} + \epsilon_{jt}
\end{aligned} \tag{4}
$$

We specify bank capital$_j$ in two different ways. First, we create bank-capitalization quartiles, by splitting the sample into firms whose main bank had very low, low, high and very high bank capital. Specifically, we average each firms' main banks' capitalization in 2012 and 2013 and set the variable equal to 0 if the firms' main bank is in the highest quartile of the distribution, 1 if it is in the second highest, 2 in the third highest and 3 if the main banks' capitalization is in the lowest quartile of the capitalization distribution. We then investigate β_2 in order to find out whether such firms suffer significantly more from the *indirect* shock. Second, we estimate a continuous interaction with the pre-flood main banks' regulatory capital ratio, which allows us to investigate the effect of the main banks' regulatory capital ratio on different levels of the distribution.

Banks' capital regulation in Germany follows EU regulation under Basel III. The total regulatory capital requirement was set to 8% in 2013, and Tier 1 capital had to be raised from 4.5 to 6% until 2019. In addition, banks have to build a conservation buffer of 2.5%, increasing the total capital requirement in normal times to 10.5% by 2019. The minimum amount of regulatory capital held by banks in our sample is 8% (table 1), which is exactly the minimum capital requirement for the years 2013-2015. At 8% regulatory capital, banks cannot extend new loans to firms without raising equity or without violating EU regulation. However, the mean bank in the sample holds twice as much capital. Because many German banks are local savings and cooperative banks, they tend to hold a little bit more capital than large commercial banks. In addition, banks are likely to hold an internal capital target ratio that is in excess of the regulatory minimum (Berger et al., 2008; Francis and Osborne, 2012; Lepetit et al., 2015), which may be binding and prevent significant lending expansions. This implies that the *regulatory channel* is difficult to identify, because the binding effect of regulation may be different for each bank, depending on their internal capital buffers.

4.4 Loan demand and loan supply

Natural disasters tend to be interpreted as loan demand shocks from the banks' perspective (Cortés, 2014; Chavaz, 2016; Cortés and Strahan, 2017; Koetter et al., 2019). Most convincingly Berg and Schrader (2012) demonstrate this finding with loan application data from Ecuador. This finding is intuitive, as bank customers in flooded areas try to secure funds for rebuilding, possibly substituted by government aid and insurance payments. Crucially, using very similar data and the same flood as identification, Koetter et al. (2019) present strong evidence in favor of this view by demonstrating that lending to disaster regions increased, without affecting banks' profitability. They also show that the share of impaired loans does not increase, suggesting that supply effects are likely not at play.

There are a few potential explanations why banks, especially those with little capital might respond to additional lending demand at all. One might think that financially constraint banks may choose to abstain from providing loans, especially to disaster areas, which may have uncertain prospects. While we cannot specifically test, whether loans to disaster areas are more profitable, Koetter et al. (2019) suggest they are at least not less profitable than ordinary loans and do not default at higher rates. Furthermore, loans to disaster areas may in fact be less risky than intuition suggests. First, most loans to disaster-affected businesses would be to finance projects that have been previously screened. The bank is now financing the same investment for a second time and it has gathered information about loan performance throughout the previous financing process. Second, government aid payments may not only limit losses on previous loans, but in fact serve as a good source of collateral, because they are cash payment promises by the government. Combined, these reasons can make lending to disaster regions more (or at least similarly) attractive to lending in non-disaster areas. Independent of *why* banks choose to lend to disaster regions, there exists strong previous evidence that they do and as a result the possibility arises that this is costly for other connected firms.

However, it cannot be completely ruled out that banks connected to flood-affected firms may also be subject to a supply shock, as they may have to write off or incur losses on loans to affected areas. While this interpretation is inconsistent with previous results from the literature, it is nevertheless an important concern. Uniquely, this paper's identification does not hinge on the shock being a loan *demand* shock to banks. Because we do not examine banks directly, but rather the banks' firm customers in non-flooded areas, it is mainly of importance that the bank was induced to reduce loans in unaffected areas. This is consistent with both a demand and a supply shock interpretation.

The *supply* shock interpretation would imply that banks cut their lending elsewhere, because they have to write-off loans in the affected areas, and might thus be induced to sell other assets quickly to compensate for the losses. A *demand* shock would result in the flood-exposed bank having to raise additional funds in order to satisfy demand in the affected area. The bank can do this by either refinancing the newly demanded loans (Chavaz, 2016) or by cutting lending elsewhere. The demand shock interpretation is heavily supported by the literature at the bank level, and none of the results in this paper suggest another interpretation. Thus, we choose to interpret the results as a negative funding shock stemming from an increase in demand, although the supply channel cannot be ruled out and it is plausible that both mechanisms are at work at the same time.

5 Results

5.1 Indirect Effect

Based on previous literature and the flood characteristics presented in section 2, we hypothesize that banks shift lending from directly unaffected areas into directly affected areas, especially if banks hold little capital. In order to satisfy the demand for new loans in disaster regions, where firms are looking to finance rebuilding efforts, banks must themselves be able to finance these new loans. In order to do this, banks have two options: raise funds on financial markets (increase liabilities), or shift existing lending away from other areas, for example by not renewing loans, increasing prices or increasing funding requirements (reducing assets).[22] If banks opt for the former option, firms in non-flooded areas should be unaffected. If banks opt for the latter, firms in non-flooded areas may become "flooded through the back-door" - i.e. unintentionally affected by a funding reduction from banks exposed to the disaster.

We thus examine whether firms' banks' flood exposure matters to the firms' loans as reported on the firms' balance sheet. We test this by estimating equation 3 using OLS with standard errors clustered at the firm level. Columns (1)-(3) report the results for firms located *outside* the flood radius, i.e. firms classified as not directly affected according to equation 1.

– Table 2 around here –

Column (1) of table 2 suggests that firms are borrowing less overall, as total liabilities decrease significantly with increasing indirect disaster exposure. Each increase in exposure by one,[23] implies a decrease in total borrowing by 0.8%. Compared to a completely

[22]Banks can also raise equity capital on financial markets, although this might be more difficult in the short term, especially for non-listed banks, which constitute the majority of the sample. This option would increase equity, which is inconsistent with the empirical results presented.

[23]Originally, the indirect disaster exposure measure stems from the 9 affected categories. It is thus theoretically limited at 1 and has a maximum of 9 (if all the banks' firms are located in the most heavily flooded regions)

unaffected firm, firms that are maximally exposed to the disaster through their bank reduce their lending by 5.5%. A firm with a strong indirectly exposure to the flood - defined as having a bank relationship to a bank whose firm customers are on average affected by the definition of equation 1 - will decrease borrowing by 2.4%.[24]

Importantly, these borrowing reductions appear to cause real effects in firms. The results indicate that there is a drop in employment by 0.7% and a decrease in tangible fixed assets by 1.5% per point increase in indirect disaster exposure for firms in non-flooded regions. This implies that the most exposed firms decrease employment by 4.8% and tangible fixed assets by 10.3% compared to firms without indirect disaster exposure. In other terms, a strongly affected firm will reduce employment by 2.1% and fixed assets by 4.5% compared to a completely unaffected firm.[25]

In line with overall credit reductions implied by a reduction in total firm borrowing, significant real effects arise both in employment and tangible assets. This is interesting, as even smaller funding shocks, such as those from the Elbe flood to indirectly affected firms, appear to entail real effects. This is a new finding which suggests, that there is no need for widespread failure of banking systems for firms to suffer consequences from a reduction in credit, implying that firms cannot switch easily to other funding sources, even in normal times.

5.2 Amplification of shock transmission

Bank Capital The effect of banks' lending shift following natural disasters from unaffected to affected regions may be dependent on the amount of bank capital available. Banks' ability to finance new loans without reducing loans elsewhere crucially depends on their ability to raise funds externally. If banks are financially constrained, they may not be able to do so and must raise funds internally. Banks are typically constrained by

[24] The maximum exposure is 7.82. Comparing a completely unexposed firm (1) to a maximally exposed firm (7.82) thus implies a decrease in total liabilities by $0.8\% \times 6.82 = 5.46\%$. Comparing a completely unexposed firm (1) to a firm one with strong indirect exposure (4) yields $0.8\% \times (4-1) = 2.4\%$.

[25] Results for additional variables can be found in table OA2 of the online appendix.

low capital ratios to raise new funds (Jiménez et al., 2017b; Gan, 2007).[26] Low capital ratios impede the banks' ability to raise external funds for two reasons: first, low capital ratios imply higher risk of lending to that bank (Modigliani and Miller, 1958). As a result banks with higher capital ratios should be able to refinance new loans more easily (*risk channel*). The second reason is mandatory regulatory capital requirements. If a bank cannot fall below a certain regulatory capital threshold, it cannot borrow more without raising new equity at the same time. Because raising equity is often difficult in the short term, sudden shocks (such as a natural disaster) may force banks into raising funds by reducing other lending assets, because borrowing additional funds would violate capital regulations (*regulatory channel*). Importantly, banks do not need to be exactly at the threshold for this effect to take hold, as they may choose to hold a (fixed) buffer above the regulatory requirement for other liquidity related reasons. Both of these channels imply that low-capital banks have to cut back lending to out-of-region firms, if they are faced with a local shock.

– Table 3 around here –

We test if banks with low capital ratios are more prone to transmit disaster shocks to firms in unaffected regions in two ways, according to the regression specified in equation 4. Table 3 shows the results of a regression using interactions with pre-flood capitalization quartiles.[27] Firms connected to banks in the lowest quartile of the capital distribution appear to be the drivers of reductions in total firm borrowing. Firms with a connection to a bank which is in the lowest quartile of the bank capital distribution, decrease overall borrowing by 1.6% per point of disaster exposure (equivalent to a 4.8% decrease for strongly affected firms), whereas disaster exposure does not change lending at any other capitalization quartiles.

[26] There is a large debate on what exactly best constitutes banks' financial constraint. The aim of the paper is not to contribute to that debate, so we focus on the most simple and policy relevant measure: banks' regulatory capital ratios. We provide results using banks' liquidity as an alternative indicator, see table OA7 and figure OA1.

[27] We take the average of 2012 and 2013 as the pre-flood regulatory capital ratio, as the flood occurs in mid 2013.

Significantly, this reduction affects firms input factors: employment outcomes are significantly worse for firms whose main bank holds little capital. These firms reduce employment by roughly 0.9% per point of exposure if they are connected to the worst capitalized banks and 0.6% if they are connected to a bank in the second lowest capitalization quartile. Since the mean firm has 56 employees, this implies that the mean firm reduces employment by about 1.5 employees, if the firm is strongly indirectly exposed to the flood.

A reduction of tangible fixed assets is also significantly amplified by low-capital banks. Indirectly disaster affected firms whose banks hold capital in the higher two quartiles are not affected by the spillover of the flood to non-flooded regions. However, tangible assets are cut back by 2% (2.5%) per point of indirect disaster exposure if the bank is located in the low (lowest) quartile of the capital distribution. Compared to a completely unaffected firm, strongly indirectly disaster affected firms thus experience a reduction in tangible fixed assets by roughly 7.5%.

The effects of this disaster spillover are sizable and are largely attributable to low capital levels. For each dependent variable only low capital banks appear to transfer the shock from flooded to non-flooded areas. Lending reductions result in large real effects, implying that firms are unable to substitute by borrowing from other sources even in normal times. The results strongly suggest that well-capitalized banks are not only important for financial stability but also for the propensity of the financial system to amplify local shocks. Bank capital appears to be relevant to absorb, instead of amplify and propagate local shocks.

– Figure 4 around here –

To further investigate the transmission of shocks at different bank capital ratios, we estimate continuous interactions with the banks capitalization. We plot the coefficient of being indirectly disaster exposed at different levels of the firms' bank capital in figure

4.[28] As higher regulatory capital ratios imply larger (differential) borrowing, employment and capital stock effects, the slope of all curves is increasing. For all dependent variables, capital ratios below roughly 20% are associated with a significant decrease in outcomes due to indirect disaster exposure. It is not the case that more capital increases lending, but that a certain level of bank' capital is required to prevent negative spillovers. This is an interesting finding as it indicates that this negative effect may be driven by banks at the lower bound of the regulatory capital ratio (*regulatory channel*). However prevention of negative effects also occur relatively far away from regulatory thresholds, which implies that the risk channel may also play a role.

Overall these results clearly indicate that banks' capital ratios are extremely important in determining whether local shocks are buffered or amplified by banks. Larger capital ratios are helpful in order to prevent banks from spreading shocks to other sectors of the economy who have no direct exposure to the shock themselves. All negative firm-level effects increase significantly if the firms' main bank is constrained by a low capital ratio. The results imply that better capitalized banks do not appear to pick up the lending reductions from badly capitalized banks, not only because firms' overall borrowing declines but especially because real effects can be measured on the firm level. In addition, we test in table OA3 in the online appendix if firms with a single bank relationship perform worse than those with multiple bank relationships, and find no difference. This indicates that even if firms have other borrowing options they are unable to compensate lost funding. Given that German SMEs, which are the vastmajority of the sample, are very often relationship borrowers, this result is not very surprising. Switching or even adding an additional bank is a costly and the unexpected lending reduction is not easily compensated.

It is not clear if higher mandatory capital requirements are a good solution to prevent spillovers from negative regional shocks, as our results suggest that firms may reduce borrowing and input factors, if their bank is constrained by mandatory capital requirements.

[28]The corresponding table (OA4) is provided in the online appendix

Since the flood is not a macro-scale shock, even capital requirements tied to macroeconomic conditions, such as the conservation buffer would not remove these concerns. This implies that banks have to be given other incentives to increase capital, if the goal is to minimize the collateral damage to firms caused by frictions in the financial sector. It is important to recognize that the negative real effects implied by low bank capital ratios can be efficient from the banks' perspective. It is reasonable and perhaps intended that banks distribute local risk from one region to another. However, our results show that firms cannot, or at least do not hedge against this risk of banks shifting lending and thus suffer real consequences as a result of an under-capitalized banking sector.

– Table 4 around here –

This result is further highlighted by regional regressions. Table 4 shows estimates for effects of higher regional average bank capital on outcomes on the German county level. In this regression, we construct the county average of the indirect exposure of all firms in the county. We then estimate a post-disaster continuous difference-in-difference model and interact it with the average level of the firms' banks' capital. The results confirm the firm-level outcomes. Counties with a larger disaster exposure on average have lower post-flood per capita GDP levels, which is buffered if this counties banks are better capitalized (column (2)). Quantitatively, an increase in average indirect exposure by one standard deviation (0.55, unreported) implies lower per capita GDP of 6.5% which is a large effect. However, an increase in one standard deviation of average county bank capitalization (0.02, unreported) decreases this effect by 1.5%. Marginsplots for the regional regressions can be found in figure 5, which displays the marginal effect of a larger share of indirect flood exposure at different levels of average bank capitalization on the county level. For high levels of bank capitalization, the previously negative effect on per capita GDP becomes insignificant and ultimately positive, confirming that the more bank-capital exists in the system, the less the negative impacts spread around to other regions. Unemployment, Insolvencies and public debt are statistically unaffected by the local spillover of the flood.

This demonstrates that the effects of higher bank capital buffering regional spillovers can not only prevent negative effects on individual firms but even to the regional economy. Thus, because local shock spillovers can be mitigated by higher bank capital ratios, our results imply a previously disregarded benefit – a positive externality – of higher bank capital. Since unexpected regional negative shocks may occur quite often, this externality may have significant macroeconomic effects, although this question requires further research.

Ex-ante disaster risk The previous section demonstrated the importance of bank capital for local shock amplification. In addition to bank capital, other factors may be highly relevant for shock transmission, which have received much less attention in the literature. One of these potential channels is the propensity of banks to re-balance their portfolio following a shock. When banks increase their exposure to a certain type of asset - in this case by lending more to disaster regions - they also increase this asset specific risk at the same time. In turn, demand for diversification may drive banks to reduce exposure to assets with similar risk structures. In the case of natural disasters, a lending increase into disaster regions, which has been often demonstrated in the previous literature, will likely increase banks' disaster exposure ex-post. To maintain diversification, banks may decrease lending to other high-disaster risk areas as a response, thereby transferring the shock to high-disaster risk areas which were yet unaffected by the 2013 flood.

– Table 5 around here –

We test this hypothesis by adding an interaction with ex-ante disaster-risk to the difference-in-difference estimation. Ex-ante disaster risk is measured on the county level by adding disaster damages from previous flood damage reports. Information on damages from previous events is provided to us similar to the 2013 damages by the German Association of Insurers. In total it is based on 6 additional flood-like events[29]. Only one of those events

[29] one in 2002, two in 2008, one in 2009, one in 2010 and one in 2011

- the flood of 2002 - is also a major disaster. The other events are minor local flood-like events, which produce flood-related insurance claims. Data is also provided in 9 damage categories as for the 2013 disaster.

The results of the estimation are presented in table 5 and demonstrate the expected results. Firms located in regions with higher ex-ante disaster risk suffer increased reductions in total borrowing, employment and tangible fixed assets. One standard deviation increase in pre-flood disaster risk is associated with a decrease in borrwing by 0.4%, a reduction in employment by 0.4% and a reduction in tangible fixed assets by 0.7%. These results are consistent with the idea that banks withdraw from other high-risk areas in order to re-balance their disaster risk. This unanticipated loan shifting to adjust risk portfolios has real effects for firms which are located in high-risk (though non-flooded in 2013) regions. To our knowledge such real effects of portfolio re-allocation are a novel finding, especially in the context of natural disasters.

5.3 Robustness

Next we test whether the baseline results hold up to several robustness tests. Table 6 presents robustness checks with tangible fixed assets as the dependent variable (column (3) of table 3). Robustness tests for columns (1) and (2) can be found in the online appendix (table OA5 and OA6). First, we ensure that the results are not driven by the selection of years and thus column (1) estimates a regression using the same length of pre- and post periods (i.e., 2010-2014). The results are displayed in column (1), and are very similar to the original result.

Next, we test whether the data satisfies the parallel trends assumption, which is crucial to difference-in-difference analysis. Since our treatment is continuous, displaying parallel trends graphically is difficult. However, we can more formally test pre-treatment similarity in growth paths of the dependent variable using a placebo regression, which is provided in column (2). Here, the year 2011 is set as the flood year, with the years

2013-2014 being excluded. As can be seen, the results are not significant, indicating that the treatment variable does not capture differing time trends.

– Table 6 around here –

Additionally, there is a concern that firms' bank choice is not orthogonal - even within region - to the flood, or more specifically the effects of the flood. Mainly, it is possible that firms choose banks where their suppliers / customers are located. If that were the case, our effect might be capturing direct flood exposure via channels other than lending. We provide two tests to account for this possibility. First, we include an interaction with the post dummy and the firm-bank distance. If the effect were driven by the distance between banks and firms this coefficient should pick up the variation. Column (3) shows that this interaction is not statistically significant and it does not eliminate the original result. Second, in order to mute concerns that "specialty" banks are driving the result, we additionally include sector×time fixed effects in column (4), again without a change in the result.

To investigate in how far the inclusion of a robust set of fixed effects is important for our findings, we provide the results of regressions with only firm fixed effects (column(5)) and no fixed effects (column(6)). Interestingly, inclusion of fixed effects are not important for the overall finding that the flood spreads through the banking network to other firms, but it does appear to be important for the importance of bank capital. This suggests that controlling for local demand through region×time fixed effects may be very important in order to understand the effects of bank capital for loan *supply*. Lastly, we check whether the results might be driven by a few banks that have extraordinary high or low capital ratios. Column (7) uses winsorized bank capital at the 5% level, to ensure that this is not the case. Indeed the results remain very similar, indicating that the results are not driven by extreme banks in the data.

6 Conclusion

This paper demonstrates the importance of bank capital to prevent real economic shock spillovers from one region to another. We demonstrate this local shock amplification effect of low bank capital, by examining a funding shock caused by banks' lending shifts following a natural disaster. As banks redirect lending from non-disaster to disaster areas, firms unaffected by the disaster, yet with a connection to a disaster-exposed bank, reduce their borrowing and as a result employment and tangible assets significantly.

This baseline effect is mainly driven by low-levels of bank capital. Firms connected to banks with low capital ratios, are most affected by such "flooding through the back door", as they experience a significant reduction in borrowing, employment and tangible assets. Firms connected to a strongly exposed low-capital bank experience a significant decrease in borrowing by 4.8%, employment by 2.7% and tangible assets by 7.5%. Estimates further show that banks in particular cut lending to areas that were currently unaffected but are otherwise exposed to a high flood risk. These results imply that even small regional shocks can be transmitted through the banking sector to otherwise non-shocked firms, especially if the level of bank capital is small. As small local shocks – which do not necessarily have to be natural disasters – are fairly common, a badly capitalized banking system may be propagating shocks across regions instead of absorbing them, especially to other areas that are at risk of flooding.

Our results highlight the importance of high bank capital ratios to prevent propagation of smaller (real economic) shocks through the financial system and avoid lending reductions to firms, even if the health of the financial system or even that of a single bank is not threatened. For banks, this shock propagation might be efficient ex-ante, but our results demonstrate that firms and the regional economy suffer real consequences if banks do not hold sufficient capital. This provides strong evidence that even on a limited regional scale, low bank capital may carry previously disregarded negative externalities. Policies aimed at increasing banks' capital may provide benefits even for non-systemically relevant banks and even if potential bank failure is not an issue.

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Figures and tables

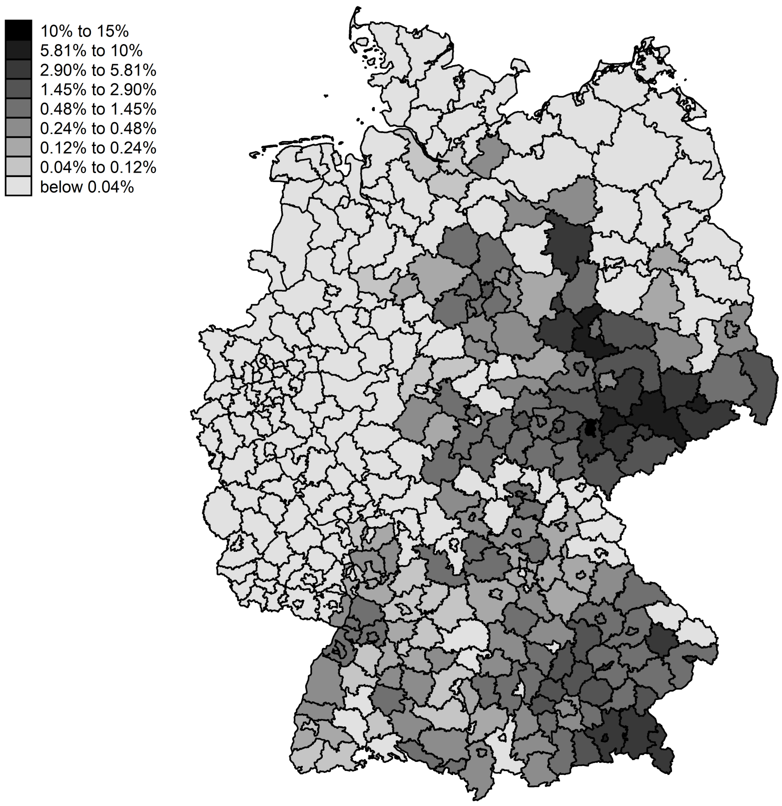


Figure 1: Affected German counties by damage categories

This figure shows the distribution of the damage sustained from flooding in Germany from May 25th through June 15th 2013, by German counties (Kreise). Flooding damage is reported as the percentage of flood-insurance contracts activated during the period and is reported in 9 categories, from 0 to 15%. Data is provided by the German Association of Insurers.

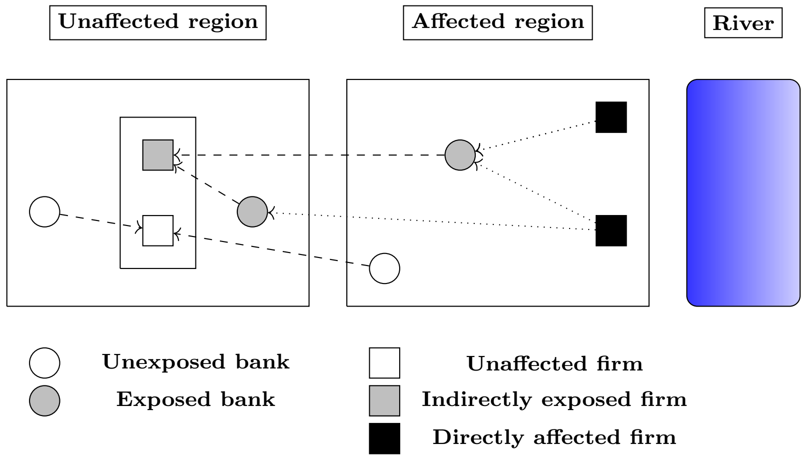
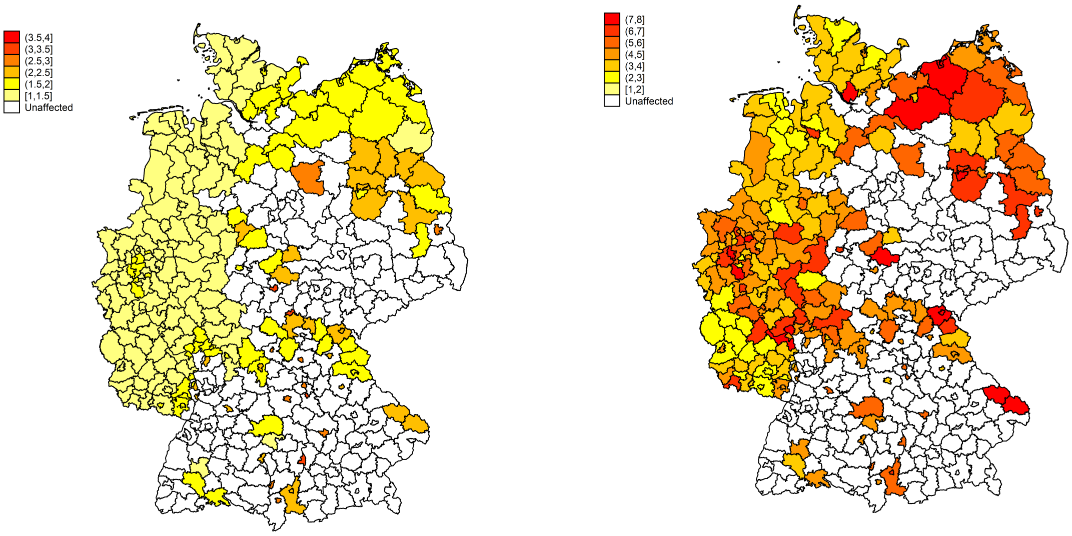


Figure 2: Indirectly disaster-exposed firms: Illustration

This figure illustrates the identification of indirectly exposed firms. Firms are depicted as rectangles, banks as circles. Directly affected firms (solid black) are identified by their location in the affected region. Exposed banks (grey circle) are defined as exposed by their customers location. As such they can also be located outside of the affected region (Koetter et al., 2019). Indirectly exposed firms are identified, if their average bank is exposed to the flood (grey rectangle). Region×time fixed effects imply a strictly within region comparison between indirectly exposed firms and not-indirectly exposed firms (as illustrated by the rectangular framework in the unaffected region).



(a) Mean exposure of *indirectly* affected firms

(b) Maximum exposure of *indirectly* affected firms

Figure 3: Distribution of *indirect* exposure of firms in non-directly affected areas

This figure shows the distribution of the firms' average exposure of its banks to the disaster (AvgExposure) by German regions. Section 4.1 describes how this measure of firms' indirect exposure to the disaster via its banks is derived. Panel (a) shows the mean exposure of all firms in the region. Panel (b) shows the maximum exposure of firms in the region. Labels are displayed in the upper left corner of each graph.

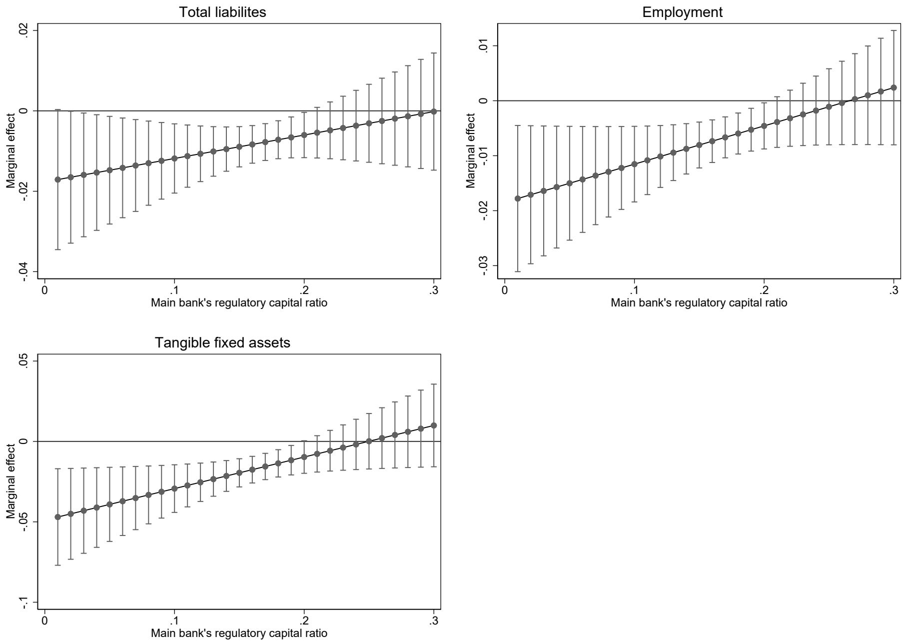


Figure 4: Marginal effect of the difference-in-difference coefficient at different values of main bank's capitalization: real effects

This figure shows the marginal effects of the difference-in-difference estimation of being exposed to a bank funding shock resulting from flooding in other regions at different values of the firms' main bank's capital ratio. The corresponding regression is provided in table 3. Capital ratios are indicated as shares on the x-axis. Each graph represents the marginal effects for a different dependent variable, as indicated by its title. Bars indicate 90% confidence intervals. The results of the regression are shown in table OA4.

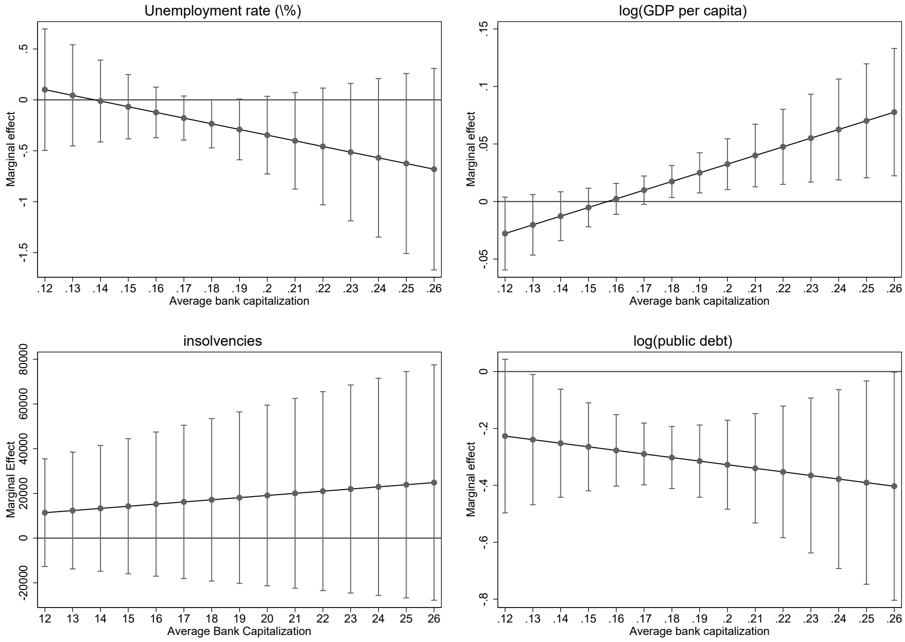


Figure 5: Marginal effect of indirect disaster exposure by different levels of average bank capital on the county level

This graph shows the marginal effect of regional indirect disaster exposure (average of all firms' indirect disaster exposure in the region) at different values of the regions average bank capital (measured as the pre-flood capital ratio of firms' banks in the region). Average capital ratios are indicated as shares on the x-axis. Each graph represents the marginal effects for a different dependent variable, as indicated by its title. Bars indicate 90% confidence intervals.

Table 1: Descriptive Statistics

	N	Mean	Median	SD	Min	Max
Identification						
Directly affected	712,204	0.31	0.00	0.46	0.0	1
Indirect disaster exposure	482,184	1.53	1.19	0.61	1.0	8
Dependent variables						
Total liabilities (mil.EUR)	482,184	8.18	0.62	252.57	0.0	45,984
Number of employees	482,184	55.63	14.00	834.14	1.0	177,559
Tangible fixed assets (mil.EUR)	482,184	3.19	0.12	69.99	0.0	19,953
Control variables						
Cash (mil.EUR)	482,184	0.94	0.08	17.04	0.0	3,405
Total assets (mil.EUR)	482,184	12.73	0.97	336.70	0.0	56,042
Capital ratio	482,184	0.33	0.29	0.27	0.0	1
Current liabilities (mil.EUR)	482,184	3.49	0.11	133.04	0.0	27,230
Differential firm exposure variables						
Main banks' reg capital ratio	482,184	0.17	0.17	0.04	0.1	0.8
Pre-2013 disaster risk	482,184	2.12	2.17	0.72	1.0	3.5

This table presents summary statistics for all variables used in the subsequent regressions. All variables except for the directly affected dummy are reported only for non-directly affected firms. Directly affected is a dummy variable based on the firms' location with regard to the flood (c.f. figure 1), according to equation 1. It is set equal to 1 if the firm is located in a county with a damage category of 4 or higher and set equal to 0 if it is located in a county with category 1. Indirect disaster exposure measures the exposure of the firm to the flood via its banks, according to equation 2. Cash, total assets and current liabilities are reported in levels, but included as logs in the regressions. Capital ratio is measured by tier 1 equity divided by total assets. All control variables are used in as first lags in the regressions. Banks' regulatory capital ratio is each firm's main bank's regulatory capital ratio prior to the flood as a mean of 2012 and 2013 values. Firms' banking characteristics are taken at pre-flood levels. All firm-level variables are taken from the Amadeus database.

Table 2: Flooded through the back door:
Firm outcomes after *indirect* disaster exposure

	Outside directly affected regions		
	(1)	(2)	(3)
	Total liabilities	Employment	Tangible fixed assets
Post×indirect disaster exposure	-0.008***	-0.007***	-0.015***
	(0.002)	(0.002)	(0.004)
Lagged cash	-0.006***	0.003***	0.009***
	(0.001)	(0.000)	(0.001)
Lagged total assets	0.270***	0.112***	0.426***
	(0.005)	(0.003)	(0.007)
Lagged current liabilities	0.000	0.000***	0.000*
	(0.000)	(0.000)	(0.000)
Lagged capital adequacy	-0.413***	0.036***	0.199***
	(0.009)	(0.006)	(0.015)
N	482,184	482,184	482,184
Number of Firms	114,398	114,398	114,398
Within R^2	0.064	0.018	0.042
Controls (lagged)	YES	YES	YES
Firm Fixed Effects	YES	YES	YES
County×Year Fixed Effects	YES	YES	YES

This table presents results of the indirect effect of flooding on firms for three different outcomes: total liabilities, employment and tangible assets. Firms are indirectly exposed if their average bank has a large flood exposure due to its firm-customer location with regard to the flood (see Section 4 for details). All regressions are strictly within non-flooded regions. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Total liabilities is the log of firms total liabilities. Employment is the log of the number of firms' employees. Tangible assets is the log of firms' tangible fixed assets. Control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. Cash is the log of all cash and cash equivalent of firms and is a proxy for the firms' liquidity. Total assets is the log of the banks total assets and is proxy for firm size. Current liabilities is the log of the firms' current liabilities and is a proxy for the firms' short-term indebtedness. Capital ratio is common equity divided by total assets, and controls for the firms' relative equity position. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Amplifying the shock:
Main bank's capital buffer

	Low capitalization quartiles		
	(1)	(2)	(3)
	Total liabilities	Employment	Tangible fixed assets
Post×disaster exposure	-0.007	-0.002	-0.006
	(0.005)	(0.004)	(0.009)
Post×indirect disaster exposure×high capital	-0.001	-0.005	-0.007
	(0.004)	(0.004)	(0.008)
Post×indirect disaster exposure×low capital	-0.001	-0.006*	-0.020**
	(0.005)	(0.004)	(0.008)
Post×indirect disaster exposure×lowest capital	-0.016***	-0.009**	-0.025***
	(0.005)	(0.004)	(0.008)
N	482,184	482,184	482,184
Number of Firms	114,398	114,398	114,398
Within R^2	0.064	0.018	0.042
Controls (lagged)	YES	YES	YES
Firm Fixed Effects	YES	YES	YES
County×Year Fixed Effects	YES	YES	YES

This table presents interactions of the continuous difference-in-difference estimation from table 2 interacted with the capitalization of the firms' main bank. Only non-directly affected firms are included. Columns (1)-(3) specify interactions with low capitalization quartile dummies which are set equal to 1 if the firms' main bank is in the lowest, low, high or highest quartile of the pre-flood capitalization distribution, respectively. The pre-flood capitalization is based on an average of the banks' regulatory capital ratio in the years 2012 and 2013. Double interaction coefficients (post×capitalization) and control variables are included, but not reported. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Total liabilities is the log of firms total liabilities. Employment is the log of the number of firms' employees. Tangible assets is the log of firms' tangible fixed assets. Control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Entire regions suffer:
Regional amplification effects of low bank capital

	(1) Unemployment (%)	(2) log(GDP)	(3) Insolvencies	(4) Public Debt
Post×indirect disaster exposure	0.769	-0.118**	-0.000	-0.076
	(0.955)	(0.052)	(0.000)	(0.408)
Post×average capital	-1.646	-1.100**	-0.000	4.127
	(10.093)	(0.529)	(0.003)	(4.215)
Post×indirect disaster exposure×average capital	-5.576	0.753**	-0.000	-1.259
	(5.544)	(0.303)	(0.002)	(2.312)
N	2,658	2,430	2,391	2,357
Number of Counties	270	270	270	266
Within R^2	0.054	0.026	0.005	0.035
County Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES

This table presents the results of county level regressions indicating the effect of low bank capital on post-disaster regional performance. The regressions span the years 2006 to 2015. Only non-directly affected (non-flooded) counties are considered. Indirect disaster exposure is a continuous variable indicating the regionally aggregated average indirect exposure of all firms in the county to the flood through their banks'. *Average capital* is a continuous variable and captures the mean level of bank capital held by firms' banks in the county prior to the flood in 2012. Post is a dummy set equal to 1 after the disaster year (2013) and 0 otherwise. Unemployment is the regional unemployment rate in %. log(GDP) is the natural logarithm of per capita regional GDP. Insolvencies are the absolute number of insolvencies. Public debt is the log of public debt in the county. We control for county and year fixed effects. Clustered standard errors on the county level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Disaster-prone areas are most affected:
Real effects in high-disaster-risk areas

	(1) Total liabilities	(2) Employment	(3) Tangible fixed assets
Post×indirect disaster exposure	0.005	0.006	0.006
	(0.007)	(0.005)	(0.013)
Post×indirect disaster exposure×pre-disaster risk	-0.006*	-0.006**	-0.010*
	(0.003)	(0.003)	(0.006)
N	482,184	482,184	482,184
Number of Firms	114,398	114,398	114,398
Within R^2	0.064	0.018	0.042
Controls (lagged)	YES	YES	YES
Firm Fixed Effects	YES	YES	YES
County×Year Fixed Effects	YES	YES	YES

This table presents interactions of the continuous difference-in-difference estimation from table 2 interacted with the pre-disaster risk of the firm's county. Only non-directly affected firms are included. Pre-disaster risk is calculated as the average damages from previous flood-related disasters from 2002-2012. Double interaction coefficients and control variables are included, but not reported. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Total liabilities is the log of firms total liabilities. Employment is the log of the number of firms' employees. Tangible assets is the log of firms' tangible fixed assets. Control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Robustness tests for low bank capital dummy: tangible fixed assets

	Equal periods	Placebo	Distance	Sector×Year	Only firm FE	No FE	Winsorized cap.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Tan. assets	Tan. assets	Tan. assets	Tan. assets	Tan. assets	Tan. assets	Tan. assets
Post×indirect disaster exposure	-0.007	-0.006	-0.009	-0.004	-0.001	-0.002	-0.006
	(0.008)	(0.012)	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)
Post×indirect disaster exposure×high capital	-0.005	0.008	-0.013	-0.004	-0.014	-0.011	-0.007
	(0.008)	(0.016)	(0.009)	(0.008)	(0.011)	(0.011)	(0.008)
Post×indirect disaster exposure×low capital	-0.018**	-0.008	-0.017**	-0.018**	-0.013	-0.012	-0.020**
	(0.008)	(0.015)	(0.009)	(0.008)	(0.011)	(0.011)	(0.008)
Post×indirect disaster exposure×lowest capital	-0.023***	-0.020	-0.029***	-0.024***	-0.019*	-0.014	-0.025***
	(0.007)	(0.015)	(0.008)	(0.008)	(0.011)	(0.011)	(0.008)
Post×distance to main bank (km)			-0.004				
			(0.003)				
N	411,604	266,310	470,838	482,184	482,184	482,184	482,184
Number of Firms	114,398	114,306	111,503	114,398	114,398	114,398	114,398
Within R^2	0.031	0.015	0.000	0.042			0.042
Controls (lagged)	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	NO
County×Year Fixed Effects	YES	YES	YES	YES	YES	NO	NO

This table presents robustness tests for the results presented in column (3) of table 3. Column (1) presents results for using equal base and post periods, here the year 2011 and 2012 are the base and 2013 and 2014 are the post period years. Column (2) presents the results of a placebo test using the year 2011 as the placebo event year (omitting the years 2013 and 2014). Column (3) includes a post-flood firm-bank distance control. Column (4) includes sector×year fixed effects. Column (5) and (6) provide estimates without county×year and firm fixed effects. Column (7) is estimated with the main banks' capital winsorized at the 5% level. High capital, low capital and lowest capital are quartile dummies which are set equal to 1 if the firms' main bank is in the lowest, low, high or highest quartile of the pre-flood capitalization distribution, respectively. The pre-flood capitalization is based on an average of the banks' regulatory capital ratio in the years 2012 and 2013. Double interaction coefficients (post×capitalization), single interactions (in columns (5) and (6)) and control variables are included, but not reported. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Tangible assets is the log of firms' tangible fixed assets. Unreported control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. Cash is the log of all cash and cash equivalent of firms and is a proxy for the firms' liquidity. Total assets is the log of the banks total assets and is proxy for firm size. Current liabilities is the log of the firms' current liabilities and is a proxy for the firms' short-term indebtedness. Capital ratio is tier 1 equity divided by total assets, and controls for the firms' relative equity position. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Robustness tests for the other dependent variables in table 3 can be found in the online appendix.

7 Online Appendix

7.1 Further Extensions

Other potential shock amplifiers: Bank Liquidity In this section we investigate other potential mechanisms that may amplify shock transfers between regions. First, we test if bank liquidity amplifies local shock spillovers. We proxy bank liquidity as the share of liquid assets over total assets, and use the pre-flood value of the main bank as the indicator for bank liquidity. Similar to the previous process with bank capital we then present the results of an interaction with 4 quartiles of the banks' liquidity in table OA7. Marginal effects of a continuous interaction are displayed in figure OA1. For total borrowing in terms of liabilities, employment and tangible fixed assets there appear to be significant amplification effects if the bank is in the second lowest liquidity quartile. However the lowest liquidity banks only show amplification of the shock for tangible fixed assets. This result is somewhat difficult to explain, but may be due to the fact that the lowest liquidity banks do not shift any loans to disaster regions in the first place, because they are already liquidity constrained.

– Table OA7 around here –

Other potential shock amplifiers: Firm characteristics The regional transmission of shocks to the real economy might also depend on the financial constraint of individual firms. In fact, if firms do not face any financial constraints, a reduction in bank credit by their banks as a result of loan reallocation following natural disasters should not matter to the firm at all, as it could substitute with alternative financing options, such as cash reserves or its own capital. Table OA8 demonstrates the results of quartile dummy interactions similar to the main regressions using both the firms' pre-flood capital ratio (columns (1)-(3)) and the firms' pre-flood cash holdings (columns (4)-(6)). There are strong indications that firms' capital is important. Significant effects of higher firm capital can be detected for borrowing, employment and (tangible) fixed assets. Additionally, firm liquidity appears to matter for the borrowing ability of firms (column (4)). These results are not very surprising, given that firm capital has been found to matter for real effects in crisis times (Jiménez et al., 2017b).

– Table OA8 around here –

Relationship lending Additional banking characteristics may play a role for lending shifts following a natural disaster. Prior literature indicates that relationship banking (Boot, 2000) might play a twofold role following natural disasters. First, relationship banks may provide more lending to areas affected by the natural disaster, because they have more proprietary information about borrowers, giving them a competitive advantage in times of crisis. As a result such banks may need to withdraw more funding from unaffected areas, simply because they lend more to disaster-affected areas. However, relationship banks may be less inclined to restrict credit to other firms, because they also want to retain their lending relationship in unaffected areas. They might thus shift less lending, or be more inclined to refinance their lending to disaster areas or fund it by raising new equity.

– Table OA9 around here –

Table OA9 provides two tests of differential effects for relationship banking indicators. First, we test whether firms, whose main bank is located closer in terms of geographical distance are more or less affected by the indirect shock from the flood. Columns (1)-(3) report the continuous interaction of the difference-in-difference estimator with the firm-bank distance in 100 kilometer intervals. There appears to be no effect on the dependent variables. This result lends some credence to the hypothesis that relationship banks do not transfer shocks as much as arms-length lenders. Next, we test whether firms with a single (relationship) bank perform differently than multiple-bank firms. We find that for total borrowing in terms of overall liabilities and employment, single relationship firms perform significantly better; the negative indirect disaster shock is almost entirely buffered if the firm has a relationship lender.

Overall, the data provides only a weak indication that relationship banking may compensate slightly for the indirect shock, or stated differently, that relationship banks do not shift lending to the extent that arms-length lenders do. The result is somewhat surprising, given that relationship lenders might be especially inclined to provide lending to affected areas, because of their advantage in acquiring information about the future profitability of borrowers following the disaster. Our findings suggest that for relationship banks, this does not occur at the cost of connected, yet not directly disaster affected firms. This may be explained by the fact that such banks are able to more credibly resell new loans on secondary markets (Chavaz, 2016) or because they tend to have larger capital or liquidity buffers they can exploit in crises.

Bank type Germany's banking system is dominated by three major categories of banks: (government) savings banks, cooperative banks and commercial banks. The bank type may be important in explaining the extent of banks' lending shifts. Government banks may be pressured into providing more loans to disaster-affected businesses, because it is politically beneficial for local and regional politicians (Carvalho, 2014). As a result, government banks might shift more lending from unaffected into affected regions. Government banks also constitute a major difference to the previous papers looking at bank lending in the aftermath of natural disasters in the United States (Chavaz, 2016; Cortés and Strahan, 2017). German savings and cooperative banks are banks that are typically restricted to a certain geographical area, although customers can also bank with more distant savings banks on occasion.[30] Nevertheless, they typically do not own distant branches, from which they are likely to shift lending to disaster areas. It is thus inter-

[30] Savings banks are not allowed to actively acquire customers outside of its own region, but also do not have to reject them if they are actively seeked out. Additionally bank customers may stick with their regional savings banks, even if they change locations as savings banks cooperate nationwide for certain banking services such as cash withdrawals.

esting whether these local German banks react differently to the disaster demand than commercial banks.

– Table OA10 around here –

We test this idea by interacting the difference-in-difference coefficient with a dummy for each of the three major bank types. The results are provided in table OA10. There is little evidence that government banks indeed cause a differentially larger reduction in real effects, although there is some indication, as the triple interaction coefficient for employment is negative and significant. Additionally, for cooperative banks there are positive and significant effects on both total borrowing and the number of employees. This indicates, although only weakly, that government savings banks may transfer the shock more strongly than other banks, and that cooperative banks may be more concerned about serving their existing customers outside of the disaster region.

7.2 Figures and tables

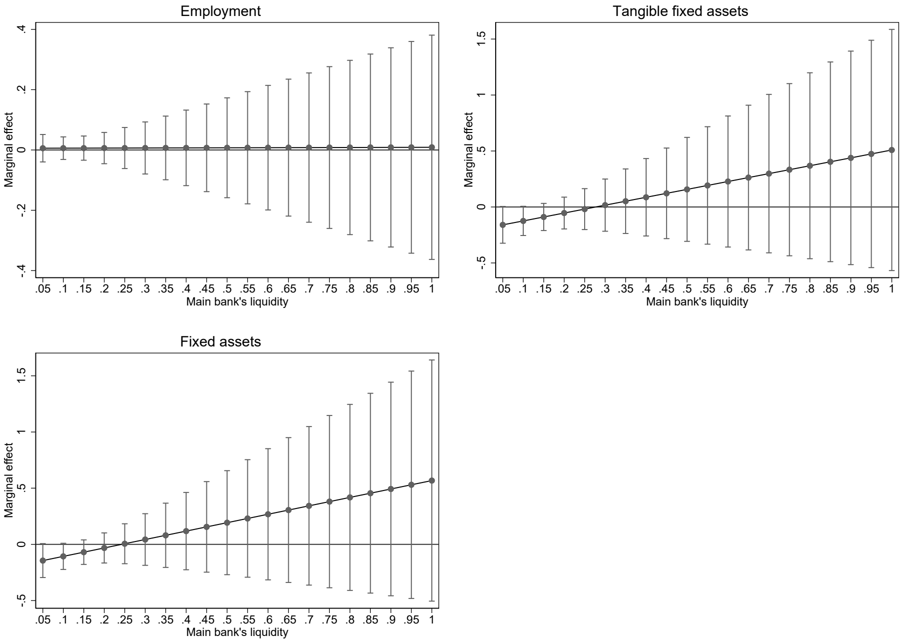


Figure OA1: Marginal effect of the interaction with the difference-in-difference coefficient at different values of banks' liquidity

This figure shows the marginal effects of the difference-in-difference estimation of being affected by a bank funding shock resulting from flooding in other regions at different values of the banks' liquidity. Bank liquidity is the share of cash on total assets, averaged over the years 2012 and 2013. Bank liquidity is depicted on the x-axis. Each graph represents the marginal effects for a different dependent variable, as indicated by its title. Bars indicate 90% confidence intervals.

Table OA1: Variable definitions

Identification Variables:	
Directly affected	Dummy variable indicating whether the firm was located in a flooded region during the 2013 flooding. A value of 1 indicates that the firm is located in a county with a claim ratio category of 4 or larger. A value of 0 indicates its located in within an unaffected county (claim ratio category 1). For a description of the categories refer to figure 1.
Indirect disaster exposure	Continuous variable indicating how extensively the firm is exposed to an indirect funding shock from its banks, stemming from the flood. A value of 1 would indicate that the firm is not indirectly exposed via its banks and a value of 9 that it is maximally exposed (all the other banks' firms are in the most flooded regions). See Equation 2 for details.
Post	Dummy variable set equal to 1 for the years 2013 and 2014 and set equal to 0 from 2009 to 2012.
Dependent Variables:	
Total liabilities	Firms' total liabilities in millions of Euros. Used as natural logarithm in the regressions.
Employment	Number of firms' employees. Used as natural logarithm in the regressions.
Tangible (fixed) assets	Firms' tangible fixed assets in millions of Euros. Used as natural logarithm in the regressions.
Control Variables:	
Cash	Cash and cash equivalent in millions of Euros.
Total assets	Total assets in millions of Euros.
Capital ratio	Shareholder funds (common equity) divided by total assets.
Current liabilities	Current liabilities in millions of Euros.
Interaction Variables:	
Main bank's reg. capital ratio	Variable set equal to 0 if the firms' main bank is in the lowest, 1 in the low, 2 in the high and 3 if it is in the highest quartile of the pre-flood capitalization distribution. The pre-flood capital distribution is the average of 2012 and 2013 values.
Pre-2013 disaster risk	Average disaster damages from 2002-2012 of other flood-related incidents in 9 claim ratio categories.

This table presents definitions of all the variables used in the regression tables and figures used in the main text and the online appendix.

Table OA2: Baseline regression for additional variables

	(1) Loans	(2) Cash	(3) Total Assets	(4) Provisions	(5) Net current assets	(6) Depreciations	(7) RoE	(8) RoA	(9) Capital Ratio
Post×indirect disaster exposure	0.077	-0.023	-0.006*	-0.004	-0.035***	-0.018	-0.388	-0.092	0.000
	(0.056)	(0.015)	(0.004)	(0.008)	(0.008)	(0.012)	(0.387)	(0.205)	(0.001)
Post×indirect disaster exposure×high capital	0.006	-0.015	-0.007**	0.008	-0.048***	0.014	0.069	-0.342*	-0.003**
	(0.075)	(0.019)	(0.003)	(0.011)	(0.007)	(0.016)	(0.514)	(0.176)	(0.001)
Post×indirect disaster exposure×low capital	-0.134*	0.016	-0.003	0.011	-0.001	0.023	-0.099	-0.264	-0.001
	(0.071)	(0.019)	(0.003)	(0.011)	(0.008)	(0.019)	(0.644)	(0.242)	(0.001)
Post×indirect disaster exposure×lowest capital	-0.044	-0.001	-0.014***	0.003	-0.032***	0.021	0.723	-0.312*	-0.000
	(0.080)	(0.019)	(0.003)	(0.011)	(0.008)	(0.017)	(0.573)	(0.188)	(0.001)
N	287,276	480,307	482,184	481,303	439,902	112,973	109,676	114,512	482,184
Number of Firms	95,030	114,354	114,398	114,343	111,382	33,215	32,814	33,662	114,398
Within R^2	0.001	0.004	0.120	0.014	0.023	0.057	0.034	0.023	0.105
Controls (lagged)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
County×Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES

This table presents interactions of the difference-in-difference estimation from table 3 with the capitalization of the firms' main bank for several firm-level variables. Loans is the log of loans. Cash is the log of cash and cash equivalent. Total assets is log of total assets. Prov is log of provisions. NCAS is log of firms net current assets. Depr is log of depreciation. RoE is return on equity. RoA is return on assets. Capital ratio is firm capital over total assets. Only non-directly affected firms are included in the regressions. All columns specify interactions with low capitalization quartile dummies which are set equal to 1 if the firms' main bank is in the lowest, low, high or highest quartile of the pre-flood capitalization distribution, respectively. The pre-flood capitalization is based on an average of the banks' regulatory capital ratio in the years 2012 and 2013. Double interaction coefficients (post×capitalization) and control variables are included, but not reported. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. Cash is the log of all cash and cash equivalent of firms and is a proxy for the firms' liquidity. Total assets is the log of the banks total assets and is proxy for firm size. Current liabilities is the log of the firms' current liabilities and is a proxy for the firms' short-term indebtedness. Capital ratio is common equity divided by total assets, and controls for the firms' relative equity position. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA3: Main bank's capital buffer by single and multiple relationship firms

	(1) Total liabilites	(2) Employment	(3) Tangible fixed assets
Post×indirect disaster exposure	-0.013*	-0.013**	-0.025*
	(0.008)	(0.006)	(0.013)
Post×indirect disaster exposure×high capital	-0.000	0.004	0.009
	(0.009)	(0.007)	(0.017)
Post×indirect disaster exposure×low capital	0.010	0.002	0.010
	(0.010)	(0.007)	(0.017)
Post×indirect disaster exposure×lowest capital	-0.002	0.001	-0.008
	(0.010)	(0.008)	(0.017)
Post×indirect disaster exposure×high capital×single bank	0.009	-0.013	-0.007
	(0.012)	(0.009)	(0.022)
Post×indirect disaster exposure×low capital×single bank	-0.005	-0.005	-0.031
	(0.012)	(0.009)	(0.022)
Post×indirect disaster exposure×lowest capital×single bank	-0.010	-0.007	-0.017
	(0.013)	(0.010)	(0.022)
N	477,661	477,661	477,661
Number of Firms	112,888	112,888	112,888
Within R^2	0.063	0.019	0.042
Controls (lagged)	YES	YES	YES
Firm Fixed Effects	YES	YES	YES
County×Year Fixed Effects	YES	YES	YES

This table presents results for an interaction of the baseline regression in table 2 with a single-bank relationship dummy. Firms with only one bank may be less able to get loans from alternative lending sources after the indirect flood shock. Only non-directly affected firms are included. Low capitalization quartile dummies are set equal to 1 if the firms' main bank is in the lowest, low, high or highest quartile of the pre-flood capitalization distribution, respectively. The pre-flood capitalization is based on an average of the banks' regulatory capital ratio in the years 2012 and 2013. Single bank is a dummy set equal to 1 if the firm has a relationship to 1 bank and set to 0 if it has a relationship with more than 1 bank. All interactions and control variables are included, but only coefficients of interest are reported. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Total liabilities is the log of firms total liabilities. Employment is the log of the number of firms' employees. Tangible assets is the log of firms' tangible fixed assets. Control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. Cash is the log of all cash and cash equivalent of firms and is a proxy for the firms' liquidity. Total assets is the log of the banks total assets and is proxy for firm size. Current liabilities is the log of the firms' current liabilities and is a proxy for the firms' short-term indebtedness. Capital ratio is common equity divided by total assets, and controls for the firms' relative equity position. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA4: Continuous interactions with the main bank's capital

	(1) Total liabilities	(2) Employment	(3) Tangible fixed assets
Post×indirect disaster exposure	-0.018*	-0.018***	-0.049***
	(0.009)	(0.007)	(0.016)
Post×indirect disaster exposure×main banks' capital (cont.)	0.058	0.070*	0.196**
	(0.054)	(0.040)	(0.094)
N	482,184	482,184	482,184
Number of Firms	114,398	114,398	114,398
Within R^2	0.064	0.018	0.042
Controls (lagged)	YES	YES	YES
Firm Fixed Effects	YES	YES	YES
County×Year Fixed Effects	YES	YES	YES

This table presents continuous interactions of the standard difference-in-difference estimation from table 2 with a continuous measure of the pre-flood capitalization of the firms' main bank. Only non-directly affected firms are included. The pre-flood capitalization is based on an average of the banks' regulatory capital ratio in the years 2012 and 2013. Employment is the log of the number of firms' employees. Tangible assets is the log of firms' tangible fixed assets. Fixed Assets is the log of firms' fixed assets. Unreported control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. Cash is the log of all cash and cash equivalent of firms and is a proxy for the firms' liquidity. Total assets is the log of the banks total assets and is proxy for firm size. Current liabilities is the log of the firms' current liabilities and is a proxy for the firms' short-term indebtedness. Capital ratio is common equity divided by total assets, and controls for the firms' relative equity position. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA5: Robustness tests for low bank capital dummy: total liabilities

	Equal periods	Placebo	Distance	Sector×Time	Only firm FE	No FE	Winsorized cap.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Liabilities	Liabilities	Liabilities	Liabilities	Liabilities	Liabilities	Liabilities
Post×indirect disaster exposure	-0.007	-0.011	-0.006	-0.005	-0.007	-0.012**	-0.007
	(0.005)	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
Post×indirect disaster exposure×high capital	-0.001	0.002	-0.004	-0.000	-0.000	0.004	-0.001
	(0.005)	(0.009)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Post×indirect disaster exposure×low capital	0.000	-0.000	0.001	0.000	0.001	-0.004	-0.001
	(0.005)	(0.010)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Post×indirect disaster exposure×lowest capital	-0.015***	-0.001	-0.016***	-0.016***	-0.012**	-0.011*	-0.016***
	(0.005)	(0.010)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
Post×distance to main bank(km)			-0.004**				
			(0.002)				
N	411,604	266,310	470,838	482,184	482,184	482,184	482,184
Number of Firms	114,398	114,306	111,503	114,398	114,398	114,398	114,398
Within R^2	0.032	0.001	0.000	0.063			0.064
Controls (lagged)	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	NO	YES
County×Year Fixed Effects	YES	YES	YES	YES	NO	NO	YES

This table presents robustness tests for the results presented in column (2) of table 3. Column (1) presents results for using equal base and post periods, here the year 2011 and 2012 are the base and 2013 and 2014 are the post period years. Column (2) presents the results of a placebo test using the year 2011 as the placebo event year (omitting the years 2013 and 2014). Column (3) includes a post-flood firm-bank distance control. Column (4) includes sector×year fixed effects. Column (5) and (6) provide estimates without county×year and firm fixed effects. Column (7) is estimated with the main banks' capital winsorized at the 5% level. High capital, low capital and lowest capital are quartile dummies which are set equal to 1 if the firms' main bank is in the lowest, low, high or highest quartile of the pre-flood capitalization distribution, respectively. The pre-flood capitalization is based on an average of the banks' regulatory capital ratio in the years 2012 and 2013. Double interaction coefficients, single interactions (in columns (5) and (6)) and control variables are included, but not reported. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Total liabilities is the log of firms' total liabilities. Unreported control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. Cash is the log of all cash and cash equivalent of firms and is a proxy for the firms' liquidity. Total assets is the log of the banks total assets and is proxy for firm size. Current liabilities is the log of the firms' current liabilities and is a proxy for the firms' short-term indebtedness. Capital ratio is tier 1 equity divided by total assets, and controls for the firms' relative equity position. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA6: Robustness tests for low bank capital dummy: employment

	Equal periods	Placebo	Distance	Sector×Time	Only firm FE	No FE	Winsorized cap.
	(1) Employ	(2) Employ	(3) Employ	(4) Employ	(5) Employ	(6) Employ	(7) Employ
Post×indirect disaster exposure	-0.003	0.001	-0.003	-0.002	0.005	0.004	-0.002
	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Post×indirect disaster exposure×high capital	-0.003	-0.011*	-0.004	-0.005	-0.005*	-0.005	-0.005
	(0.003)	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Post×indirect disaster exposure×low capital	-0.006	-0.000	-0.005	-0.007*	0.000	-0.000	-0.006*
	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Post×indirect disaster exposure×lowest capital	-0.010**	0.003	-0.009**	-0.008*	-0.005	-0.005	-0.009**
	(0.004)	(0.007)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Post×distance to main bank (km)			-0.002				
			(0.001)				
N	411,604	266,310	470,838	482,184	482,184	482,184	482,184
Number of Firms	114,398	114,306	111,503	114,398	114,398	114,398	114,398
Within R^2	0.014	0.008	0.000	0.018			0.018
Controls (lagged)	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	NO	YES
County×Year Fixed Effects	YES	YES	YES	YES	NO	NO	YES

This table presents robustness tests for the results presented in column (3) of table 3. Column (1) presents results for using equal base and post periods, here the year 2011 and 2012 are the base and 2013 and 2014 are the post period years. Column (2) presents the results of a placebo test using the year 2011 as the placebo event year (omitting the years 2013 and 2014). Column (3) includes a post-flood firm-bank distance control. Column (4) includes sector×year fixed effects. Column (5) and (6) provide estimates without county×year and firm fixed effects. Column (7) is estimated with the main banks' capital winsorized at the 5% level. High capital, low capital and lowest capital are quartile dummies which are set equal to 1 if the firms' main bank is in the lowest, low, high or highest quartile of the pre-flood capitalization distribution, respectively. The pre-flood capitalization is based on an average of the banks' regulatory capital ratio in the years 2012 and 2013. Double interaction coefficients, single interactions (in columns (5) and (6)) and control variables are included, but not reported. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Employment is the log of firms' employees. Unreported control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. Cash is the log of all cash and cash equivalent of firms and is a proxy for the firms' liquidity. Total assets is the log of the banks total assets and is proxy for firm size. Current liabilities is the log of the firms' current liabilities and is a proxy for the firms' short-term indebtedness. Capital ratio is tier 1 equity divided by total assets, and controls for the firms' relative equity position. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA7: Other potential shock amplifiers: banks' liquidity

	(1) Total liabilities	(2) Employment	(3) Tangible fixed assets
Post×indirect disaster exposure	0.001	-0.002	-0.027**
	(0.006)	(0.006)	(0.012)
Post×indirect disaster exposure×high liquidity	-0.005	-0.003	-0.011
	(0.005)	(0.004)	(0.009)
Post×indirect disaster exposure×low liquidity	-0.013***	-0.007**	-0.022***
	(0.004)	(0.003)	(0.007)
Post×indirect disaster exposure×lowest liquidity	-0.003	-0.002	-0.017**
	(0.005)	(0.003)	(0.008)
N	482,406	482,406	482,406
Number of Firms	114,013	114,013	114,013
Within R^2	0.063	0.019	0.042
Controls (lagged)	YES	YES	YES
Firm Fixed Effects	YES	YES	YES
County×Year Fixed Effects	YES	YES	YES

This table presents interactions of the continuous difference-in-difference estimation from table 2 interacted with the liquidity of the firms' main bank. Only non-directly affected firms are included. Columns (1)-(3) specify interactions with low liquidity quartile dummies which are set equal to 1 if the firms' main bank is in the lowest, low, high or highest quartile of the pre-flood liquidity distribution, respectively. The pre-flood liquidity is based on an average of the banks' liquid assets divided by total assets in the years 2012 and 2013. Double interaction coefficients and control variables are included, but not reported. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Total liabilities is the log of firms total liabilities. Employment is the log of the number of firms' employees. Tangible assets is the log of firms' tangible fixed assets. Control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. Cash is the log of all cash and cash equivalent of firms and is a proxy for the firms' liquidity. Total assets is the log of the banks total assets and is proxy for firm size. Current liabilities is the log of the firms' current liabilities and is a proxy for the firms' short-term indebtedness. Capital ratio is common equity divided by total assets, and controls for the firms' relative equity position. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA8: Other potential shock amplifiers: firms' capitalization and liquidity

	Capitalization			Liquidity		
	(1) Total liabilites	(2) Employment	(3) Tangible fixed assets	(4) Total liabilites	(5) Employment	(6) Tangible fixed assets
Post×indirect disaster exposure	-0.009*	-0.006*	-0.014*	-0.002	-0.003	-0.015*
	(0.005)	(0.003)	(0.007)	(0.004)	(0.003)	(0.008)
Post×indirect disaster exposure×high firm capital	-0.003	-0.009***	-0.017**			
	(0.004)	(0.003)	(0.007)			
Post×indirect disaster exposure×low firm capital	-0.005	-0.003	-0.009			
	(0.004)	(0.004)	(0.007)			
Post×indirect disaster exposure×lowest firm capital	-0.011***	-0.010***	-0.028***			
	(0.004)	(0.003)	(0.008)			
Post×indirect disaster exposure×high firm liquidity				-0.003	-0.002	-0.004
				(0.006)	(0.004)	(0.010)
Post×indirect disaster exposure×low firm liquidity				-0.017***	-0.009**	-0.003
				(0.005)	(0.004)	(0.010)
Post×indirect disaster exposure×lowest firm liquidity				-0.004	-0.004	0.009
				(0.006)	(0.004)	(0.010)
N	482,406	482,406	482,406	481,627	481,627	481,627
Number of Firms	114,013	114,013	114,013	113,755	113,755	113,755
Within R^2	0.050	0.019	0.042	0.062	0.019	0.042
Controls (lagged)	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
County×Year Fixed Effects	YES	YES	YES	YES	YES	YES

This table presents interactions of the standard difference-in-difference estimation from table 2 with firm financial constraint indicators. Columns (1)-(3) specify interactions with low *firm* capitalization quartile dummies which are set equal to 1 if the firms is in the lowest, low, high or highest quartile of the pre-flood liquidity distribution, respectively. The pre-flood capitalization is based on the average firm capital in the years 2012 and 2013. Columns (4)-(6) specify interactions with low *firm* liquidity quartile dummies which are set equal to 1 if the firms is in the lowest, low, high or highest quartile of the pre-flood liquidity distribution, respectively. The pre-flood liquidity is based on an average of the firms' liquid assets divided by total assets in the years 2012 and 2013. Double interaction coefficients and control variables are included, but not reported. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Total liabilities is the log of firms total liabilities. Employment is the log of the number of firms' employees. Tangible assets is the log of firms' tangible fixed assets. Control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. Cash is the log of all cash and cash equivalent of firms and is a proxy for the firms' liquidity. Total assets is the log of the banks total assets and is proxy for firm size. Current liabilities is the log of the firms' current liabilities and is a proxy for the firms' short-term indebtedness. Capital ratio is common equity divided by total assets, and controls for the firms' relative equity position. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA9: Relationship banking

	Firm-bank distance			Single bank relationship		
	(1) Total liabilites	(2) Employment	(3) Tangible fixed assets	(4) Total liabilites	(5) Employment	(6) Tangible fixed assets
Post×indirect disaster exposure	-0.007**	-0.006**	-0.011*	-0.012***	-0.011***	-0.020***
	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.006)
Post×indirect disaster exposure×bank firm distance	0.002	0.000	-0.004			
	(0.002)	(0.002)	(0.003)			
Post×indirect disaster exposure×single bank dummy				0.008**	0.009***	0.006
				(0.004)	(0.003)	(0.007)
N	467,554	467,554	467,554	477,661	477,661	477,661
Number of Firms	110,396	110,396	110,396	112,888	112,888	112,888
Within R^2	0.064	0.018	0.042	0.063	0.019	0.042
Controls (lagged)	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
County×Year Fixed Effects	YES	YES	YES	YES	YES	YES

This table presents interactions of the standard difference-in-difference estimation from table 2 with relationship banking indicators. Columns (1)-(3) provide the results of a continuous interaction with the distance between the firm and its main bank (bank firm distance). Distance is measured in 100 km intervals. Columns (4)-(6) provide the results of an interaction with a dummy variable indicating if the firm has a relationship to only 1 bank. This dummy is set equal to 0 if the firm has a relationship to more than 1 bank and set to 1 if it has a relationship to only 1 bank. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Total liabilities is the log of firms total liabilities. Employment is the log of the number of firms' employees. Tangible assets is the log of firms' tangible fixed assets. Control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. Cash is the log of all cash and cash equivalent of firms and is a proxy for the firms' liquidity. Total assets is the log of the banks total assets and is proxy for firm size. Current liabilities is the log of the firms' current liabilities and is a proxy for the firms' short-term indebtedness. Capital ratio is common equity divided by total assets, and controls for the firms' relative equity position. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table OA10: Bank Type Differentiation

	Savings banks			Cooperative banks			Commercial banks		
	(1) Total liabilites	(2) Employment	(3) Tangible fixed assets	(4) Total liabilites	(5) Employment	(6) Tangible fixed assets	(7) Total liabilites	(8) Employment	(9) Tangible fixed assets
Post×indirect disaster exposure	-0.012***	-0.004*	-0.018***	-0.012***	-0.011***	-0.024***	-0.005	-0.005**	-0.018***
	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.005)	(0.003)	(0.003)	(0.006)
Post×indirect disaster exposure×savings bank dummy	0.003	-0.010***	-0.006						
	(0.005)	(0.004)	(0.009)						
Post×indirect disaster exposure×cooperative bank dummy				0.010*	0.013***	0.014			
				(0.005)	(0.004)	(0.008)			
Post×indirect disaster exposure×commercial bank dummy							0.003	0.009**	-0.001
							(0.007)	(0.005)	(0.011)
N	482,406	482,406	482,406	482,406	482,406	482,406	482,406	482,406	482,406
Number of Firms	114,013	114,013	114,013	114,013	114,013	114,013	114,013	114,013	114,013
Within R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Controls (lagged)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
County×Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES

This table presents interactions of the standard difference-in-difference estimation from table 2 with three major German bank types: savings banks, cooperative banks and commercial banks. Savings is a dummy set equal to 1 if the firms' main bank is a savings bank and 0 if it is any other type of bank. Coop is a dummy set equal to 1 if the firms' main bank is a cooperative bank and 0 if it is any other type of bank. Comm is a dummy set equal to 1 if the firms' main bank is a commercial bank and 0 if it is any other type of bank. Indirect disaster exposure is a continuous variable measuring the exposure of the firm to the flood via its banks, according to equation 2. Total liabilities is the log of firms total liabilities. Employment is the log of the number of firms' employees. Tangible assets is the log of firms' tangible fixed assets. Control variables are cash, total assets, current liabilities and the capital ratio. All controls are included as first lags. Cash is the log of all cash and cash equivalent of firms and is a proxy for the firms' liquidity. Total assets is the log of the banks total assets and is proxy for firm size. Current liabilities is the log of the firms' current liabilities and is a proxy for the firms' short-term indebtedness. Capital ratio is common equity divided by total assets, and controls for the firms' relative equity position. We control for firm and county×year fixed effects. Clustered standard errors on the firm level of the point estimates are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.