When the Dam Almost Breaks: Disasters and Credit Risk*

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Abstract

How does risk perception in credit markets change after observing a nearby catastrophic event? We combine detailed geospatial data on ex-ante flood risk of German firms with credit register data and show that after a major flood in 2021, loan rates *decrease* for high-flood risk firms that were not directly affected. This negative indirect effect is strongest for banks with a large loan portfolio exposure to the flood. Firms that were affected by earlier, but similar floods do not experience rate reductions. The decrease is also strongest in areas with low climate change belief, while high climate change belief areas experience rate increases. Overall, our evidence points to a novel near-miss effect in lending markets after natural disasters, where a close disaster "miss" may be misinterpreted as a reduction in fundamental risk.

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1 Introduction

The frequency of natural disasters is likely to increase due to climate change (IPCC, 2023). While the direct consequences of natural disasters on financial markets are relevant and serious, disasters may also change risk perception in financial markets in high-risk but not (yet) affected areas. And while the direct effects of natural disasters are often regionally contained, such indirect consequences can affect a large number of financial market participants. Consequently, investigating the reaction of financial markets in high-risk, but not directly affected areas after a nearby salient disaster is important to understand the aggregate implications of climate-change related natural disasters.

To shed light on this question, we use extremely granular flood risk maps and link them to firms' addresses in Germany via their geographical coordinates. We then combine this ex-ante firm-level flood risk data with supervisory credit register data that covers the near-universe of lending to businesses in Germany. We exploit a significant flooding event in Germany – the 2021 "Ahrtal Flood" – as an exogenous shock to banks' risk perception of firms with high ex-ante flood risk. The credit register data allows us to investigate banks' lending reactions in detail, including changes to interest rates, loan volumes, collateral and the estimated probability of default. The data also allows us to control for an extensive set of fixed effects, ruling out alternative explanations, such as the proximity of certain industries to riverbanks.

Using this novel data, we show that interest rates on loans to unaffected firms with high ex-ante flood risk *decrease* after the flood. We also present evidence of increases in loan volumes and decreases in collateral and the probability of default. We find that this effect follows a slight U-shape: banks with a small or medium share of disaster-exposed loans decrease rates most, while an extremely large exposure is associated with smaller decreases. This suggests that our results are partially consistent with papers that find an overestimation of ex-post flood risk, stemming from increased disaster salience (Alok et al., 2020). We also provide evidence that the reduction in post-disaster, high-risk interest rates is experience-dependent. As opposed to firms without any disaster experience, loans to firms who have experienced a previous significant flood in 2002 or 2013 do not experience a rate reduction. This is in line with existing research using ex-post disaster risk measures, which finds a small and positive shock to interest rates (Correa et al., 2022). Overall, our results suggest that while there are positive effects on risk perception of natural disasters under certain conditions as the literature suggests, a much larger *negative* shock might exist in parallel that has not been previously explored.

We propose three different mechanisms to explain our results and test them against our data. First, we hypothesize that banks rationally update disaster risk, which could be due to unexpectedly high recovery payments from insurance companies and governments. If this were the case, we would expect firms in directly affected areas to experience a similar decrease in rates. Yet, our results document the opposite: directly affected firms pay a larger post-flood loan spread. This potential mechanism is also difficult to square with non-linear effects on banks' disaster exposure described above. Second, we hypothesize that banks might induce changes in non-affected firms' ex-ante flood risk. For example, banks could condition post-flood lending on firms purchasing flood insurance or implementing other preventive disaster measures. To validate the plausibility of this mechanism, we test if rates decrease more, where implementation of flood risk measures may prove easier: areas with high climate and environmental consciousness, which we proxy by the degree of support in the local population for the German "Green" party. However, we find the opposite effect: rates decrease less in regions with high support for climate-friendly policies.

Instead, our evidence is most consistent with a third mechanism: lowered risk perception after a near-miss event. The extant literature on this phenomenon mostly concerns *self* risk perception (Dillon and Tinsley, 2008; Arias et al., 2017; Gao et al., 2020). It suggests that after close, but not-too-close disaster misses, agents may perceive a decrease in risk, despite no changes in underlying risk. Our results are consistent with the interpretation that such a near-miss change in disaster risk perception may also apply to banks extending credit. This mechanism is consistent with a non-linear effect of loan portfolio exposure and a decreased effect in climate-conscious regions.

Our paper contributes to a growing literature that investigates the effects of climate-change related physical risk. In general, investors are aware of such climate related physical risk (Krueger et al., 2020) and it is generally priced in financial markets (Huynh et al., 2020; Acharya et al., 2022).[1] This is also true for lending markets. For example, Giglio et al. (2021) and Bernstein et al. (2019) show that long-term physical climate risk from natural disasters is generally priced in the housing market,[2] with expected implications for mortgage lending (Nguyen et al., 2022) and bank returns (Schubert, 2021). Similar findings apply in the case of corporate loans (Javadi and Masum, 2021). Our results are consistent with this cross-sectional view outside of flooding events. Conditional on many observables, higher flood risk is associated with higher interest rates in our setting, indicating that lending markets charge an interest rate premium for physical flood risk.

Beyond the pricing of disaster risk in normal times, our paper relates to papers researching the direct impact of disasters and abnormal weather events on banks and the loans they extend.[3] Disasters have been shown to affect lending volumes (Cortés and Strahan, 2017; Koetter et al., 2020; Blickle et al., 2021; Meisenzahl, 2023), collateral (Garbarino and Guin, 2021) and banks' financial stability (Schüwer et al., 2019). The effects on interest rates, in particular for small- and medium-sized enterprises have received less attention. Brown et al. (2021) is one of the few papers using credit register data to investigate the effect of unexpected snowfall on bank lending and interest rates.[4] In the Appendix, we conduct an analysis of the direct impact of natural disasters on interest rates that largely confirms the findings of this extant literature: natural disasters lead to higher loan rates for directly impacted borrowers.

[1]There is a vast literature discussing the effects of climate risk more generally on various asset classes (Bolton and Kacperczyk, 2023; Pástor et al., 2022; Goldsmith-Pinkham et al., 2022). See Giglio et al. (2021) for a review of this literature.

[2]On the other hand, Murfin and Spiegel (2020) finds no effects of projected sea level rise on house prices.

[3]de Bandt et al. (2024) provide an overview.

[4]Barth et al. (2022) and Barth et al. (2024) also investigate interest rates following natural disasters.

Instead of focusing on the direct effects of disasters, we propose a different, *indirect* effect of disasters on other high-risk firms, following a major disaster in nearby areas. Closest to our paper in this question is Correa et al. (2022), who use past natural disasters to proxy for disaster risk and find small positive indirect effects on interest rates following a renewed disaster. Our paper contrasts with their approach in several significant areas. First, our granular loan-level data has much larger coverage. In particular, it focuses on lending to small and medium-sized enterprises. This larger sample also allows us to control for a more granular set of fixed effects. Most importantly, we use a detailed ex-ante flood risk measure that is based on predicted flood-risk exposure at the firm level.[5] As our results demonstrate, this is significant because past disasters may mask a substantial negative effect of initial disasters on interest rates (see section 4.4). And while our results are consistent with their finding once accounting for past floods, our novel finding of a *negative* indirect effect on high-disaster risk firms allows us to uncover and investigate significantly different mechanisms.

Furthermore, we expand on evidence suggesting that managers react to salient events that do not reflect changes in underlying risk. For example, Dessaint and Matray (2017) show that managers temporarily increase corporate cash holdings after a hurricane, even though the future risk is unchanged. Because we do not investigate the direct impact of disasters, our results are closely related to a strand of literature studying "near-misses", complementing existing literature researching the effect of close-call misses of disastrous events. Bernile et al. (2017) show, for example, that CEOs who experience fatal disasters without extremely negative consequences lead riskier firms, while extreme disaster experience leads to reduced risk taking. Tinsley et al. (2012) show that near-misses from disasters are often not interpreted as signals that they might occur in the future, but instead as a signal that they did not occur, leading people to underestimate the resulting risk. Further, when disasters are interpreted as events that almost happened, the reverse effect can be observed. The lines of thought in this literature align well with our result that extremely large disaster

[5]Due to data limitations the set of papers using firm-level forward-looking measures of physical risk is very limited (Ginglinger and Moreau, 2023; Faiella and Natoli, 2019).

exposures are related to increases in interest rates (higher risk perception), but medium exposures are related to decreases in interest rates.

We suggest that such near-miss experiences might extend to financial intermediaries such as banks. This finding has important implications because it could suggest that banks consistently underestimate their exposure to climate-change related physical risk from natural disasters, even in the presence of good risk modeling.

2 The Ahrtal Flood in Germany

On the 14th and 15th of July 2021, a massive flood struck Western Europe causing widespread devastation in Germany, Belgium, the Netherlands, France, and Luxembourg. In Germany, particularly the western and southern parts were affected. In some areas of Rhineland-Palatinate and North Rhine-Westphalia, up to 94.5 liters of rainfall per square meter were recorded within 24 hours—an amount exceeding the region's typical total rainfall for the entire month of July. This heavy rainfall combined with already saturated soil and steep topography intensified the destructive force of the floodwaters (BMI (2021), WDR (2024)).

In the German public discourse, the event is often referred to as the "Ahrtal (Ahr Valley) flood", in recognition of the extreme devastation that occurred in the region around the river "Ahr". Within a few hours, the usually calm Ahr river rose by at least five meters above its typical depth of less than one meter. At that point, the power supply for the equipment measuring the water level failed. Despite warnings from the national weather service of heavy rainfall, many residents were not alerted in time by the authorities. As a result, more than 183 people lost their lives and 800 were injured (WDR (2024)). In addition to the west German Ahr Valley region, widespread damage was also reported in the southern and eastern parts of the country. Over 18,000 emergency personnel were mobilized to support the catastrophe management (BMI (2021)). Although, Germany had already experienced the 2002 and 2013 Elbe river floods, which had previously ranked among the country's most severe natural disasters, an event of such a scale and intensity of the 2021 flooding was still largely unforeseen (GDV (2013)).

In the affected area, roads, bridges, and other critical infrastructure were destroyed, and reconstruction efforts remain ongoing more than three years after the event. The monetary costs of the damage by far surpassed that of earlier events: the 2002 and 2013 floods caused losses of about €11 billion and €6–8 billion, respectively (GDV (2013)). The overall damages from the Ahr Valley flood to households, businesses, and public infrastructure are estimated at €33 billion—equivalent to nearly 1% of Germany's 2021 GDP (BMI (2021), Destatis (2024)). Despite the experience gained from earlier major floods, only €8.75 billion of these recent losses were covered by insurance, leaving a significant gap to be addressed through government aid and private funding (GDV (2024)).

In response, the German federal and state governments created a special €30 billion relief fund (BMF (2021)). This allocation involved maneuvering around Germany's well-established fiscal orthodoxy—embodied by the "debt brake" (Schuldenbremse)—to secure urgent reconstruction financing. Affected individuals, companies, and other institutions were eligible to apply for compensation covering up to 80% of documented damages, with the possibility of receiving full (100%) reimbursement in cases of severe hardship (Bundesregierung (2023)). Despite the substantial size of the relief fund, only €3.3 billion of the allocated amount had been approved as of the latest reports. A lack of expert professionals for evaluating damages, complicated planning and application procedures, as well as a shortage of skilled labor, slowed down the disbursement of relief funds (Capital (2024)). As a result, even this generously funded program fell short, leaving many victims to rely on private savings or take on debt to cover the costs of rebuilding.

The 2021 flood disaster underscored Germany's ongoing vulnerability to large-scale natural catastrophes, in spite of the lessons learned from the 2002 and 2013 Elbe floods. While some flood protection measures have been improved over the years, the widespread destruction caused by the 2021 floods highlighted weaknesses in infrastructure resilience and emergency communication systems. Additionally, inadequate insurance coverage continues to be a major issue and slow approval processes for government aid have hindered timely assistance across the affected regions.

3 Data and Empirical Estimation

We combine geolocalized data on river flood risk from the European Commission's Joint Research Centre (JRC) with confidential loan-level data on bank lending to firms from AnaCredit, the euro-area credit register. To calculate interest rate spreads, we merge information on loan-level interest rates with risk-free interest rates derived from government bonds provided by the European Central Bank (ECB). Additionally, we enhance our dataset with bank-level balance sheet data from the confidential Bundesbank monthly balance sheet statistics (BISTA). Our sample period ranges from June 2019 to July 2023, such that we have a symmetric window around the treatment event in July 2021 (with 2 years of observations each before and after). All variables and sources are described in detail in the following section.

3.1 Flood risk data

3.1.1 Granular flood risk maps

To capture ex-ante flood risk of individual firms, we obtain flood risk maps from the European Union Joint Research Centre (JRC). JRC data files are available in geospatial format and contain geographic features in the form of coordinates (longitude, latitude) and the locations' level of inundation (in meters) in case of a flood event. The data have an extremely granular resolution of 100×100 meters, allowing a precise identification of firms' ex-ante exposure to potential flooding. For example, the data allow to differentiate between risks of a firm located directly at the riverbank and those of another firm located in a distance of 100 meters from the river. Inundation levels are reported for several hazard return periods, reflecting the likelihood of a flood event occurring in the following intervals: 10, 20, 50, 100, 200 and 500 years.

3.1.2 Firm-level flood risk

To derive ex-ante firm-level flood risk, i.e. the level of inundation per hazard return period for each firm, we use information on firms' registered addresses (city, postal code, street address) from the Register of Institutions and Affiliates Database (RIAD), a confidential business register maintained by the European Central Bank in cooperation with EU central banks. The geocoding of firms' individual addresses (i.e. the transformation into geographic coordinates) and linking them to the flood risk maps has been conducted by the European Central Bank (ECB) and has been made available to ECB member institutions, including the Bundesbank, see ECB (2023).

The merged data provides us with information on each individual firm's ex-ante exposure to flooding at various hazard return periods. In other words, the data allow us to identify which firms are likely to be flooded in a flood event that occurs on average at return periods of 10, 20, 50, 100, 200 and 500 years. Finally, we translate inundation levels into damage costs (damage as a share of tangible fixed assets) via damage functions Huizinga et al. (2017). Based on reported damages in past flood events, damage functions allow us to link the severity of flooding (in terms of meters of water depth) to the average severity of damage (normalized to a share between 0 and 1). See figure A1 in the Appendix for a representative visualization of the damage function.

The final risk measure used in our analysis is the variable *expected annual losses*, which takes a value between 0 and 1 and represents a firms' share of tangible assets that is at risk of being destroyed by river floods in a given year. The measure is computed by combining damage costs and the annual probability of a river flood hazard to occur at a certain intensity. More specifically, the variable *expected annual losses* (EAL) of firm i, expressed as a share of total tangible assets, is computed using the following formula:

$$EAL_i = \sum_{rp} dmf_{rp,i} \times pb_{rp}, \tag{1}$$

where $dmf_{rp,i}$ is firm i's value of the damage function by return period and pb_{rp} is the annual hazard probability for each return period, measured as the inverse ratio of the return period (e.g. 1/500 for the 500 years hazard frequency).

– Figure 1 around here –

Figure 1 provides an illustrative example of the flood risk data based on firms located in an anonymous German city. Each node in the figure represents one firm, where node size is proportional to the expected annual losses from river flooding. Thus, a large node indicates that the corresponding firm has a relatively higher flood risk compared to smaller nodes. The figure highlights that granularity is key when it comes to investigating flood risk, as variations in the locations as small as 100 meters may alter the outcome drastically. While proximity to a river is an important criterion for overall flood risk, it is not the only one. Other geological features, including the slope and material of the surface in the area, are all relevant factors for determining overall flood risk.

3.2 Credit register data

3.2.1 Sample and main variables

We use confidential loan-level data on German banks' domestic lending to businesses from AnaCredit, the European credit register maintained by the ECB and euro area national central banks (Bundesbank (2024)). The minimum reporting threshold for loans in AnaCredit is set to 25,000 euros. We restrict the sample to newly originated loans from German banks to German business borrowers in non-financial sectors.[6] Data are reported at instrument-level

[6] Hence, we exclude all interbank-loans or loans between banks and other financial intermediaries. We filter out loans to financial companies by excluding borrowers in the NACE sectors 64, 65 and 66.

in monthly frequency and a large number of loan characteristics are available. We exclude loan instruments related to credit card debt, overdrafts, reverse repurchase agreements, trade receivables, finance leases and interbank deposits. Hence, our loan data set focuses on the main categories of business loans, which are credit lines, revolving credit and term loans. We include only loans with either fixed or variable rates, omitting loans with hybrid rate terms.[7] We exclude loans originated by banks owned primarily by state authorities, e.g. public mortgage banks or special purpose banks, and by branches of foreign banks. Moreover, we require banks to have issued new loans in at least three consecutive months during both the pre- and post-window periods.

We derive loan spreads by deducting from each loan-specific interest rate the corresponding risk-free rate. Our source of risk-free rates is the ECB database on euro area yield curves, which provides average yields (in per cent) by maturity (in months) across all euro area government bonds traded in the spot market. Our key variable for identifying the maturity of a loan is the legal final maturity of each instrument as reported in AnaCredit. We drop all loans with missing information on the legal maturity. We also drop loans with missing information or implausibly low values (smaller or equal to zero) for agreed interest rates. We use the maximum maturity of risk-free rates (360 months) as a reference for all loans exceeding this duration, and rely on 3 month risk-free rates for all loans below 3 month maturity or with flexible interest rates.

In addition to interest rates, we examine the lending volume, which represents the nominal amount granted to the counterparty at the time of origination. Furthermore, we analyze the impact on the share of collateral. The collateral share is defined as the protection value assigned to the loan divided by the lending volume.[8] Lastly, we investigate the probability of default (PD), as determined by banks' risk models. It refers to the likelihood that a

[7]In a few cases, single loans are reported in multiple instruments, i.e. there are several instruments with identical loan terms from one bank to the same borrower reported in one month. To prevent that this may have any impact on our estimation results, we aggregate multiple instruments to one if several characteristics are identical: inception date, bank id, firm id, instrument type, interest rate level, interest rate type, maturity, protection value.

[8]We winsorize this variable at the 1% and 99% level, as we observed a few implausibly high outliers.

counterparty will default within a one-year period.[9]

We are able to merge loan data and flood risk data based on a common identifier (the firm ID both used in AnaCredit and RIAD), resulting in the successful joining of 94.6% of observations.[10]

3.2.2 Loan-level control variables

We control for observable loan characteristics based on information in AnaCredit. The type of instrument may influence the determination of loan conditions, which we capture by including dummy variables for credit lines and revolving credit (term loan is the baseline). We also include the dummy variable *variable rate*, which equals one if the loan has a variable rate and zero if the loan has a fixed interest rate. To absorb any influence of loan size on loan conditions, we include the logarithm of the loan amount committed at inception (in Euros) in all regressions, where loan size is not the dependent variable. Finally, the amount of collateral deposited for a loan may have an impact, e.g. a loan with low collateral may be regarded as more risky, translating into higher spreads. We therefore include the collateral ratio in all regressions where it is not the dependent variable. We calculate the collateral ratio by using the loan-level share of the total sum of collateral in total loan volume committed at inception and then take the natural logarithm.

3.2.3 Bank control variables

To control for observable bank-specific characteristics, we include several bank balance sheet variables at monthly frequency in our empirical model. Specifically, we control for the size of banks by considering banks' log of total assets. Banks' abundance of liquidity is proxied by the *liquidity ratio*, which reflects the share of liquid assets in total assets. We capture

[9]PDs are only reported by banks that use an Internal Ratings-Based Approach (IRB). Banks report PDs either based on the loan or based on the counterparty. In case the PDs are produced at the loan level, the counterparty's PD at the reporting reference date is the exposure-weighted average PD. If both counterparty-level PDs and loan-level PDs are estimated, the counterparty-level PD is reported to AnaCredit.

[10]The reason why a complete merge was not possible is that address information are incomplete for some firms, which precludes the estimation of the flood risk measure.

banks' solvency by means of the *equity ratio*, i.e. the proportion of equity relative to total assets. Banks' *portfolio quality* is reflected in the sum of impairments and provisions over total assets. Finally, we control for the influence of banks' *funding structure* by including the ratio of deposits over total assets. The source for all of the balance sheet indicators is the confidential Bundesbank database BISTA (*'Monthly balance sheet statistics'*).

3.3 Descriptive statistics

Our monthly sample spans from June 2019 - July 2023 and contains 2,872,638 observations at the loan-level, reflecting 369,547 distinct bank-firm relationships, 766 unique creditors, and 267,761 unique borrowers, indicating that our sample includes many small- and medium-sized enterprises. For all variables used in the analyses, table A1 provides the variable definitions and sources, while table 1 presents summary statistics. Our main dependent variable, the interest rate spread, has a mean of 3.01%. The average log loan amount is 10.42 or 771,147€ in absolute terms, while the average log collateral ratio is 2.76 or 53.1%. For the probability of default, we have observations for only half of the sample. The mean log probability of default is -4.14 or 0.027.

– Table 1 around here –

2% of firms are located in flood-affected counties where a disaster alert was issued during the flood. Figure A2 displays these German counties graphically. Firms with a positive flood risk across Germany, which were not directly impacted by the Ahrtal flood, account for 22% of observations. We depict the cumulative distribution of ex-ante flood risk in figure A3, which shows that most firms are not subject to any significant flood risk. Regarding loan types, 81% of the loans are term loans, 18% are revolving credits, and 1% are credit lines. In 29% of the cases, these loans have a variable interest rate, while the rest are fixed interest rate loans.

– Figure 2 around here –

Figure 2 shows the distribution of flood risk across Germany, by plotting the share of firms with positive flood risk in each county. Figure A4 alternatively plots the average expected annual loss from flooding. As opposed to the U.S., flood risk in Germany is largely centered around rivers. For example, flood risk is highest in the lower-Rhine and Mosel valleys (western corner of the map) and the Main around Frankfurt (west-middle of the map). Flood risk is also large in individual cities close to the Saale river (Jena and Dessau; yellow spots in the middle-eastern part of the map). In general, flood risk is regionally heterogeneous across Germany, making it unlikely that our analysis is driven by regional specificities.

3.4 Main specification

We assess the indirect impact of flooding on post-disaster lending patterns for firms with high flood risk. Specifically, we analyze the effect of the "Ahrtal" flood event on loan terms of firms located in at-risk areas that were *not* directly impacted by the flood event. For this purpose, we estimate the following difference-in-difference regression over the sample period from July 2019 to July 2023. We use detailed firm-level flood risk calculated from geospatial data (see section 3.1) and combine it with loan level data to quantify banks' lending adjustments after the occurrence of a major flood with respect to other high-disaster-risk firms. Because we are interested in the *indirect* effect of the disaster, we exclude regions that are directly affected by the disaster for this analysis. Concretely, we implement the following regression:

$$\begin{aligned} Y_{l,b,f,t} &= \beta_1 \cdot \text{Flood risk}_f + \beta_2 \cdot \text{Flood risk}_f \times \text{post}_t + X_{b,t} + Z_{l,b,f,t} \\ &+ \gamma_b + \phi_{i,L,(s),t} + \mu_f + \varepsilon_{l,b,f,t}, \end{aligned} \tag{2}$$

where $Y_{l,b,f,t}$ are loan characteristics of loan l from bank b to firm f in month t. Our focus is on investigating the effect of the flood on the interest rate spreads, the volume of lending, the share of collateral and the probability of default (PD) from banks' risk models.

Flood risk$_f$ is our novel firm-level indicator of ex-ante exposure to flooding hazards. Post$_t$

is an indicator variable equal to one starting in August 2021, i.e. after the flood disaster on 14 and 15 July 2021, and zero otherwise. Our main coefficient of interest is β_2, which captures any change in banks' lending behavior vis-à-vis high-risk borrowers after the flood disaster.

We include a rich set of control variables and fixed effects in our models. $X_{b,t}$ is a vector of bank-time-varying control variables, containing the following variables: bank size, liquidity ratio, equity ratio, portfolio quality and funding structure. We add instrument type (credit line, revolving credit or term loans) and interest rate type as loan-level control variables in the vector $Z_{l,b,f,t}$. To control for unobserved supply-side effects we account for bank fixed effects (γ_b) in all regressions. We also include industry-location-time or industry-location-size-time fixed effects ($\phi_{i,L,(s),t}$) to account for demand-side factors (Degryse et al., 2019). We additionally account for firm fixed effects (μ_f) in several specifications.

4 Baseline, Exposure and Experience: Main Results

How does lending to high-flood-risk firms change after a major flood has occurred elsewhere? One argument might be that a distant flood makes flood risk elsewhere more salient and thus interest rates are likely to increase. On the other hand, banks might learn that disaster payments by insurance companies and the government are sufficient to cover flood risk and thus bank rates do not need to account for this risk. Banks might also induce their customers to take flood prevention measures. Overall, the effect is theoretically ambiguous.

In this section, we show that loan spreads significantly *decrease* for firms with high ex-ante flood risk after the "Ahrtal" flood. This decrease is persistent, robust, and is stronger for banks' with a larger share of directly flood-affected borrowers. We also show that this effect is largely absent when banks had experience with significant prior flooding.

4.1 Baseline results

We estimate equation 2 and provide the results in table 2. First, we note that in general, higher flood risk appears to be reflected in loan terms in the expected directions. Higher ex-ante flood risk is associated with higher interest rates (see *Flood risk* coefficient in column (1)). In terms of economic magnitude a 1 percentage-point increase in expected annual flood losses (as a share of tangible assets) is associated with an increase in 4.7 basis points. Or put differently, a one standard deviation (1.11 pp) higher flood risk is associated with an increase in the loan spread by about 5 basis points. Higher ex-ante flood risk is also associated with larger collateral requirements (column (5)) and higher estimated probability of default (column (7)), while the loan volume is unaffected (column (3)).

Next, we document a surprising effect of the "Ahrtal" flood on ex-ante high-flood-risk firms located outside of the disaster area. We find that for such directly unaffected, but high-risk firms, loan spreads *decrease* significantly (see coefficient for the interaction term *Post* × *Flood risk* in column (1)). Here, a one percentage-point increase in expected annual flood losses is associated with a decrease in interest rates by about 3.7 basis points. This post-flood effect thus erases a large part of the flood-risk premium that firms pay on their loans before the "Ahrtal" flood. This finding is statistically robust when accounting for firm fixed effects (column (2)), although the economic magnitude is smaller. This result is counterintuitive, since we might expect banks and firms to update their (perceived) flood risk upwards, after a major flood has occurred elsewhere. Indeed, the extant literature seems to document upwards updating (Dessaint and Matray, 2017; Correa et al., 2022), potentially conflicting with our results. However, in contrast to this literature our measure of flood risk is not based on *flood-experience*, but instead on future projections, a difference we will highlight later in section 4.4. In addition, our large credit register data allows for the inclusion of stringent industry-location-size-time fixed effects to control for changes in loan demand following the disaster.

We suggest three potential explanations for this negative result. First, banks might adjust their rates downward, because they learn that dealing with the ramifications of a flood is not risky after all. Post-disaster recovery funds from insurance, government and other sources may be large enough to cover most losses, consequently banks bear little ultimate risk. Second, it could be that banks condition post-disaster credit on flood-prevention measures at firms, or push them to take up insurance, thus removing concerns about future flood risk to bank lending. Third, it might be the case that near-miss disaster experiences lead banks to underestimate future disaster risk (Tinsley et al., 2012; Bernile et al., 2017). We try to disentangle these potential mechanisms in section 5.

– Table 2 around here –

In addition to lowering spreads, banks also provide a larger volume of loans to high-disaster-risk firms (column (3)). Yet, this increased lending to post-disaster risk firms disappears when we account for firm fixed effects in more stringent specifications (column (4)). Nevertheless, we do not find evidence that banks adjust their lending downward, as might be expected if banks think disaster strikes have become more likely for at-risk firms. We also do not find that banks require more post-disaster collateral (columns (5) and (6)). Instead, the coefficient for *Post×Flood risk* is negative, but statistically insignificant. A similar finding applies to banks' estimated probability of default, where we find negative, but statistically insignificant coefficients (columns (7) and (8)). Given the decrease in spreads, this finding is somewhat surprising and suggests that changes in post-disaster risk are not so fundamental that they enter banks probability of default models. On the contrary, it makes it likely that changes in spreads stem from loan officers using some discretion in setting interest rates, either accounting for difficult-to-observe changes in disaster adaptation measures, or loan officers being subject to a near-miss bias.

4.2 Persistence, placebo and robustness

Persistence and Placebo Ex-ante, it is unclear whether changes in risk perceptions will be permanent or transitory. For example, Dessaint and Matray (2017) suggest that risk perception among CEOs after hurricanes is more likely to be transitory and Correa et al. (2022) similarly find evidence of a transitory effect that disappears over time. Kong et al. (2021) also find a transitory effect for analysts. Consequently, we test whether our effect is transitory or persistent, by varying the $Post_t$ dummy in our regression across different quarters. Specifically, we re-estimate our regression using $Post_{t-k}$ where k varies between -4 and 4 and denotes quarters relative to the "Ahrtal" flood in July 2021. We display the coefficient of our difference-in-difference effect using these dummies in figure 3.

– Figure 3 around here –

The figure demonstrates that the effect of the disaster on spreads of high-disaster-risk firms is only measurable after the disaster has occurred. This placebo-type regression indicates that our results are unlikely to be the result of a violation of the parallel trends assumption. Importantly, the figure also shows that the negative effect on high-disaster-risk firms that occurs after the flood is persistent over the 4 quarters after the disaster. While the effects are strongest one quarter after the disaster, the effects are still statistically significant one year after the flood has occurred. Thus, as opposed to the extant literature, we show that banks persistently adjust their spreads downwards for ex-ante high risk clients.

Robustness We show that these findings are robust in several different ways. First, the results remain unchanged when including bank × year fixed effects as demonstrated in table A2. Additionally, since flood risk is zero for a large share of the firms in our sample (see figure A3), we show in table A3 that our results remain when using an indicator variable instead of a continuous measure. The results are also unchanged when using the same sample across regressions to ensure comparability (table A4).

4.3 Disaster exposure

Exposure to disaster-affected firms In principle, banks can learn lessons from the 2021 "Ahrtal" flood in two different ways. First, they can learn through publicly available information. For example, they might learn from the media that disaster relief was stronger than expected. Second, they may learn through their own experience with disaster-affected customers. Consequently, before investigating the mechanism, we investigate *how* banks learn about the (perceived) change in disaster risk, by interacting our difference-in-difference coefficient with banks' loan exposure share to the disaster region. This exposure share is the ratio of all business lending of each bank going to disaster-affected firms relative to all business loans.

– Table 3 around here –

The results of this triple interaction on loan spreads are displayed in table 3.[11] The negative interaction coefficients of *Post* × *Flood risk* × *Exposure share* in columns (1) and (2) indicate that banks with a larger exposure to the disaster area are the main driver of the observed decrease in spreads for high-disaster-risk firms after the "Ahrtal" flood. For easier interpretation, we split the exposure variable into tercile dummies and interact our difference-in-differences coefficient with these dummies. Column (3), using industry-location-time fixed effects, indicates that there is a statistically significant negative effect on spreads for high ex-ante flood-risk firms. Spreads decrease by about 2 basis points for a firm with a one-standard deviation higher ex-ante flood risk after the occurrence of the "Ahrtal" flood. This effect changes to a decrease of 7 basis points for lending from banks with a medium exposure share and a decrease of 8.6 basis points from banks within the top exposure tercile.[12] Different sets of fixed effects largely confirm these findings (column (4)).

Next, we test if this effect might be non-linear and include an interaction with the squared exposure share in our regression. The positive coefficient estimate of this interaction with

[11] The results are robust to using a harmonized sample (table A5).

[12] $-1.83 * 1.11 + (-4.70 * 1.11 * 1) = -7.24; -1.83 * 1.11 + (-5.88 * 1.11 * 1) = 8.55$

the squared term suggests that there might be a non-linear effect of disaster exposure on post "Ahrtal" interest rates to non-affected but high-disaster risk firms (column (5)). However, the effect is very small and practically irrelevant in the reasonable range of the exposure distribution. Certainly, the effect never turns positive.

4.4 Experience with prior disasters

If banks permanently update their perceptions about disaster risk after a natural disaster, the effect should be limited to one significant disaster. After disaster expectations have adjusted, banks should show little change after subsequent disasters. To see if this might be the case, we turn to previous disasters. Conveniently for our analysis, Germany was hit with three once-in-a-century[13] flooding events since the turn of the millenium. The first major flood occurred in 2002 and was focused around southern and eastern Germany. The second major flood occurred in 2013 and happened mostly in eastern Germany. The "Ahrtal" flood constitutes the third major flood. We obtain data on firms affected by these floods from Noth and Rehbein (2019) and Koetter et al. (2020) and merge them with our credit register data.[14] Next, we interact this dummy of firms being affected by a prior flood with our difference-in-differences interaction.

– Table 4 around here –

The results are displayed in table 4. First, independent of the 2021 "Ahrtal" flood, firms with higher flood risk that have been subject to a previous flood (coefficient of *Flood Risk* × *Past Flood*) are charged lower interest rates relative to firms without such prior disaster experience. This suggests that at-risk firms subject to past disasters are generally not charged higher rates, indicating that disaster risk is not systematically underestimated.

Similarly to the baseline, loans to high disaster-risk firms have reduced loan spreads after the "Ahrtal" flood. Column (1) indicates 6.8 basis points lower spreads for a one percentage

[13] Based on the historical hydrological frequency of river flood levels.
[14] Rehbein and Ongena (2022) also use the 2013 flood data.

point increase in annual expected flood losses after the "Ahrtal" flood.

Interestingly, this effect is essentially reduced to 0 for loans to firms who have experienced the 2002 flood, because the coefficient of $Post \times Flood\ risk \times Past\ flood$ is positive, significant and of almost the same size as the baseline difference-in-differences effect. This finding is similar when including firm fixed effects (column (2)). For the 2013 flood, we also find a similar pattern: loans to firms who have not been affected by the 2013 flood experience a significant reduction in credit spreads, while this effect is not present in firms who have experienced the 2013 disaster (column (3)). In this case however, the post-disaster positive effect does not remain significant when using firm fixed effects (column (4)). Combining both disasters reveals similar results: Spreads are significantly lower for high-flood-risk firms after the "Ahrtal" flood, but this effect cancels out when the firm has been subject to a prior disaster in 2002 or 2013 (column 5). When including firm fixed effects in this regression, the effects are economically smaller, but remain statistically significant (column 6).

– Figure 4 around here –

Reactions in interest rates of high ex-ante flood risk firms significantly differ between firms who have *experienced* previous floods and those who have not. Spreads of loans to firms located in regions which have experienced a significant previous flood generally have *increased* after the "Ahrtal flood". This is evidenced by the positive – although only marginally significant – coefficient estimates of $Post \times Past\ Flood$ in table 4. This result is consistent with findings in Correa et al. (2022), who similarly show an increase in spreads in high-disaster-experience regions after another salient disaster has taken place. As we show in figure 4, this positive effect on spreads also disappears over the medium term. This is also in line with results from Correa et al. (2022) and Dessaint and Matray (2017) and suggest that firms with previous flood experience receive a short term increase in rates after another flood that does not directly affect them, perhaps stemming from increased disaster salience. At the same time, while this flood *experience* effect is positive, a negative and much larger *ex-ante flood risk* effect exists in parallel. This negative effect is the focus of our analysis.

Generally speaking these results indicate two key findings: interest rates on loans for high-flood-risk firms adjust significantly *downward* after a natural disaster. This effect is also present when looking at previous disasters, i.e. high-disaster-risk firms with previous disaster exposure are charged relatively lower rates. More importantly, the downward adjustment in interest rates is limited to firms that have not experienced a prior disaster. Firms with prior disaster experience get lower rates from their exposure to the prior disaster, but do not experience a further decline after the 2021 "Ahrtal" flood.

5 Mechanisms

We propose three potential mechanisms that might explain the *decrease* in interest rates on high-flood risk loans following a major flood in other areas. First, observing the reaction of insurance companies and governments, banks learn that they bear less risk than anticipated and reduce risk premiums. Second, the disaster induces flood-risk adaptation measures at the local or firm level that result in reductions of risk premiums. Third, banks interpret the flood as a near miss event, falsely thinking that non-flooded customers are at lower risk than previously thought simply because they were not affected by this particular flood (Dillon and Tinsley, 2008; Arias et al., 2017; Gao et al., 2020).

5.1 Climate change beliefs

Because interest rates decrease after a disaster *once*, but do not change in subsequent disasters (see section 4.4), one might hypothesize that banks generally observe that they overestimated losses from flood risk in affected areas. One implication of this hypothesis is that rates may also decrease in flood-affected areas. We investigate this question in detail in Appendix A1 and find that rates *increase* in flood-affected areas after the disaster (as indicated by the positive and significant coefficient for *Disaster region* × *Post* in column (1) of table A6). Nevertheless, there might be different reasons other than changed expectations about future losses (such as the loss of collateral) that may explain this change in premiums.

Consequently, we expand our analysis by asking whether the effects are heterogeneous with respect to climate change beliefs in the population. If interest rates are rationally updated, climate change beliefs should not play a large role. On the other hand, if stronger climate change beliefs are related to stronger reductions in interest rates, this might be an indication that changes in post-disaster flood prevention mechanisms play a role.

We implement this test using the share of voters for the Green party in the general election in September 2021 as a proxy for climate change beliefs. Climate change beliefs should be larger in counties with a higher share of Green voters. As an alternative, we rely on the share of right-wing voters, i.e. voters for the party "Alternative für Deutschland" (AfD), which is a party openly denying the existence of human-made climate change. Climate change beliefs should thus be low in counties with a high share of voters for the right-wing party. We then interact these respective voter shares with our difference-in-difference coefficient from equation 2 and present the results of this implementation in table 5.

Table 5 column (1) shows that in counties with higher share of Green votes in the 2021 general election, spreads are adjusted less after the flood compared to counties with low shares of Green votes. At the median of the share of Green party votes (18.67), the combined effect is very close to zero. In other words, we observe *decreases* in spreads on high-flood-risk loans mainly for areas with *low* green party support. We find a similar pattern when splitting the Green party vote into terciles (column (2)). In areas with high-green party support, interest rates on high-flood-risk loans *increase*.

The pattern is also similar for the share of AfD votes. While we do not find any evidence for a differential effect in continuous interactions (column (3)), we find a strong negative interaction effect when splitting the distribution into terciles (column (4)). Here, we find clear indication that interest rates increase, when the support for the AfD is relatively low (positive post×flood risk coefficient), but is negative when the AfD vote share is in the median tercile or the top tercile, where the effect is most strongly negative.

These results provide evidence against both a rational updating hypothesis (where we would expect null results) and against the future prevention hypothesis, where we would expect the strongest decreases to occur in areas where flood-adaptation measures are perhaps most likely to be undertaken – areas with high Green party support. Instead, rates increase when climate-change beliefs are strong. The finding is consistent with the near-miss hypothesis, where Green areas are less likely to interpret the flood as a near-miss and instead as an indication of higher future flood risk. This interpretation is also consistent with evidence in Correa et al. (2022) that interest rates rise most when attention to climate change is high. It also aligns well with findings from Baldauf et al. (2020) which show that houses at flood-risk sell at a discount only in high climate-change belief areas.

6 Conclusion

This paper investigates how bank lending changes after a major flood event, in particular to firms unaffected by the disaster but with high future flood risk. Using detailed firm-level ex-ante flood risk data combined with confidential and granular loan-level data from AnaCredit, we document a surprising post-disaster decrease in lending rates to high-risk firms in areas unaffected by the Ahrtal flooding in 2021 in Germany. Specifically, a one standard deviation higher flood risk is associated with a 4.1 basis point reduction in interest rates. We additionally present evidence of higher loan volumes, reduced collateral requirements, and lower probabilities of default for high risk but not directly affected firms.

The decrease in interest rates is robust and persistent, with the results remaining statistically significant even one year later. Banks, which initially had a large exposure to directly affected borrowers in the disaster region, lower interest rates most to the unaffected, yet high-flood risk borrowers after the flood. We also demonstrate that firms affected by prior disasters are not affected by this significant decrease in post-flood interest rates and that decreases in interest rates are centered in climate-denying regions.

We propose three mechanisms that could explain our results. First, one possible explanation for banks lowering their rates is the recognition that dealing with the aftermath of a flood carries negligible risk. This could be due to substantial recovery funds from insurance, government, and other sources, which may absorb most losses and limit the risk borne by banks. We show that this is unlikely to be the case, as directly affected firms pay a larger post-flood loan spread. Moreover, such an explanation is inconsistent with our finding that climate-change aware regions show the least strong decreases in interest rates.

Second, banks might require firms to adopt flood-prevention measures or take out insurance after a disaster, reducing concerns about future flood risks for lending. We show that this is unlikely to be the case, as interest rates increase in counties with strong climate and environmental awareness, measured by election results for the Green party. If, instead bank-induced flood prevention measures were the culprit, we would expect the reverse effect: rates would decrease most when the willingness to implement protective measures is highest.

Third, we propose a "near-miss" channel; a cognitive bias where an event that was almost experienced alters the perception of risk. Instead of recognizing the event as a warning of potential future danger, banks may interpret the near-miss as evidence that the risk is less than previously assumed. We suggest that such a near-miss change in disaster risk perception also takes place in credit markets and that such an effect might lead banks to underestimate future disaster risk. Consequently, examining how financial markets respond with respect to high-risk but unaffected firms following a nearby salient disaster is crucial for understanding the aggregate implications of climate-change related natural disasters.

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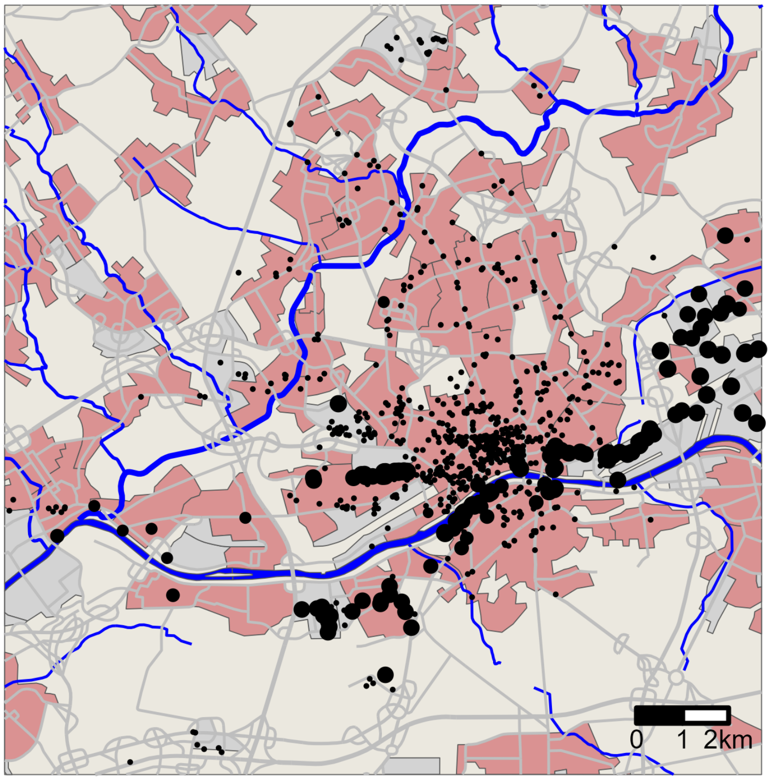
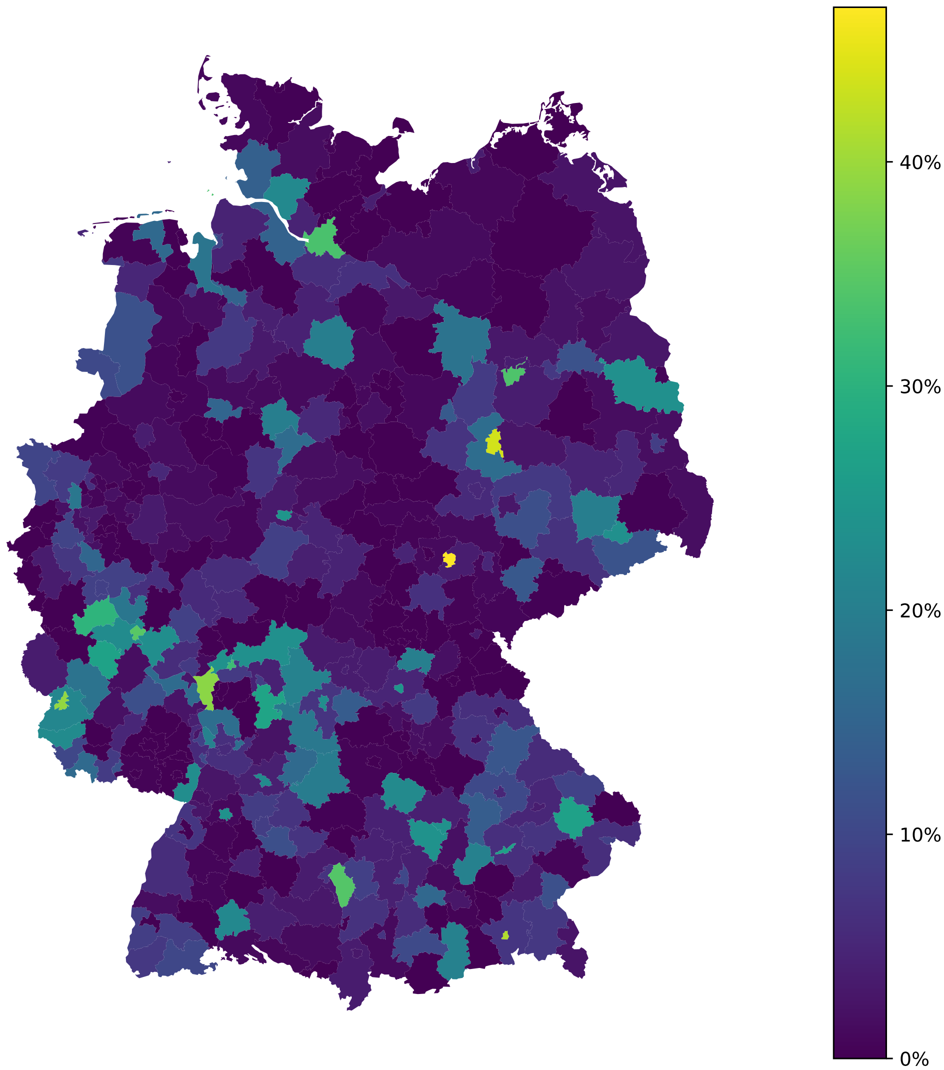
Figures & Tables

Figure 1: Illustration of firm-level flood risk data



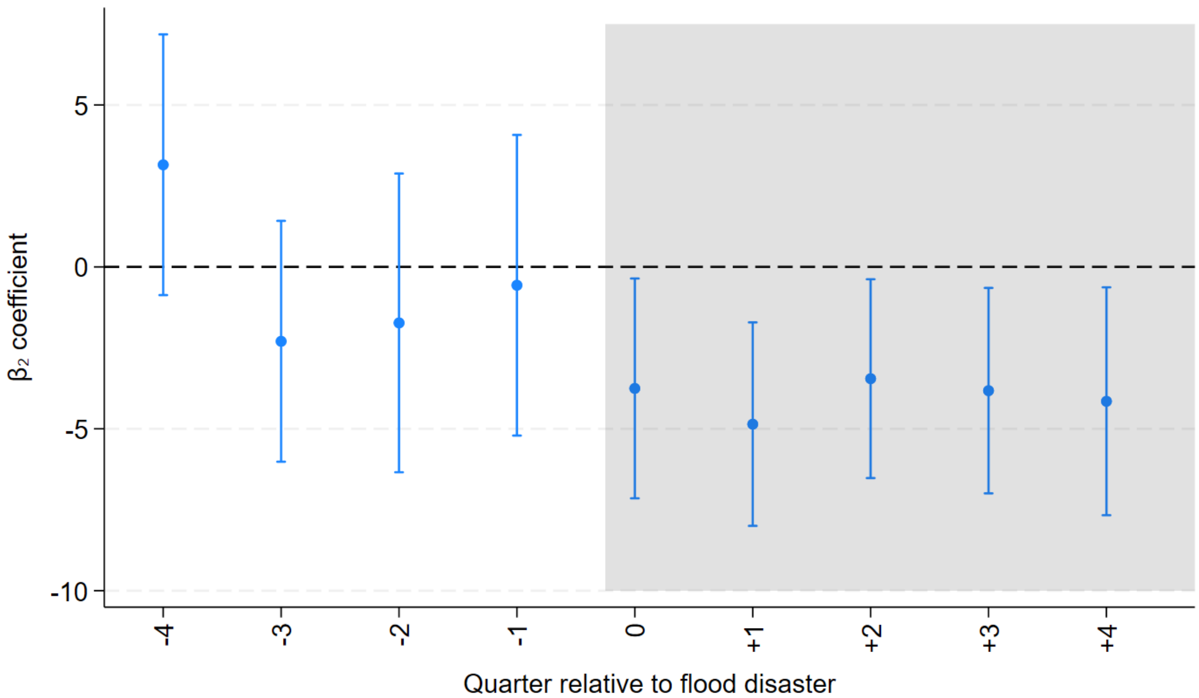
Note: The figure illustrates the firm-level flood risk data based on observations for an anonymous German city. Each node represents one firm. Node size is proportional to flood risk exposure: large nodes indicate large expected losses in the event of flooding, small nodes reflect small or no losses.

Figure 2: Distribution of ex-ante firm-level flood risk across Germany



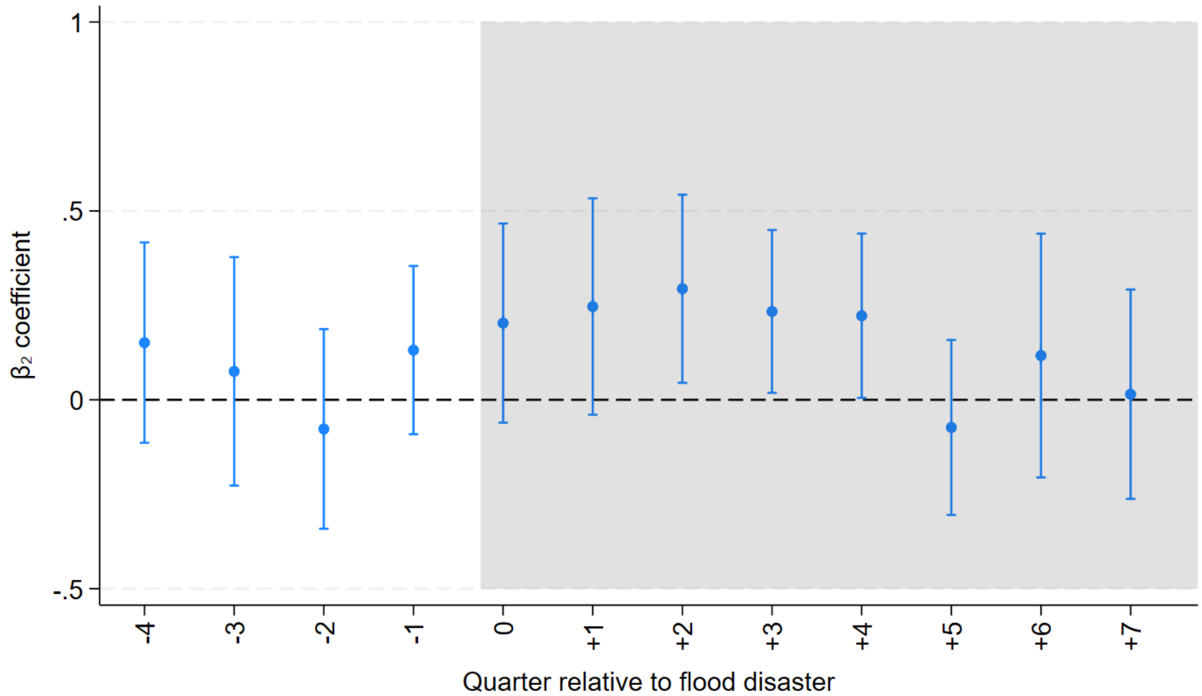
Note: This map displays the share of firms in each county with a positive expected flood damage in the sample period from June 2019 to July 2023. The share of firms is determined by dividing the number of firms in a county that have a positive flood risk by the total number of firms in that county. Flood damage is defined as individual firms' expected annual losses from river floods per year. Expected annual losses are calculated by multiplying each firm's damage function by its tangible assets and the probability of flood risk (see section 3.1.2 for further details).

Figure 3: Persistence of Flood Risk Perception: Effects on spreads over time



Note: The figure plots the results when the interaction term *flood risk* × *post* is allowed to vary in each quarter around the disaster event. Specifically, we amend our baseline regression in equation (2) by adding separate dummies for each quarter after the disaster and for each of the four quarters prior to the disaster. In formula notation, the regression is as follows: $Spread_{l,b,f,t} = \beta_1 \cdot floodrisk_f + \sum_{k=-4}^{7} \beta_{2,k} \cdot floodrisk_{f,t} \times post_{t+k} + X_{b,t} + Z_{l,b,f,t} + \gamma_b + \phi_{i,L,t} + \mu_f + \varepsilon_{l,b,f,t}$, where k denotes the quarter relative to the July 2021 Ahrtal flood. The figure shows the quarterly point estimates for the main coefficient of interest, $\beta_{2,k}$, together with 5-95% confidence intervals Standard errors are clustered at the firm-time level.

Figure 4: Dynamics of spread pricing around flood event for past flood events interaction



Note: The figure plots the quarterly point estimates for the interaction coefficient of $Post_t$ and $Past\ flood_f$, $\beta_{2,k}$ together with 5-95% confidence intervals from the following regression: $Spread_{l,b,f,t} = \beta_1 \cdot Pastflood_f + \sum_{k=-4}^{7} \beta_{2,k} \cdot Pastflood_f \times Post_{t+k}) + X_{b,t} + Z_{l,b,f,t} + \gamma_b + \phi_{i,L,t} + \mu_f + \varepsilon_{l,b,f,t}$, where k denotes the quarter relative to the July 2021 Ahrtal flood. $Post_{t+k}$ is a dummy variable, capturing each of the quarters between four quarters prior to the Ahrtal flood until 7 quarters after the event. $Pastflood_f$ is a dummy variable indicating if firm f has been affected by any of the previous flood events in 2002 and 2013. $X_{b,t}$ is a vector of bank-time-varying control variables, $Z_{l,b,f,t}$ includes loan-level controls, γ_b represent bank fixed effects, $\phi_{i,l,t}$ are industry-location-time fixed effects and μ_f represent firm fixed effects. Standard errors are clustered at the firm-time level.

Table 1: Descriptive statistics

	N	Mean	SD	5th	25th	Median	75th	95th
Spread (%)	2,872,638	3.01	2.48	1.15	1.88	2.49	3.29	5.66
Loan amount (log)	2,872,638	10.42	1.69	7.99	9.68	10.35	10.95	13.74
Collateral ratio (log)	2,872,638	2.75	2.15	0	0	4.35	4.44	4.67
PD (log)	1,546,842	-4.14	1.10	-6.03	-5.09	-3.78	-3.44	-3.00
Post	2,872,638	0.49	0.50	0	0	0	1	1
Flood risk (x100)	2,872,638	0.22	1.11	0	0	0	0	0.65
Disaster region	2,872,638	0.02	0.14	0	0	0	0	0
Term loan	2,872,638	0.81	0.39	0	1	1	1	1
Revolving credit	2,872,638	0.18	0.39	0	0	0	0	1
Credit line	2,872,638	0.01	0.08	0	0	0	0	0
Variable rate	2,872,638	0.29	0.45	0	0	0	1	1
Bank size	2,872,638	16.97	1.26	14.45	17.05	17.14	17.70	18.15
Funding structure	2,872,638	0.59	0.19	0.33	0.44	0.62	0.75	0.84
Equity ratio	2,872,638	0.08	0.03	0.04	0.06	0.07	0.08	0.12
Portfolio quality	2,872,638	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Liquidity ratio	2,872,638	0.16	0.13	0.02	0.06	0.11	0.28	0.38
Exposure share	2,872,638	2.27	3.39	0	2.05	2.08	2.58	2.83
Green voting share	2,864,416	18.43	7.28	6.5	13.10	18.67	23.80	30.05
Right-wing voting share	2,826,373	7.52	4.78	2.83	4.54	6.10	8.29	18.30
Flood 2002	2,872,638	0.26	0.44	0	0	0	1	1
Flood 2013	2,872,638	0.19	0.39	0	0	0	0	1
Past flood	2,872,638	0.36	0.48	0	0	0	1	1

Note: The table shows the descriptive statistics for all variables used in the analyses, i.e. the number of observations, mean, standard deviation (SD), 10th percentile, 25th percentile, median , 75th percentile, and 90th percentile for each variable. Detailed definitions for each of these variables can be found in table A1.

Table 2: Indirect effects: Loans to firms outside disaster regions

	Spreads		Volumes		Collateral ratio		PDs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood risk	4.72***		-0.59		2.13***		5.28**	
	(0.73)		(0.38)		(0.62)		(2.29)	
Post x flood risk	-3.73***	-1.55***	1.52***	-0.50	-1.29	-0.33	-2.42	-0.55
	(0.85)	(0.36)	(0.53)	(0.48)	(0.84)	(1.90)	(2.62)	(1.12)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ILT FE	No	Yes	No	Yes	No	Yes	No	Yes
ILST FE	Yes	No	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
No. of obs.	2,276,389	2,532,713	2,276,389	2,532,713	2,276,389	2,532,713	1,357,505	1,450,964
Adj. R^2	0.93	0.94	0.67	0.71	0.73	0.71	0.89	0.90

Note: This table shows the results from estimating equation (2). The dependent variable is the interest rate spread. *Flood risk* is a continuous variable reflecting the exposure to flood risk at the individual firm. *Post* is a dummy variable equal to one for the period after the July 2021 flood in Germany and zero otherwise. Industry-location-time (ILT) fixed effects are used based on firms' 2-digit NACE code, their NUTS region (level 3) and monthly time period. For ILST (industry-location-size-time) fixed effects we additionally capture firm size based on deciles of firms' total assets. Observations from borrowers and banks located in disaster regions have been omitted from the analysis. We take logs of the variables volumes, collateral ratio and PDs. ***, ** and * denote significance at the 1%, 5%, and 10 %-level, respectively. Standard errors clustered at the firm-time level are shown in parentheses.

Table 3: Influence of banks' exposure to flood regions on loan pricing

	Dependent variable: Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Flood risk	-1.70*	-0.05	-1.83*	-0.26	0.06	0.24
	(0.96)	(0.70)	(1.05)	(0.50)	(1.21)	(1.01)
Post x Flood risk x Exposure share	-1.01***	-0.67**			-2.07***	-0.87*
	(0.29)	(0.28)			(0.58)	(0.47)
Post x Flood risk x Med. exposure share			-4.70***	-2.11***		
			(1.71)	(0.64)		
Post x Flood risk x Top exposure share			-5.88**	-4.46**		
			(2.29)	(2.10)		
Post x Flood risk x Exposure share^2					0.05***	0.02
					(0.01)	(0.01)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
ILT FE	No	Yes	No	Yes	No	Yes
ILST FE	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes
No. of obs.	2,276,389	2,532,713	2,276,389	2,532,713	2,276,389	2,532,713
Adj. R^2	0.92	0.94	0.92	0.94	0.93	0.94

Note: The dependent variable is the interest rate spread. *Flood risk* is a continuous variable reflecting the exposure to flood risk at the individual firm. *Post* is a dummy variable equal to one for the period after the July 2021 flood in Germany and zero otherwise. The variable *Exposure share* captures bank-level exposures (as a % of total exposures) in June 2021 to firms located in counties subject to disaster alert during the July 2021 flood. We obtain information on the residency of firms from the credit register, allowing us to identify firms in counties with disaster alert based on zip codes. We then aggregate for each bank the loan volumes granted to these identified firms and divide it by each bank's total business lending amount. The dummy variables *Med. exposure share* and *Top exposure share* indicate if a bank belongs to the medium or top percentile, respectively, of all banks in terms of *Exposure share*. Industry-location-time (ILT) fixed effects are used based on firms' 2-digit NACE code, their NUTS region (level 3) and monthly time period. For ILST (industry-location-size-time) fixed effects we additionally capture firm size based on deciles of firms' total assets. Observations from borrowers and banks located in disaster regions have been omitted from the analysis. ***, ** and * denote significance at the 1%, 5%, and 10 %-level, respectively. Standard errors clustered at the firm-time level are shown in parentheses.

Table 4: Influence of previous flood events on risk pricing adjustment

	Flood 2002		Flood 2013		2002 and 2013 combined	
	(1)	(2)	(3)	(4)	(5)	(6)
Flood risk x Past flood	-3.51***		-4.87***		-3.71***	
	(1.36)		(1.29)		(1.38)	
Post x Past flood	0.13*	-0.03	0.13	0.23***	0.14*	-0.04
	(0.07)	(0.04)	(0.12)	(0.07)	(0.07)	(0.04)
Post x Flood risk	-6.81***	-2.32***	-4.00***	-1.54***	-7.12***	-2.11***
	(1.22)	(0.41)	(0.92)	(0.38)	(1.38)	(0.42)
Post x Flood risk x Past flood	6.97***	3.86***	3.54**	-0.16	7.34***	2.39***
	(1.61)	(0.83)	(1.61)	(1.13)	(1.62)	(0.78)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
ILT FE	No	Yes	No	Yes	No	Yes
ILST FE	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes
No. of obs.	2,276,389	2,532,713	2,276,389	2,532,713	2,276,389	2,532,713
Adj. R^2	0.93	0.94	0.93	0.94	0.93	0.94

Note: The dependent variable is the interest rate spread. *Flood risk* is a continuous variable reflecting the exposure to flood risk at the individual firm. *Post* is a dummy variable equal to one for the period after the July 2021 flood in Germany and zero otherwise. *Past flood* represents a dummy variable that captures firms located in counties affected by the 2002 flood (columns (1) and (2)), the 2013 flood (columns (3) and (4)) or either of them (columns (5) and (6)). Our identification relies on the methodology used in Noth and Rehbein (2019) and Koetter et al. (2020), which defines counties as affected if the percentage of flood insurance contracts activated during the flood period is above or equal 0.24 percent. Industry-location-time (ILT) fixed effects are used based on firms' 2-digit NACE code, their NUTS region (level 3) and monthly time period. For ILST (industry-location-size-time) fixed effects we additionally capture firm size based on deciles of firms' total assets. Observations from borrowers and banks located in disaster regions have been omitted from the analysis. ***, ** and * denote significance at the 1%, 5%, and 10 %-level, respectively. Standard errors clustered at the firm-time level are shown in parentheses.

Table 5: Influence of green and right-wing voter shares on spreads

	Dependent variable: Spreads			
	Green Party vote share		AfD Party vote share	
	(1)	(2)	(3)	(4)
Post x flood risk	-5.19***	-2.13	-0.02	1.72***
	(0.73)	(1.54)	(0.61)	(0.40)
Post x flood risk x vote share	0.31***		-0.02	
	(0.04)		(0.06)	
Post x flood risk x Med. tercile vote share		0.30		-2.65***
		(2.22)		(0.60)
Post x flood risk x Top tercile vote share		5.01***		-3.54***
		(1.74)		(0.67)
Bank controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
IST FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
No. of obs.	2,460,465	2,465,124	2,460,465	2,466,693
Adj. R^2	0.90	0.90	0.90	0.90

Note: The dependent variable is the interest rate spread. *Flood risk* is a continuous variable reflecting the exposure to flood risk at the individual firm. *Post* is a dummy variable equal to one for the period after the July 2021 flood in Germany and zero otherwise. The variable *Vote share* for Green and AfD party at 2021 general election is measured at the county-level ('Landkreis') of the borrower to account for the fact that business loans are typically channeled via banks' local branches. *Med. exposure share* and *Top exposure share* indicate if a firm belongs to the medium or top percentile, respectively, of all firms in terms of *Vote share*. Regressions include industry-size-time (IST) fixed effects, while location fixed effects (NUTS3 regions) are omitted due to collinearity with the county-level vote share. Observations from borrowers and banks located in disaster regions have been omitted from the analysis. ***, ** and * denote significance at the 1%, 5%, and 10 %-level, respectively. Standard errors clustered at the firm-time level are shown in parentheses.

Appendix

A1 Direct Effects of Flooding

In this section, we estimate the direct effect of flooding on post-flood lending patterns. To this end, we estimate the following regression equation for the sample period July 2019 - July 2023:

$$\begin{aligned} Y_{l,b,f,t} &= \beta_1 \cdot \text{Disaster region}_f + \beta_2 \cdot \text{Disaster region}_f \times \text{Post}_t + X_{b,t} + Z_{l,b,f,t} \\ &+\gamma_b + \phi_{i,L,(s),t} + \mu_f + \varepsilon_{l,b,f,t}, \end{aligned} \tag{A1}$$

where $Y_{l,b,f,t}$ are loan characteristics of loan f from bank b to firm f in month t. Specifically, we investigate the direct effect of the flood on the interest rate spread, the volume of lending, the share of collateral and the probability of default (PD) from banks' risk models. The interest rate spread is calculated by deducting from each loan-specific interest rate the corresponding risk-free rate (see 3.2.1). Volume of lending corresponds to the nominal amount granted to the counterparty at the date of inception. Collateral ratio is the protection value allocated to the respective loan divided by the volume of lending. The Probability of Default (PD) is defined as the counterparty's probability of default over one year.

Our main independent variable, Disaster region$_f$, is a dummy variable indicating if a borrower is located in a county in which the state of emergency was declared after the 2021 "Ahrtal" flood. In Germany, any county administration can declare a state of emergency if the disaster damages severely affect daily life or lives are threatened. The precise conditions for issuing such an alert are set by the civil protection laws of the federal states. We obtain the information about the counties that declared a state of emergency from the Ministry of Internal Affairs (BMI (2021)). Fig. A2 shows all counties that declared the state of emergency in July 2021.

Post$_t$ is an indicator variable equal to one from August 2021, i.e. after the flood disaster on 14 and 15 July 2021, and zero otherwise. $X_{b,t}$ is a vector of bank-time-varying control variables, containing the following variables: bank size, liquidity ratio, equity ratio, portfolio quality and funding structure. We also include instrument type (credit line, revolving credit or term loans) and interest rate type as loan-level control variables in the vector $Z_{l,b,f,t}$.

All regressions include bank fixed effects (γ_b) to control for unobserved supply-side effects. We also add industry-location-time fixed or industry-location-size-time fixed effects ($\phi_{i,L,(s),t}$) to account for demand-side factors (Degryse et al., 2019). We additionally account for firm fixed effects (μ_f) in several specifications. In the extant literature, Brown et al. (2021) is one of the few papers that uses credit register data to investigate the effect of unexpected snowfall on bank lending and interest rates. While we also use credit register data, our data is monthly and covers an even broader sample of firms. Consequently, the data allows us to account for bank and industry-location-sector-time fixed effects, allowing for a better separation of demand- vs. supply-side effects. Our data also allows us to investigate two novel dependent variables that have been neglected in the literature so far: collateral and default probabilities.

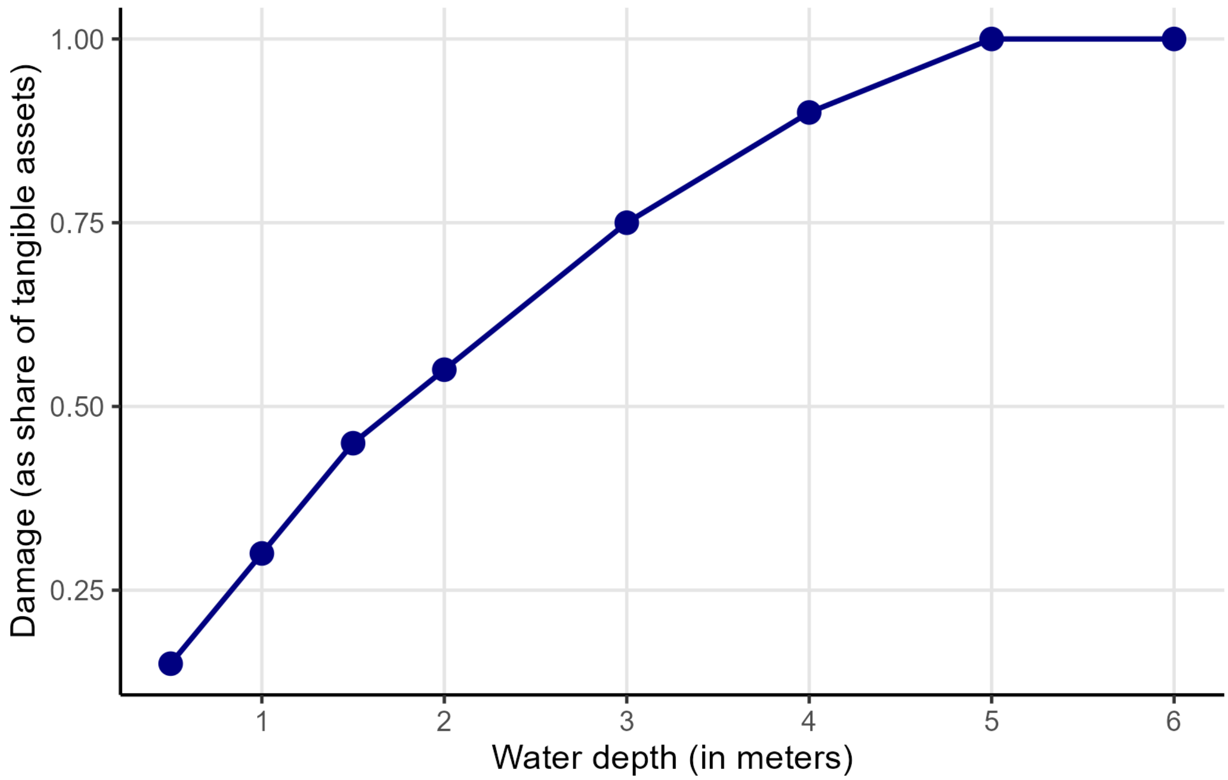
We estimate equation A1 using OLS and report the results in table A6. Firms in the disaster regions have lower spreads (column (1)), despite having a higher probability of default (column (7)). Columns (3) and (5) might provide some indication for this discrepancy: disaster region firms' credit volumes are lower and they provide larger collateral. Because only relatively few regions are affected (see figure A2), it is difficult to exclusively attribute any of these ex-ante differences purely to disaster risk. The difference-in-difference estimates provides a picture that is largely in line with prior results. Consistent with Brown et al. (2021), disaster-affected firms charge higher spreads (column (1)), although these effects become statistically insignificant once accounting for firm fixed effects (column (2)). This might be an indication that the effect of direct natural disaster impact on loan spreads might not be as strong as previously suspected. For loan volumes, we also find evidence generally consistent with prior studies. In specifications without firm fixed effects, the difference-in-difference coefficient is positive but insignificant (column(3)). Once we control for firm fixed effects, the effect is statistically significant (column (4)). For the "Ahrtal" flood, loan volumes are 22% higher in disaster regions after the occurrence of the flood compared with unaffected regions. This result is generally in line with the findings from prior literature, but much larger in size. While the prior literature suggest an effect on lending volumes of around 3% (Brown et al., 2021; Koetter et al., 2020), our effect is 7 times larger, perhaps owing to the very localized and intense flooding experienced in the Ahrtal region (see section 2).

Next, we ask whether banks' collateral requirements change after disaster-impact. Presumably due to the lack of data, this question has not received much attention in the literature so far. We find that generally collateral requirements *decrease* after the disaster (columns (5) and (6)). One simple explanation for this finding is that firms' collateral in the flooded regions is destroyed and thus it cannot be pledged as collateral. Further, government aid payments may serve as implicit collateral, replacing the need for collateralization using other assets. Insofar as the increased lending to disaster areas is difficult to be supported with destroyed collateral, these results are in line with the literature documenting positive effects of post-disaster lending volumes. Finally, we estimate the effect of the disaster on banks' estimated probability of default. Surprisingly, we find that the probability of default is not changed, or even decreases slightly, although the effect is only marginally significant (columns (7) and (8)).

Overall the results are in line with the existing literature documenting that disasters generally impact lending into the disaster area with more lending at higher rates (Brown et al., 2021; Koetter et al., 2020). In addition to this literature, we provide novel evidence that loans into disaster regions require significantly less collateral, while the probability of default from banks' internal models is not much affected by the disaster.

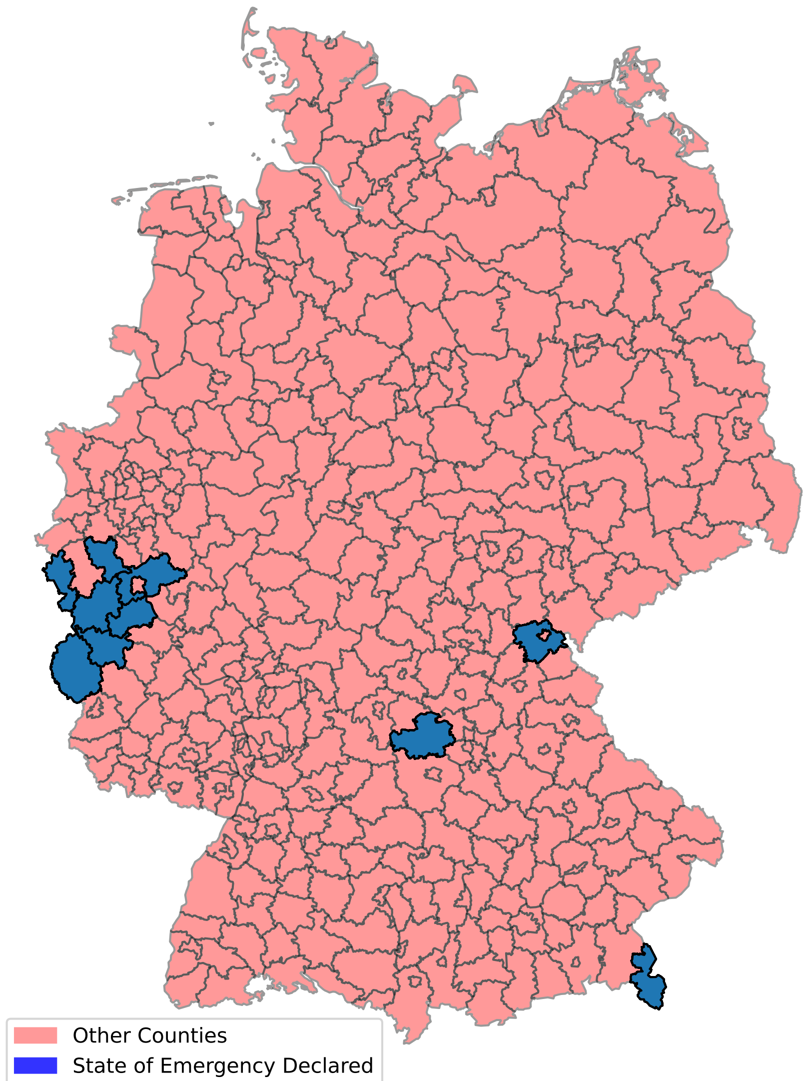
A2 Appendix Tables & Figures

Figure A1: Damage function for commercial buldings (Huizinga et al., 2017)



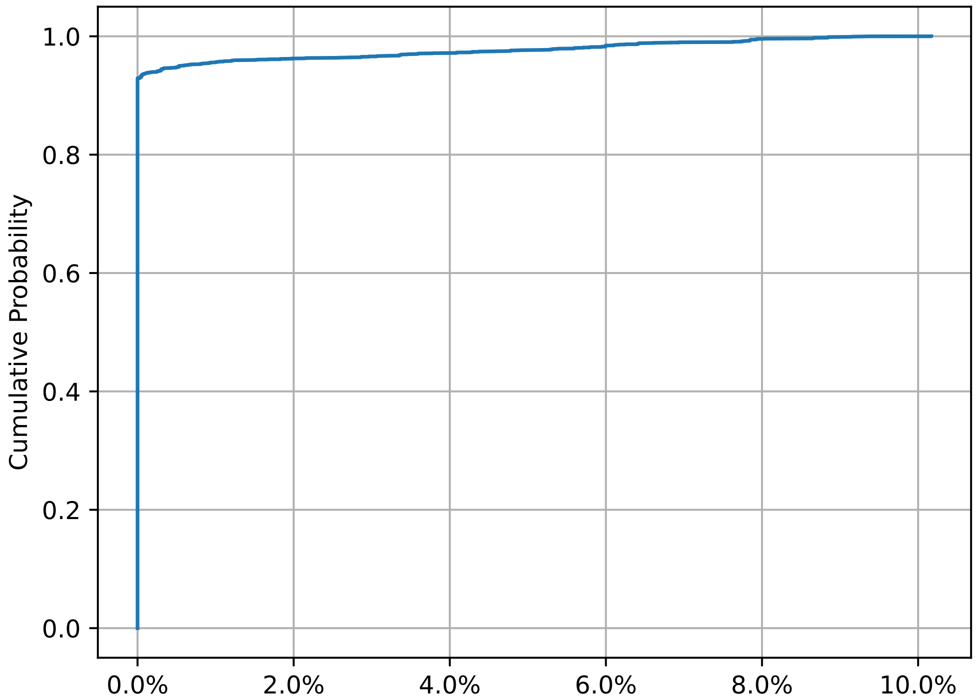
Note: This figure depicts the damage function for commercial buildings in Europe as calculated by Huizinga et al. (2017), which is used in the calculation of our ex-ante firm-level flood risk measure (Eq. 1). Based on reported damages in past flood events, damage functions allow us to link the severity of flooding (in terms of meters of water depth) to the average severity of damage (normalized to a share between 0 and 1).

Figure A2: Counties with state-of-emergency declaration



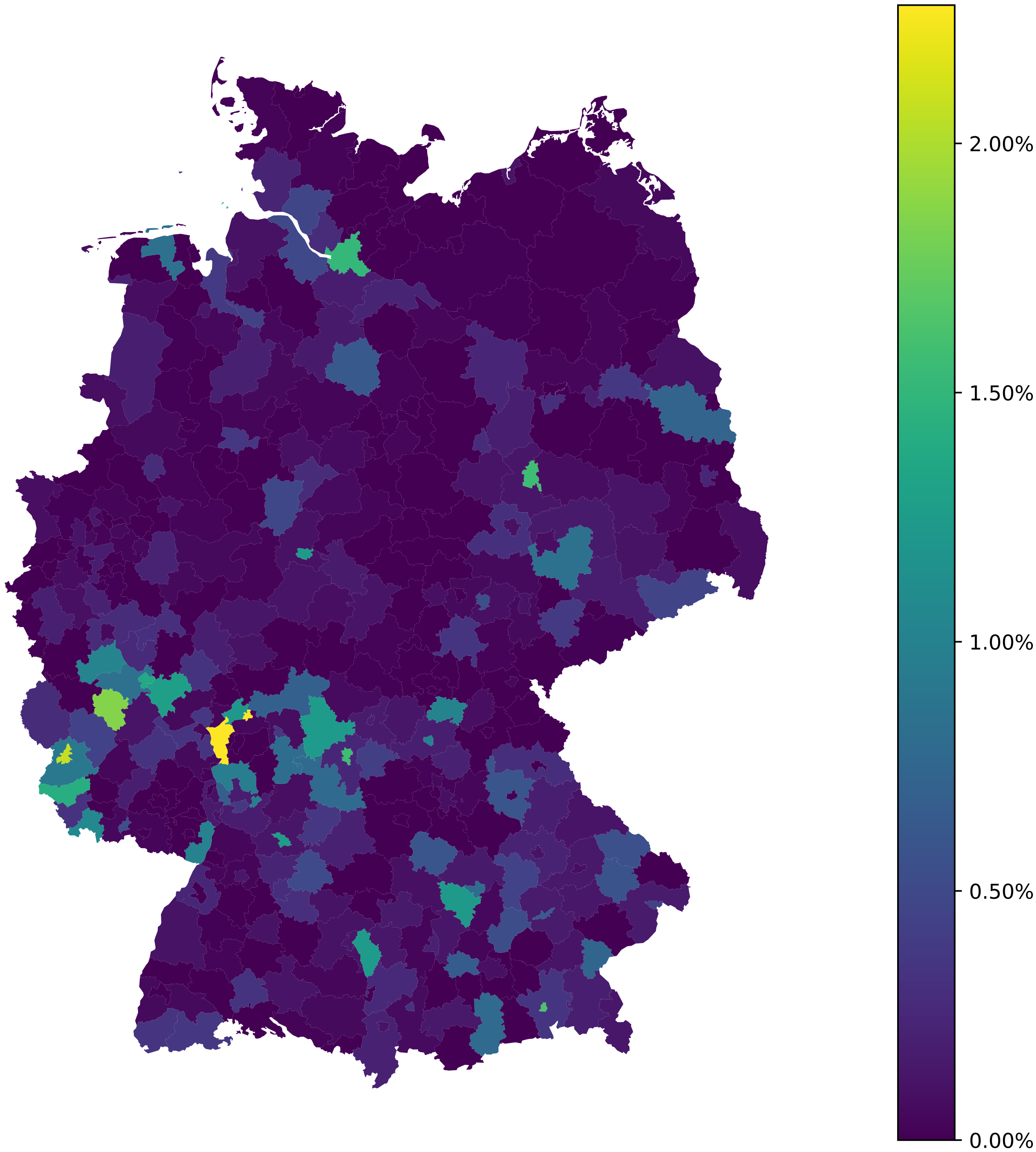
Note: This map shows all Counties that declared a state of emergency after the flood.

Figure A3: Cumulative distribution of ex-ante flood risk



Note: The figure displays the cumulative distribution of flood risk for firms included in AnaCredit. Flood risk is defined as individual firms' expected annual losses from river floods per year. Expected annual losses are calculated by multiplying each firm's damage function by its tangible assets and the probability of flood risk.

Figure A4: Average expected flood damage per county



Note: This map shows the average of firms' flood damage per county. Flood damage is defined as individual firms' expected annual losses from river floods per year. Expected annual losses are calculated by multiplying each firm's damage function by its tangible assets and the probability of flood risk. The mean loss per county is calculated for the sample period from June 2019 to July 2023

Table A1: Variable definitions and sources

Variable	Definition	Source
Spread	Difference between loan interest rate and maturity-matched risk free rate (in %)	AnaCredit/ECB
Loan Volume	Natural logarithm of loan volume committed by bank at the inception of the loan	AnaCredit
Collateral ratio	Loan-level share of collateral over total loan volume (in %)	AnaCredit
PD	Natural logarithm of probability of default	AnaCredit
Post	Dummy variable equal to 1 from August 2021 (after Ahrtal flood event)	Public sources
Flood risk	Individual firms' expected annual losses from river flood per year (share of tangible assets)	EU Joint Research Center/ECB
Disaster region	Dummy variable equal to 1 if borrower is located in disaster region (based on NUTS3 code)	BMI (2021) and AnaCredit
Revolving credit	Dummy variable equal to one if the loan is a revolving credit and zero otherwise	AnaCredit
Credit line	Dummy variable equal to one if the loan is a credit line and zero otherwise	AnaCredit
Variable rate	Dummy variable equal to one if the loan has a variable rate and zero if the loan has a fixed interest rate	AnaCredit
Bank size	Natural logarithm of banks' total assets	Bundesbank monthly balance sheet statistics (BISTA)
Liquidity ratio	Liquid assets over total assets	Bundesbank monthly balance sheet statistics (BISTA)
Equity ratio	Equity over total assets	Bundesbank monthly balance sheet statistics (BISTA)
Portfolio quality	The sum of impairments and provisions over total assets	Bundesbank monthly balance sheet statistics (BISTA)
Funding structure	Deposits over total assets	Bundesbank monthly balance sheet statistics (BISTA)
Green voting share	Share of votes for Green party (in %) at German federal election in 2021	Public sources
Right-wing voting share	Share of votes for the party 'Alternative für Deutschland' (in %) at German federal election in 2021	Public sources
Exposure share	Bank-level proportion of loans to firms located in disaster regions shortly before disaster (June 2021, as % of each bank's total business loan exposure)	AnaCredit
Past flood	Dummy variable that equals 1 if firm is located in counties that were affected by flood events in 2002 or 2013	Rehbein and Ongena (2022)

Note: The table provides an overview of the variables used in the analyses, along with their definitions and sources.

Table A2: Robustness Spreads: Bank $\times$ year FE

	Spreads			
	(1)	(2)	(3)	(4)
Flood risk	4.72***		4.18***	
	(0.73)		(0.61)	
Post x flood risk	-3.73***	-1.55***	-3.34***	-1.53***
	(0.85)	(0.36)	(0.73)	(0.28)
Bank controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
ILT FE	No	Yes	No	Yes
ILST FE	Yes	No	Yes	No
Bank FE	Yes	Yes	No	No
Bank-year FE	No	No	Yes	Yes
Firm FE	No	Yes	No	Yes
No. of obs.	2,276,389	2,532,713	2,276,389	2,532,713
Adj. R^2	0.93	0.94	0.93	0.94

Note: ***, ** and * denote significance at the 1, 5 and 10 %-level, respectively. Clustering of standard errors at firm-time level. *Flood risk* is a continuous variable reflecting the exposure to flood risk at the indiviual firm. *Post* is a dummy variable that equals one for the period after the July 2021 flood in Germany. Industry-location-time (ILT) fixed effects are used based on firms' 2-digit NACE code, their NUTS region (level 3) and monthly time period. For ILST (industry-location-size-time) fixed effects we additionally capture firm size based on deciles of firms' total assets. Observations from borrowers and banks located in disaster regions have been omitted from the analysis. We take logs of the variables volumes, collateral ratio and PDs.

Table A3: Indirect effects: Loans to firms outside disaster regions (Indicator treatment)

	Spreads		Volumes		Collateral ratio		PDs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood risk	0.02*		-0.02		-0.04		0.01	0.02***
	(0.03)		(0.19)		(0.05)		(0.00)	(0.01)
Post x flood risk	-0.13***	-0.08***	-0.03	-0.04***	-0.04	-0.02	-0.01	-0.01
	(0.04)	(0.01)	(0.03)	(0.01)	(0.05)	(0.04)	(0.00)	(0.00)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ILT FE	No	Yes	No	Yes	No	Yes	No	Yes
ILST FE	Yes	No	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
No. of obs.	2,276,389	2,532,713	2,276,389	2,532,713	2,276,389	2,532,713	1,396,921	1,295,696
Adj. R^2	0.92	0.92	0.66	0.71	0.73	0.71	0.56	0.87

Note: This table shows the results from estimating equation (2). The dependent variable is the interest rate spread. *Flood risk* is an indicator treatment variable reflecting the exposure to flood risk at the individual firm. *Post* is a dummy variable equal to one for the period after the July 2021 flood in Germany and zero otherwise. Industry-location-time (ILT) fixed effects are used based on firms' 2-digit NACE code, their NUTS region (level 3) and monthly time period. For ILST (industry-location-size-time) fixed effects we additionally capture firm size based on deciles of firms' total assets. Observations from borrowers and banks located in disaster regions have been omitted from the analysis. We take logs of the variables volumes, collateral ratio and PDs. ***, ** and * denote significance at the 1%, 5%, and 10 %-level, respectively. Standard errors clustered at the firm-time level are shown in parentheses.

Table A4: Robustness: Loans to firms outside disaster regions, harmonized sample

	Spreads		Volumes		Collateral ratio		PDs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood risk	5.63***		-1.27***		2.73***		5.84**	
	(0.85)		(0.61)		(0.73)		(2.51)	
Post x flood risk	-4.54***	-1.90***	1.95***	-0.69**	-1.57	0.74	-2.92	-1.46
	(0.98)	(0.37)	(0.61)	(0.31)	(0.96)	(1.99)	(2.76)	(1.17)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ILT FE	No	Yes	No	Yes	No	Yes	No	Yes
ILST FE	Yes	No	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
No. of obs.	2,210,006	2,210,006	2,210,006	2,210,006	2,210,006	2,210,006	1,351,917	1,351,917
Adj. R^2	0.94	0.95	0.68	0.70	0.74	0.71	0.89	0.89

Note: This table shows the results from estimating equation (2). The dependent variable is the interest rate spread. *Flood risk* is a continuous variable reflecting the exposure to flood risk at the individual firm. *Post* is a dummy variable equal to one for the period after the July 2021 flood in Germany and zero otherwise. Industry-location-time (ILT) fixed effects are used based on firms' 2-digit NACE code, their NUTS region (level 3) and monthly time period. For ILST (industry-location-size-time) fixed effects we additionally capture firm size based on deciles of firms' total assets. Observations from borrowers and banks located in disaster regions have been omitted from the analysis. We take logs of the variables volumes, collateral ratio and PDs. ***, ** and * denote significance at the 1%, 5%, and 10 %-level, respectively. Standard errors clustered at the firm-time level are shown in parentheses.

Table A5: Robustness: Influence of banks' exposure to flood regions on loan pricing, harmonized sample

	Dependent variable: Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Flood risk	-1.47	-1.81	-0.02			
	(1.22)	(1.15)	(0.70)			
Post x Flood risk x Exposure share	-0.50	-1.45***	-0.82			
	(0.38)	(0.45)	(0.54)			
Post x Flood risk x Med. exposure share				-0.39***	-4.09***	-1.64**
				(1.19)	(1.89)	(0.65)
Post x Flood risk x Top exposure share				-4.54***	-6.21**	-5.72**
				(1.71)	(2.55)	(2.27)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
ILT FE	Yes	No	Yes	Yes	No	Yes
ILST FE	No	Yes	No	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes
No. of obs.	2,210,006	2,210,006	2,210,006	2,657,504	2,276,389	2,532,713
Adj. R^2	0.90	0.94	0.94	0.90	0.94	0.94

Note: The dependent variable is the interest rate spread. *Flood risk* is a continuous variable reflecting the exposure to flood risk at the individual firm. *Post* is a dummy variable equal to one for the period after the July 2021 flood in Germany and zero otherwise. The variable *Exposure share* captures bank-level exposures (as a % of total exposures) in June 2021 to firms located in counties subject to disaster alert during the July 2021 flood. The dummy variables *Med. exposure share* and *Top exposure share* indicate if a bank belongs to the medium or top percentile, respectively, of all banks in terms of *Exposure share.* Industry-location-time (ILT) fixed effects are used based on firms' 2-digit NACE code, their NUTS region (level 3) and monthly time period. For ILST (industry-location-size-time) fixed effects we additionally capture firm size based on deciles of firms' total assets. Observations from borrowers and banks located in disaster regions have been omitted from the analysis. ***, ** and * denote significance at the 1%, 5%, and 10 %-level, respectively. Standard errors clustered at the firm-time level are shown in parentheses.

Table A6: Direct effects: K-alarm regions

	Spreads		Volumes		Collateral ratio		PDs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disaster region	-0.79***		-0.16*		1.16***		0.82***	
	(0.16)		(0.08)		(0.13)	(0.23)	(0.14)	
Disaster region x Post	0.65***	0.07	0.04	0.22**	-0.85**	-0.23	0.08	-0.45*
	(0.16)	(0.15)	(0.12)	(0.10)	(0.34)	(0.34)	(0.17)	(0.25)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ILT FE	No	Yes	No	Yes	No	Yes	No	Yes
ILST FE	Yes	No	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
No. of obs.	2,326,094	2,585,173	2,326,094	2,585,173	2,326,094	2,585,173	1,389,051	1,482,786
Adj. R^2	0.93	0.93	0.66	0.71	0.73	0.71	0.89	0.90

Note: This table shows the results from estimating equation (1). The dependent variable is the interest rate spread. *Disaster region* is a dummy variable equal to one if a firm is located in a postal code directly affected by the July 2021 flood and zero otherwise. *Post* is a dummy variable equal to one for the period after the July 2021 flood in Germany and zero otherwise. Industry-location-time (ILT) fixed effects are used based on firms' 2-digit NACE code, their NUTS region (level 3) and monthly time period. For ILST (industry-location-size-time) fixed effects we additionally capture firm size based on deciles of firms' total assets. We take logs of the variables volumes, collateral ratio and PDs. ***, ** and * denote significance at the 1%, 5%, and 10 %-level, respectively. Standard errors clustered at the firm-time level are shown in parentheses.