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Flooded credit markets: physical climate risk and small business lending

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Abstract

We document that European banks charge higher interest rates on loans granted to small and medium-sized firms located in areas at high risk of flooding. At 6 basis points, the average risk premium does not adequately reflect the deterioration of loan performance in the aftermath of flood episodes, however. Firms in flooded counties are more likely to default on their loans than non-disaster firms. Floods reduce securitised credit in the local markets, suggesting that physical risks associated with climate change are borne within the banking sector.

Keywords: climate change, loan default, loan pricing, natural disasters
JEL codes: C55, G21, Q51, Q54

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Non-technical summary

Extreme weather events and climate-related natural hazards are becoming more frequent and severe with the rise in global temperatures. Floods are already among the most damaging hazards in Europe, where the economic and social costs of physical damage and relocation of people and businesses have been material. While the increase in flood risk at the European scale is substantial, its financial implications are still far from being fully understood.

Using a large cross-country data set of securitised loans, we study the impact of flooding on credit to European small and medium-sized enterprises. First, exploiting detailed information on loans at origination, we explore to what extent physical risk from flooding is priced into small business loans. We find that banks charge higher interest rates on loans to firms in counties that are exposed to a high risk of flooding. Moreover, flood risk appears already salient for lenders, as we do not find evidence that recent flood events change the perception and assessment of flood risk, and, hence, the extent of the risk premium.

In the second part of the paper, we investigate whether the occurrence of flood events has a bearing on the deterioration of loan performance. Our findings point to a sizeable impact of flooding on loan delinquency. Moreover, we uncover also an indirect effect of flooding on the worsening of loan performance. Loans originated in the aftermath of flood events are more likely to enter default than other loans. This intrinsic fragility is suggestive of risk-taking behaviour by banks in granting post-disaster recovery lending.

All in all, the intensification of climate disasters due to climate change may become an important source of financial vulnerability for European small and medium-sized businesses and, consequently, for the banks financing them. We show that the estimated average flood risk premium does not accurately reflect the increased credit risk that banks face on the loans granted to borrowers impacted by natural disasters. Moreover, we find that floods decrease the amount of securitised credit in the local markets. This result points to reduced risk-sharing possibilities for lenders exposed to firms in counties hit by natural hazards. Coupled with the finding that flood risk is inadequately priced into new loans, these results suggest that a large part of physical climate risk may still be borne within the banking sector.

1 Introduction

With the rise in global temperatures extreme weather events and climate-related natural hazards are becoming more frequent and severe. Floods are already among the most damaging hazards in Europe, where the economic and social costs of physical damage and relocation of people and businesses have been material (European Environment Agency, 2022). While the increase in flood risk at the European scale is substantial, its financial implications are still far from being fully understood. In addition to the direct economic losses, flooding may entail indirect financial costs stemming, for instance, from the reduction in the value of at-risk assets. Moreover, damage to physical capital and business disruptions jeopardise the ability of borrowers to meet their debt obligations. This induced financial fragility may act as an important propagation mechanism to the financial sector, eventually forcing banks to fire sale assets and ration credit (Financial Stability Board, 2020). Both physical damage and the deterioration of financing conditions are likely to turn out particularly costly for smaller firms, given the localised nature of their operations and their high reliance on domestic bank credit as a source of finance (Hoffmann et al., 2022).

Using a large cross-country data set of securitised loans, we study the impact of flooding on credit to European small and medium-sized enterprises (SMEs). First, exploiting local variation in the exposure and vulnerability to flooding, we explore to what extent physical risk is priced into new small business loans. We document that banks charge higher interest rates on loans to firms in counties at high risk of flooding. At 6 basis points, the magnitude of the average risk premium appears rather small. However, it turns sizeable for smaller borrowers, and in the case of local specialised lenders, that is, cooperative and savings banks. Moreover, we do not find evidence that recent flood events change the perception and assessment of flood risk, and, hence, the extent of the risk premium. Thus, if not to the full extent of its implications for credit risk, flood risk appears already salient for lenders.

Next, as our data allows us to track loans during their lifetime, we use survival analysis to investigate whether the occurrence of flood events has a bearing on the deterioration of loan performance, and, potentially, default. Our findings point to a significant impact of flooding on loan delinquency. Firms exposed to a flood are more likely to fail to repay their existing loans than firms in non-disaster areas by up to 1.5 times in the second year after the water hazard. Moreover, we uncover an indirect effect of flooding on the worsening of loan performance. For given financial characteristics, loans originated in the aftermath of flood events are more likely to enter default status than other loans. The result holds even as we account for the occurrence of floods during the loan lifetime. This intrinsic fragility suggests that banks tend to take on more risk when they grant post-disaster recovery lending.

Our results indicate that flooding affects businesses not only through direct physical damage, but also by worsening their financial conditions, notably by jeopardising their ability to service debt and, partly, by increasing their cost of capital. Hence, while the full impact of climate change is expected to materialise in the long run (Pörtner et al., 2022), climate-related disasters and extreme weather events may have disruptive consequences on firm operations in the short and medium term, not only in a direct way (Fatica et al., 2022a), but also through the financial channel. This effect is exacerbated by the high reliance of SMEs on bank funding, and their limited access to capital markets, which reduces the possibility of substituting away from bank credit for alternative sources of finance (Cingano et al., 2016; Iyer et al., 2013).

All in all, our findings suggest that the intensification of climate disasters due to climate change may become an important source of financial vulnerability for European small and medium-sized businesses and, consequently, for the banks financing them. In a simple setup, we show that the estimated average flood risk premium does not accurately reflect the increased credit risk that banks face on the loans granted to borrowers impacted by natural disasters. Moreover, when considering aggregate quantities at the county level, we find that flood events decrease the amount of securitised credit in the local markets. Hence, there appear to be reduced risk-sharing possibilities for lenders exposed to firms in counties hit by natural hazards. Coupled with the fact that flood risk is inadequately priced into new loans, these results suggest that a large part of physical climate risk is still borne within the banking sector.

Our paper relates and contributes to two main strands of the literature. First, we add to the fast-growing literature on the pricing of climate risk into financial assets (Giglio et al., 2021). When it comes to physical risk in particular, so far the attention has focused mainly on real estate valuation and, through this channel, on the mortgage market and the implications thereon of long-term risks, such as sea level rise (Baldauf et al., 2020; Bernstein et al., 2019; Nguyen et al., 2022). As for other assets, Acharya et al. (2022) explore the pricing of heat stress in municipal and corporate bond as well as equity markets. The literature on physical risk and corporate lending is also expanding, with analyses that focus exclusively on syndicated loans (Correa et al., 2022; Jiang et al., 2023). Against this background, the extent to which physical climate risk is accounted for in the pricing of loans to smaller businesses is still practically unexplored. To the best of our knowledge, we are the first to fill this gap with evidence for Europe. In this respect, our work complements recent evidence on the pricing of transition risk by Euro area banks (Altavilla et al., 2023) to provide a full picture of how climate-related risks affect business credit conditions in Europe.

Second, our paper relates to the literature on the impact of climate-related natural disasters (Skouloudis et al., 2020), and, in this context, on the role of financial variables as an amplifying mechanism for real economy vulnerabilities (Campiglio et al., 2022). There is a large number of studies on bank lending and bank behaviour in the aftermath of natural disasters. This literature documents that, as a result of the need to rebuild destroyed or damaged physical capital, natural hazards bring about an increase in the demand for credit in affected areas (Berg and Schrader, 2012; Cortés and Strahan, 2017; Koetter et al., 2020; Chavaz, 2016; Celil et al., 2022). Importantly, to meet increased credit demand for reconstruction purposes, banks may change the geographic composition of their lending, diverting credit away from non-disaster areas (Rehbein and Ongena, 2022). While these studies extensively characterise natural disasters as a demand shock from the lender's perspective, there is still limited evidence on the existence of a supply channel stemming from negative post-disaster loan performance (Noth and Schuewer, 2018; Barth and Zhang, 2019).

Our paper contributes to this literature by providing novel evidence in this direction for climate-related disasters. First and foremost, our results that floods are a significant risk factor for loan defaults indicate that an important supply effect is at play in recovery lending. Hence, banks may have to write off or incur losses on existing loans to businesses located in areas impacted by natural disasters, while at the same time they appear to be taking on more risk when extending new loans to disaster firms. Second, our analysis points to the implications that projected and realised flood risks have on financial outcomes. While we find that loan spreads are not affected by realised risk, we also show that projected physical risk is incorporated into the pricing of small business credit, albeit to an extent that does not adequately reflect the actual deterioration in credit risk in the aftermath of flood episodes. Fully characterising these supply effects is important to shed light on bank credit as an amplification mechanism for the transmission of climate-related shocks to the real economy, and on the potential financial stability implications (Noth and Schuewer, 2018).

The remainder of the paper is structured as follows. Section 2 introduces the data. Section 3 presents the analysis of loan pricing alongside descriptive evidence on the sample of loans at origination. Loan default is investigated in Section 4. In Section 5 we discuss to what extent risk pricing adequately reflects the observed deterioration in loan performance. Section 6 studies how flooding affect the securitisation of bank lending in local credit markets using a staggered difference-in-differences model. Finally, Section 7 concludes.

2 Data

2.1 Loan-level data

We obtain data on loans to SMEs from the European DataWarehouse (EDW), a centralised securitisation repository part of the European Central Bank (ECB) loan-level initiative to collect, validate, and distribute standardised data for European countries. Through this program, banks provide asset-backed securities as collateral in the ECB repurchase (repo) financing operations. As from January 2013, financial institutions that access the repo borrowing facility are mandated to report information on their securitised portfolios on a quarterly basis according to a standardised format. We consider securitised loans in four European countries, namely Belgium, France, Italy and Spain, which are among the most active in the securitisation of SME loans in Europe (see Ertan et al., 2017 and Van Bekkum et al., 2018 for a detailed description of the EDW data and the securitisation process for SME loans in this framework). For each securitised credit facility, the data set provides a number of loan characteristics, as well as information on the borrower and on the lending institution.[1] In particular, among the loan-level variables, the original loan balance and the final maturity date are reported, together with other credit terms, such as the type and the purpose of the loan, its amortisation profile, and the presence of collateral. This information is recorded at the exact date of origination, which is also reported. Information on the lender is limited to the bank name. As for the borrower, mandatory reporting is foreseen about the legal form or business type, the economic sector of the activity , and its geographic location, according to the Nomenclature of Territorial Units for Statistics (NUTS) classification. In particular, we have information on borrowers' location the NUTS3 level, which identifies local units corresponding approximately to counties in the United States.[2] We exploit the information on the geographic area where the borrower is located to match the loan-level data with the data on flooding described hereinafter.[3]

In addition to the 'static' information recorded at origination, the EDW database contains a number of variables that allow us to assess loan performance over time. This 'dynamic'

[1] The SME loan level reporting requirements include mandatory and optional variables, broadly covering loan, asset-backed security pool and bank identifiers, borrower information and financials, loan characteristics, loan interest rate details and loan performance information.

[2] NUTS3 local entities correspond to different administrative units across European countries, i.e. provinces in Italy, or departments in France. We refer to them as counties throughout the paper.

[3] Moreover, we augment the data set with macroeconomic variables, namely yearly Gross Domestic Product (GDP) and employment growth rates at NUTS3 level.

information is updated on a quarterly basis at the different cut-off dates when the periodic reporting for each pool of securitised loans occurs. Time-varying loan characteristics include the loan balance and, potentially, the interest rate, as well as the loan status, notably also whether the credit facility is in delinquency. In that case, other relevant information is provided, such as the delinquent amount and number of days in arrears. In our analysis, we select loans originated from 2008 until the end of 2019, relying on information reported from 2015 onward. We refer to Appendix A for a description of the several cleaning steps performed on the loan-level data.

2.2 Data on flooding

We draw data on flooding from the Risk Data Hub (RDH) of the European Commission's Joint Research Centre (Faiella et al., 2020). The RDH is a web-based geographical information system platform that contains harmonised risk data and methodologies for disaster risk assessment in Europe.[4] In the context of the new EU Strategy on adaptation to climate change, the RDH is set to become the reference platform for standardising of the recording and collection of comprehensive and granular climate-related losses and physical climate risk data at the EU level.[5] It also provides input to the analysis of climate risks from a macro-prudential perspective and to the development of climate stress tests by European financial supervisors (European Central Bank and European Systemic Risk Board, 2021). The information in the RDH is structured into two modules covering risk analysis and historical events, respectively. We describe these in turn.

Flood risk. The Risk Analysis Module of the RDH provides indicators that allow for multi-sector assessment of potential risks and losses from natural hazards at the European level (Antofie et al., 2019). The risk indicator (R) captures the potential impact of a hazard

[4] More details are available at `https://drmkc.jrc.ec.europa.eu/risk-data-hub/#/methodologies`.

[5] See European Commission (2021) "Forging a climate-resilient Europe - the new EU strategy on adaptation to climate change", COM(2021) 82 final, 24 February.

(H) for a specific area or community in a given period of time (t). As such, it compounds two different metrics associated to the occurrence of a natural hazard, namely exposure (E) and vulnerability (V), as in:

$$R = f(t, H, E, V). \tag{1}$$

The exposure component combines geolocalised information on relevant flood metrics, such as frequencies and intensities, with layers for physical assets. Flood frequency is assessed starting from data measuring the area at risk of being inundated by floods with different return periods. The simulated return periods are for 10, 50, 100, 200 and 500 years.[6] Then, the associated potential impacts are determined, accounting for land use at the local level. Specifically, within each territorial unit, the indicator uses information on the share of industrial/commercial, residential and agricultural area at risk of being flooded by a flood with a specific return period. The average expected impacts are assessed at different projection horizons, namely for 1, 2, 5, 10, 15 and 25 years, computing the probabilities of occurrence associated to floods with the specified return periods. As events are assumed independent, the expected exposure is defined as the sum of the exposure level weighted by corresponding probabilities (Antofie et al., 2020).

By construction, the exposure indicator captures the maximum potential impact of flooding in a given location. As such, it is not, in itself, a sufficient metric to determine flood risk, since it is possible to be exposed but not vulnerable to a particular hazard.[7] The vulnerability component aims at assessing precisely the predisposition, deficiencies or lack of capacity of the exposed elements to withstand the natural hazards. It is conceived as a multidimensional indicator comprising a social, economic, political, environmental, and physical dimension.

Thus, the overall risk indicator provides a measure of the potential impacts of hazards

[6]The simulated inundation maps as a measure of the areal extent of the flood-prone areas are derived from the hydraulic model LISFLOOD (Dottori et al., 2022).

[7]Flood protection measures, such as water-proofing of buildings, for instance, reduce the vulnerability of flood-exposed areas, making them not necessarily at risk.

on different assets, after combining exposures and vulnerabilities. As the paper analyses business lending, we employ the risk indicator for commercial buildings, defined at county level and averaged across the different projection periods.[8] The values of the risk indicator at the local level are normalised within country, on a scale ranging from 0 to 10, which indicate, respectively, minimum and maximum risk. Figure 1 provides a graphical representation of flood risk for commercial buildings across counties, with darker shades corresponding to higher levels of flood risk. In the empirical analysis, we classify as high-risk those counties for which the value of the flood risk indicators is above the median value of the distribution of the normalised risk scores.[9]

Flood events. Data on flood events is drawn from the historical module of the RDH. This is an EU-wide disaster loss database that provides information on past events with records on the impact (quantified as human losses and economic damage) and geographical location of the hazard. The module collects information from multiple databases, including the International Disasters Database (EM-DAT), and other sources of metadata.[10] Available information includes the type of hazard, the date of the event, and the affected local areas, classified at NUTS3 level. Additional variables that further qualify the event – such as the size of the flooded area, the number of injured and dead people, as well as the economic losses associated with the event – are provided for roughly half of the recorded events in our

[8] Other available assets are residential real estate and agricultural areas.

[9] An alternative indicator of flood risk is the one constructed by Four Twenty Seven, an affiliate of Moody's, which is increasingly used for the climate risk assessment. Although the JRC RDH flood risk indicator and the Four Twenty Seven are broadly similar, in our analysis we privilege the JRC RDH one for three reasons. The Four Twenty Seven indicator is built at the firm-level, but SME borrowers in our sample are anonimised, so we cannot match the Four Twenty Seven flood risk indicator with our firm-level data. Moreover, the Four Twenty-Seven indicator covers only partially the universe of EU firms, and calculating an average score at NUTS3 level may produce some bias, given the unequal distribution of firms in each NUTS3 unit. For these reasons we prefer to use an index already aggregated at the level of Local Administrative Units. Finally, we prefer to use a single data provider for flood data: we extract from the RDH also historical flood data that are not published by Four Twenty Seven. We refer to European Central Bank and European Systemic Risk Board (2021) for further discussion and a thorough comparison of the two indicators.

[10] Faiella et al. (2020) discuss in detail the criteria for inclusion of natural disasters in the RDH database. They are generally based on the number of fatalities or of people affected by the natural disaster, and/or a declaration of a state of emergency, and/or a call for international assistance. The exact criteria slightly vary, depending on the specific source, as the database is constructed using multiple sources.

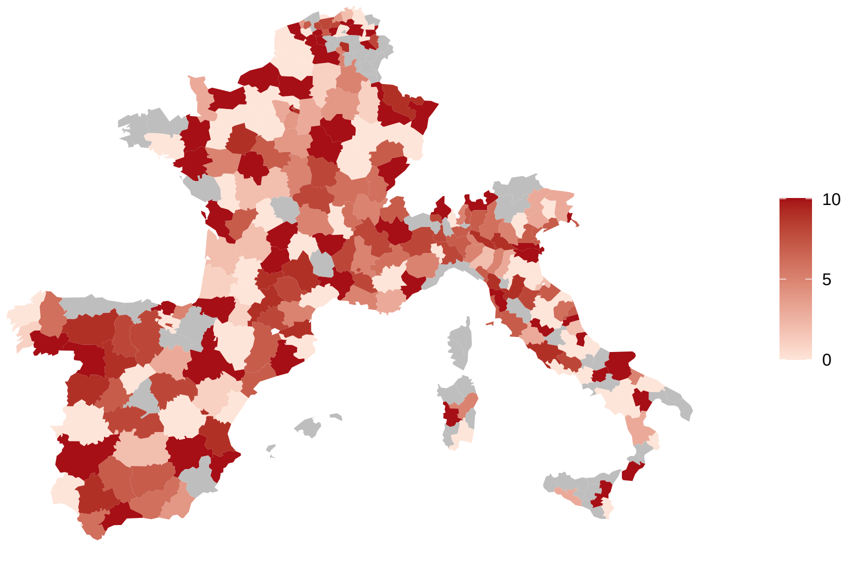

Figure 1: **Flood risk.** The figure shows the map of flood risk across counties (NUTS3 units). The flood risk indicator is averaged across the projections years (i.e., 1, 2, 5, 10, 15 and 25 years) and normalised within country over the $[0, 10]$ scale. Low (high) values indicate low (high) flood risk, i.e. potential impact of flooding. For counties in grey the indicator is not available.

sample.[11] We retain information on events classified as river floods, flash floods and coastal floods, while we disregard flooding connected to other major disasters, such as avalanches and landslides. Figure 2 reports the number of floods by NUTS3 observed over the period from January 2007 to December 2018. On average, the counties in our sample are hit by 3 floods. There is no significant difference in flood frequency among coastal counties - potentially subject to coastal and fiver floods - and land-locked areas, exposed only to river floods. With 2 floods on average per county, Belgium and France are the least affected countries, while Spain is the most impacted, with 4 floods on average. The Spanish county of Valencia is the one recording the highest number of flood events - 9 over the period under analysis.

We use the records of flood events to create measures of realised flood risk at the local level. We combine the information about the localisation and dating of flood events with the

[11] As detailed in Faiella et al. (2020), information about the precise amount of damage from natural disasters is scarce, and direct economic losses may be reported ex-post with measurement error. Hence, we do not consider the distribution of losses in our analysis, but we make only the distinction between flood events with and without economic losses. The former can be considered as a proxy for more severe hazards.

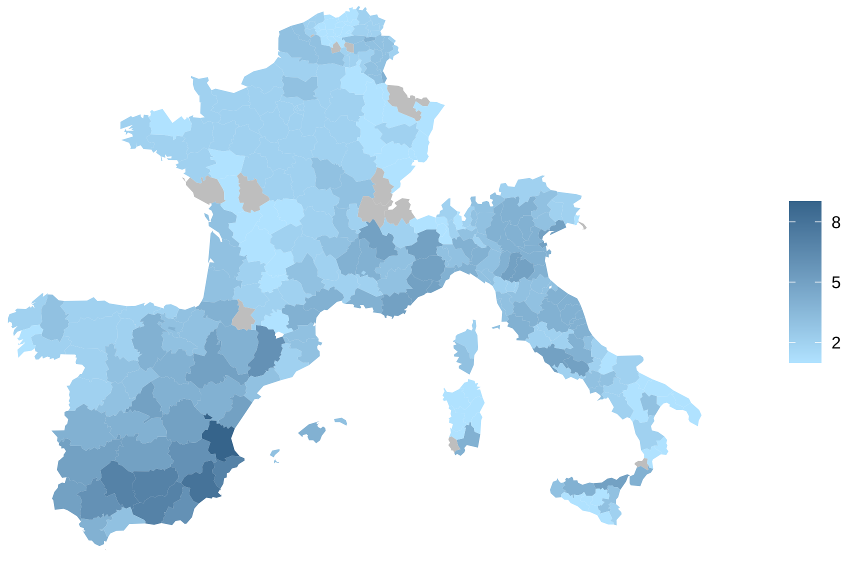

Figure 2: **Flood events.** The figure maps the number of flood events across counties (NUTS3 units) over the 2007-2018 period. Counties in grey reported no floods in the indicated period.

loan-level data set to characterise the impact of flooding on local credit market conditions. For that, we create a set of binary variables that indicate whether in the q months before the observation date there has been at least one flood event in the county where the borrower is located. In the baseline case, we consider $q = 6$. However, where appropriate, we also experiment with alternative time ranges, namely 12 and 24 months. These extended time frames are particularly relevant for the analysis of loan performance.

Importantly, in the loan-level analysis, we account for the realisation of flood risk that occurs before loan origination as well as during the lifetime of the credit facility. Hence, for each loan, we can disentangle whether it was originated in the aftermath of a flood episode, and, in case it entered delinquency, whether that happened following a flood episode. In the former case, the reference date with respect to the flood is the date of loan origination. In the latter case, the reference time is the date(s) after origination when the loan is observed, namely the reporting dates where we draw relevant information on the performance and the status of the credit facility.

3 Loan pricing

This section studies whether flood-related physical risk affects the pricing of SME loans, focusing on the interest rate applied at loan origination.[12]

3.1 Descriptive evidence

Table 1 reports the descriptive statistics on the main loan-level characteristics recorded at the time of loan origination. Our final estimating sample contains approximately 1 million unique credit facilities. The interest rate applied at origination is 234 basis points (bps) on average, and ranges from 55 to 592 bps moving from the 5th to the 95th percentile of the distribution. The average loan term is 68.5 months, that is slightly less than 6 years. The average loan balance is around EUR 94,000. The lower panel of Table 1 reports summary statistics for the sub-sample of loans extended in high-risk counties, i.e. those with a flood risk measure that is above the median of risk scores. At 249 bps, the average interest rate on credit facilities to borrowers facing a high risk of flooding is higher than the one in the full sample. The average loan amount is also higher (around EUR 102,420), whereas the average loan term and the fraction of highly collateralised credit lines in the two samples are comparable.

Figure 3 displays the distribution of the balance at origination and the term of the loans in our sample. The distributions are skewed towards small amounts and short maturities, which is not surprising since borrowers are small and medium enterprises. We do not have information about firm characteristics, including the specific firm dimension (medium, small or micro enterprises). The data set contains some information about the firm's legal form though. Roughly 84% of the firms in our sample are classified as limited companies, 8.3% are individual companies, and 2.2% are reported as partnerships. We may consider individual

[12] The EDW data set does not explicitly include such information, while it provides the interest rate type and the current interest rate observed at the different reporting dates. Hence, we consider all loans with a fixed interest rate. Then, among the loans with a floating interest rate, we consider only those for which the current interest rate has been observed within 12 months from the date of origination.

Table 1: **Descriptive statistics at loan origination.**
Mean, standard deviation (std. dev.) and selected percentiles for the interest rate, loan term, loan balance and the fraction of highly collateralised loans. All variables are as observed at origination. Summary statistics are provided for the full sample of loans, and for the sub-sample of loans originated in high-risk counties.

	Mean	Std. dev.	p5	p25	p50	p75	p95
Full sample							
Interest rate (bps)	233.96	167.01	55	115	180	310	592.30
Loan term (months)	68.47	41.03	13.02	48.03	60.03	83.11	179.11
Loan balance ('000 EUR)	93.78	269.91	5	14.80	28.66	60	320
Collateralised	0.59	0.49	0	0	1	1	1
High-risk counties							
Interest rate (bps)	249.38	177.38	54.30	120	197	340	600
Loan term (months)	67.7	41.08	13.02	48.03	60.03	83.01	179.11
Loan balance ('000 EUR)	102.42	296.74	5	14.90	29	62.13	365
Collateralised	0.61	0.49	0	0	1	1	1

companies and partnerships as a proxy for smaller and micro-enterprises.[13]

Table 2 details the number of loans originated after flood episodes, in the full sample (top panel) and in the sub-sample that includes only counties at high risk of flooding (bottom panel). As explained in Section 2, we consider the time windows of 6, 12, and 24 months following a flood episode. Although floods are not frequent, we observe a sizeable absolute number of loans that are originated in the aftermath of water hazards. Approximately 114,000 individual loans, or almost 11% of the total number of loans in our estimating sample, are originated within two quarters following a flood episode. When we consider a two-year window after flooding, the share reaches 40%. Conditional on being originated in the aftermath of flood episodes, about 40% of loans are extended after disasters with reported economic losses. Floods, even if not severe enough to cause economic losses, are relatively rare events within the very short time windows we consider: almost all the post-disaster loans are originated after a single flood rather than after multiple flood events. The fraction of post-disaster loans originated after multiple floods ranges from 2% when we focus on the half-year time span, to 13% in the 2-year period. At 3% and 14% respectively,

[13]Small and especially micro-enterprises may be under-represented in our sample of securitised loans because of their higher riskiness.

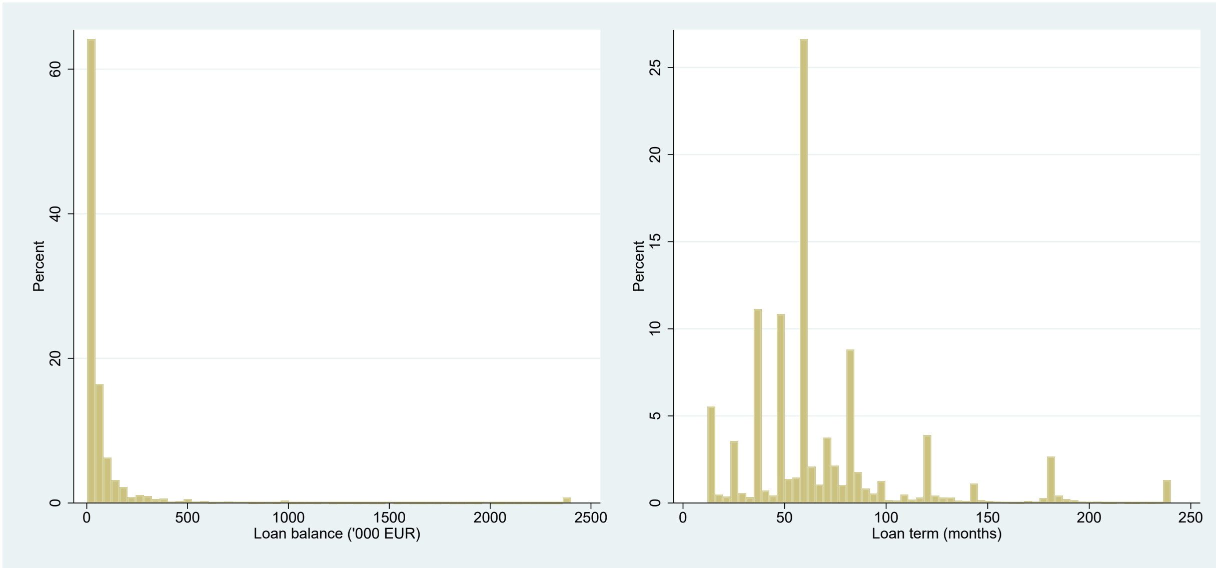

Figure 3: **Distribution of loan balance at origination and loan term.** The left panel reports the distribution of the loan balance (thousands of EUR). The right panel reports the distribution of the loan term (months).

the shares are practically unchanged when we consider only the high-risk counties. Flood frequency becomes compelling when we take a medium-term perspective, however. For each month-year when we observe new loans, we calculate the cumulated number of floods in each county from the beginning of the sample period. Then, we define as flood-prone those counties exposed to a number of floods above the median value of the distributions of flood episodes. Around 36% of loans are originated in flood-prone counties.

3.2 The empirical model

The baseline regression model for loan pricing takes the following form:

$$ir_{ibj,t} = \alpha + \beta Highrisk_j + \gamma X_{ij,t} + \varphi_{bl,y} + \varepsilon_{ibj,t}. \tag{2}$$

The dependent variable, $ir_{ibj,t}$ is the interest rate on loan i granted at time t to firm b, located in county j. Our main variable of interest is $High\,risk_j$ is an indicator variable that takes value 1 if the normalised flood risk indicator for the county where the loan is extended

Table 2: **Number of loans originated after a flood.**
Number of loans originated 6, 12, and 24 months after at least one flood (first row), a flood with reported economic losses, multiple flood episodes, and in flood-prone counties, for the full sample (top panel) and for high-risk counties (bottom panel). The total number of loans in the full sample is 1,045,110, of which 585,276 in high-risk counties, and 376,978 in flood-prone counties.

	6 months	12 months	24 months
Full sample			
At least one flood	113,742	231,522	413,559
Flood with reported losses	41,176	84,757	157,559
Multiple floods	2,174	7,911	56,649
Flood in flood-prone county	71,816	142,654	250,012
High-risk counties			
At least one flood	62,871	127,899	230,881
Flood with reported losses	23,066	47,526	92,234
Multiple floods	1,789	5,620	34,268
Flood in flood-prone county	42,116	83,771	147,654

is above the median of the empirical distribution of risk scores. Hence, counties with risk scores below the median are considered at low risk of flooding (i.e., $High\,risk_j = 0$). In Equation (2), the estimate of β measures the average interest rate premium for high flood risk. $X_{ij,t}$ is a vector of covariates defined at the loan and at the county levels. As loan-level information, we include the loan term (expressed in months), and the amount borrowed (in million euros), both taken in the logarithmic scale. We also control for non-price lending conditions by including a dummy variable that takes value 1 for highly collateralised loans, and 0 otherwise.[14] Growth rates for the county GDP and employment are included to account for the general macroeconomic conditions at the local level. Further, $\varphi_{bl,y}$ denote sets of fixed effects defined at the borrower (b), lender (l) and year (y) levels, as specified below, aimed at tightening our identification strategy. In practice, with the borrower fixed effects we control for unobserved firm-level heterogeneity in direct exposure and vulnerability to flooding. Fixed effects defined at the lender and the year level account for unobserved heterogeneity on the supply side and time varying shocks that could affect loan pricing. Finally, $\varepsilon_{ibj,t}$ is the stochastic disturbance term.

[14]We consider a loan as highly collateralised if the value of pledged collateral is above 50% of the loan amount.

3.3 Results

3.3.1 Baseline results

Table 3 reports the results from estimating different versions of Equation (2).[15] The specification in column (1) includes borrower fixed effects, in addition to variables for loan characteristics and macroeconomic controls. The coefficient of the $High\,risk_j$ indicator is positive and statistically significant at 10%. The point estimate indicates an average flood risk premium of around 6 bps. The coefficient on the loan term is positive and highly statistically significant, suggesting that the term structure of interest rates on loans to SMEs is positively sloped. Similarly, there is a positive and statistically significant correlation between the loan amount and its cost at origination. Finally, highly collateralised loans bear on average a lower interest rate, in line with their perceived lower riskiness, ceteris paribus.

Column (2) adds lender fixed effects, which take care of unobserved heterogeneity on the supply side of credit. The estimates of the flood risk premium increase to 8.4 bps, and is statistically significant. The coefficients of the control variables are qualitatively and quantitatively unchanged. In column (3) we add year fixed effects. Controlling for time-varying unobserved shocks that affect loan pricing slightly reduces the flood risk premium, estimated at 7.4 bps, without altering its high statistical significance. Finally, in column (4), we interact the lender fixed effects with the year dummies. This allows us to take care of time-varying supply factors that may drive loan interest rates, and ensures that we are identifying the impact of floods on the cost of credit based on multiple loans originated from the same bank. The point estimate for the flood risk premium is around 5.8 bps, which is around 2.5% of the average value of the interest rate at loan origination in the sample. It appears rather small in magnitude, also in comparison with evidence on the pricing of physical climate risk into financial assets. For instance, Correa et al. (2022) document that, in the case of hurricanes, syndicated loans bear a risk premium for at-risk but unaffected borrowers in the range of 19 bps. When it comes to debt capital markets, Acharya et al.

[15]We implement the estimation using the `reghdfe` command by Correia (2014).

(2022) find that exposure to local heat stress leads to municipal bond yield spreads that are higher by around 15 basis points per annum.

Table 3: **Flood risk and loan pricing.**
The table reports estimation results for different variants of Equation (2). The dependent variable is the interest rate at loan origination (in bps). *High risk* is an indicator variable equal to one for counties at high risk of flooding, and zero otherwise. The regressions include loan-level controls, macroeconomic controls, and sets of fixed effects as specified. Standard errors, robust for heteroskedasticity and clustered at the county level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
High risk	6.181*	8.407***	7.323***	5.689***
	(3.738)	(2.225)	(2.228)	(1.674)
Loan term	45.055***	45.233***	25.589***	26.372***
	(2.849)	(2.852)	(1.912)	(1.990)
Loan balance	4.739**	4.782**	4.319**	3.930**
	(2.311)	(2.309)	(2.025)	(1.992)
Collateralised	-47.466***	-47.454***	-5.589***	-4.790***
	(4.232)	(4.242)	(1.189)	(0.972)
Macroeconomic controls	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Lender FE	No	Yes	Yes	No
Time FE	No	No	Yes	No
Lender X Time FE	No	No	No	Yes
Adjusted R-squared	0.731	0.732	0.809	0.823
Observations	1,045,110	1,045,110	1,045,110	1,045,110

3.3.2 Robustness

In this section, we provide several robustness checks for the baseline estimates presented in column (4) of Table 3. Specifically, we test the definition of our dependent variable, the granularity of the fixed effects and the adequacy of our main explanatory variable measure to capture localised risk. The results are reported in Table 4.

In column (1) we adopt an alternative definition of the dependent variable using the spread of the loan interest rate over the 3-month monthly Euribor. This allows us to account

Table 4: **Flood risk and loan pricing: robustness of the baseline results.**
The table reports estimation results for different variants of Equation (2). $High\,risk$ is an indicator variable equal to one for counties at high risk of flooding, and zero otherwise. The dependent variable in column (1) is the spread of the interest rate at loan origination over the 3-month EURIBOR (in bps). In columns (2) and (3), the dependent variable is the loan interest rate at origination (in bps). In column (2), interaction time fixed effects are defined at year-month level. In column (3), the high risk indicator is defined based on the highest riskiness quartile of the counties bordering the NUTS3 unit where the loan is extended. The regressions include loan-level controls, macroeconomic controls, and sets of fixed effects as specified. Standard errors, robust for heteroskedasticity and clustered at the county level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1) Interest rate spread	(2) Year-month FE	(3) Bordering counties' risk
High risk	6.176***	5.454***	2.062
	(1.620)	(1.681)	(4.254)
Loan term	26.662***	26.375***	26.375***
	(1.955)	(2.088)	(1.991)
Loan balance	3.453*	3.865*	3.938**
	(1.878)	(1.984)	(1.992)
Collateralised	-4.049***	-2.376**	-4.798***
	(0.954)	(0.931)	(0.973)
Macroeconomic controls	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes
Lender X Time FE	Yes	Yes	Yes
Adjusted R-squared	0.762	0.832	0.823
Observations	1,045,110	1,044,009	1,044,222

for money market conditions at the time the loan is extended that may affect its pricing. At 6.2 bps, the estimated risk premium is in line with the baseline estimates. The specification in column (2) considers more granular fixed effects to address the concern of confounding factors on the supply side of credit. Specifically, we introduce year-month fixed effects interacted with lender fixed effects to allow for supply-side shocks occurring at a higher frequency than in the baseline specification. Again, the coefficient estimate for the flood risk premium is quantitatively and qualitatively unchanged with respect to the baseline model in column (4) of Table 3 .

Finally, we test the validity of our risk measure. Specifically, we address the concern that it may capture other unobserved characteristics in the broad geographic area. To rule out the possibility that our main results are driven by spurious correlation, we consider the riskiness of the counties bordering the ones where each loan is extended. Hence, in column (3) the *High risk* indicator for above-median flood risk is defined on the basis of the highest value of the flood risk indicator among all the counties bordering the one when the loan is originated. This variable should not affect the pricing of bank credit extended in counties exposed to a different level of flood risk. The coefficient estimate is not statistically significant, which indirectly confirms the relevance of the local flood risk measure in the pricing of small business loans.

3.3.3 Mechanisms

In this section, we focus on the factors driving heterogeneity in the flood risk premium to get a better understanding of the mechanisms through which flood risk is priced into small business credit. We consider relevant features on the demand as well as on the supply side of credit.

Specifically, we first gauge the extent of the risk premium across different types of borrowers, based on characteristics that are indicative of their broad financial vulnerability and, hence, arguably, of their capacity to cope with the localised impact of climate change. The results are reported in Table 5. In column (1), we consider only borrowers that have legal form as partnerships or individual firms. These, presumably smaller, borrowers do not benefit from limited liability legal provisions. At around 10.5 bps, the estimated risk premium is larger than the average one in the full sample. It is statistically significant at the 5% level.

To formally test the implications of firm size, in column (2) we estimate the pricing model only on firms classified as small or micro, according to the official definition of the European Commission.[16] This reduces the sample to roughly 126,000 observations. The estimated flood risk premium for small and micro firms is in the range of 38 bps, and highly statistically

[16] The classification is available at `https://ec.europa.eu/growth/smes/sme-definition` and is based on average values of total assets, turnover and employees.

significant. The much larger magnitude of the interest rate mark-up presumably reflects considerations on credit worthiness and financial fragility of small and micro businesses (Fatica et al., 2022b), which arguably contributes to making them particularly vulnerable also to the impact of physical climate risks.

Next, we explore the implications of banks' valuation of borrowers' creditworthiness for regulatory purposes by retaining only firms classified as retail borrowers under Basel III. The classification implies an ad hoc valuation of credit risk compared to corporate asset classes. In column (3), the flood risk premium is estimated at 6.8 bps, only marginally higher than the value for the full sample. Hence, regulatory credit risk considerations do not significantly alter the assessment of prospective climate risk exposure.

We further verify the bearing of the economic features of the borrower on the flood risk premium. Specifically, we focus on firms' reliance on intangible assets as indicative of their potential vulnerability to the manifestation of physical risk. Hence, we drop from the estimating sample firms belonging to knowledge-intensive sectors, as a proxy for the intensity of intangibles in the production process. The estimates in column (4) do not provide strong evidence of the existence of sectoral differences in the risk premium driven by the potential damage to fixed assets caused by flooding.

Next, we turn to the supply side of credit to test whether the magnitude of the risk premium changes across bank types. Based on the reported bank names, we retrieve the banks' specialisation, distinguishing among commercial, savings, cooperative banks and specialised governmental credit institutions.[17] Then, we retain only savings and cooperative banks in the estimating sample. The results reported in column (5) point to a higher risk premium charged by these banks compared to the full sample that includes also commercial banks, which may be indicative of smaller lenders' awareness of climate risk or of their need to price it given their presumably limited capacity to geographically diversify their loan portfolio.

[17] We draw information on bank specialisation from Moody's ORBIS Bank Focus.

Finally, we turn to considerations about loan duration. It is held that since the most disruptive consequences of climate change will fully materialise at longer horizons, pricing climate risk should be particularly compelling for loans with longer maturities. The argument is especially relevant for mortgage lending, whose duration usually extends for several decades (Nguyen et al., 2022). Nonetheless, as the nature of flood risk makes it relevant also in the short and medium term, the long-run aspects are surrounded by more uncertainty. Hence, it is still an open question whether its pricing changes with loan maturity. Business loans, particularly those extended to SMEs, have much shorter maturities, however (Chodorow-Reich et al., 2021). The median loan term in our sample is 5 years, with maturities ranging from 1 year to slightly less than 15 years moving from the 5th to the 95th percentile of the empirical distribution. To shed light on the role of loan term, we run the baseline regression model on two sub-samples having duration below and above the sample median, respectively. The results are reported in columns (6) and (7) of Table 5. Loans with shorter maturities display a lower risk premium than loans with longer duration (3.7 vs 6 bps), which corroborates the view that climate risk considerations are taken into account, particularly at longer horizons.[18]

3.4 Projected or realised risk?

The results from the pricing analysis highlight that physical risk related to flooding is incorporated into the cost of loans to SMEs, although the magnitude of the average premium appears modest. As it is based on probabilistic scenarios and modelling simulations, our measure of flood risk captures projected risks and impacts. Hence, our empirical results should ideally capture expectations on the prospective impact of flooding. However, it may well be that the interest rate mark-up estimated in our pricing empirical model reflects lenders' considerations on the short-term damage from realised risk rather than concerns for

[18]Another option banks have is to shorten duration of loans in order to have the right to reprice more frequently and be less exposed to the flooding risk overall. We do not find that flood risk significantly affect contractual loan maturity. Results are available upon request.

Table 5: **Flood risk and loan pricing: mechanisms.**
The table reports estimation results for Equation (2) on different subsamples. The dependent variable is the interest rate at loan origination (in bps). *High risk* is an indicator variable equal to one for counties at high risk of flooding, and zero otherwise. Column (1) considers only borrowers having legal form as partnerships and individual firms. Column (2) considers only borrowers classified as small and micro firms. Column (3) restricts the estimating sample to borrowers classified as retail under Basel III. Column (4) excludes from the estimating sample borrowers from knowledge-intensive sectors. Column (5) uses only loans extended by cooperative and savings banks. Columns (6)-(7) split the sample into loans with short and with long duration, respectively, using the median loan term at origination as threshold. The regressions include loan level controls, macroeconomic controls, and sets of fixed effects as specified. Standard errors, robust for heteroskedasticity and clustered at the county level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High risk	10.469**	38.215***	6.830***	6.250***	9.780***	3.707*	5.967**
	(4.241)	(13.499)	(2.239)	(1.714)	(3.366)	(2.082)	(2.348)
Loan term	23.357***	10.765*	19.592***	27.549***	35.772***	15.045***	44.693***
	(4.164)	(5.843)	(2.483)	(2.205)	(5.314)	(2.602)	(2.871)
Loan balance	12.170***	24.100***	8.171**	3.756**	-0.928	10.090**	-5.084***
	(4.514)	(4.192)	(3.763)	(1.840)	(1.070)	(4.301)	(0.388)
Collateralised	-10.844***	-14.154***	-8.402***	-4.512***	-1.672**	-3.706*	-7.941***
	(4.029)	(3.644)	(1.270)	(0.989)	(0.782)	(1.935)	(0.666)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender X Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.703	0.622	0.776	0.825	0.779	0.806	0.870
Observations	154,528	125,629	599,271	918,625	442,563	317,814	577,712

current and prospective climate risk development. In this section, we test this hypothesis making use of the information on flood events as a measure of realised risk.

The results are reported in Table 6. First, we use a time-varying measure of flood frequency over the medium term to gauge the influence of realised risk on loan pricing. Specifically, we calculate the cumulative sum of flood events for each county and month-year since the beginning of our sample period. Then, we define an indicator variable (*Flood prone*) that equals 1 for the counties above the median value of the cumulative flood events, and 0 otherwise. Column (1) in Table 6 reports the coefficient estimates from the empirical pricing model in Equation (2), augmented with the indicator for flood-prone counties. While the estimated coefficient for flood risk is qualitatively and quantitatively similar to the baseline case, the time-varying measure of flood frequency is not estimated with precision. Hence, the occurrence of flood events in itself does not influence loan pricing. Moreover, controlling for this backwards-looking measure of realised risk over the medium term does not affect the explanatory power of our measure of high prospective risk.

Next, we test several alternative backwards-looking measures of risk, with a focus on the short term, that is, on the occurrence of flood episodes in the months before the date of loan origination. In particular, using the information on dates for both loan origination and flood events, for each loan in our sample we consider whether it was originated during the 6 months following at least one flood episode. Then, we define an indicator variable *Flood* that takes the value of 1 for loans extended in the semester after flooding, and 0 otherwise. The results are reported in column (2) of Table 6 - panel *a*. The coefficient on the indicator for recent flooding is positive, but not statistically significant. Hence, loans extended in the aftermath of the disaster are not priced differently than loans originated in non-flooded areas. This evidence is in line with the results in Koetter et al. (2020) who find that recovery lending extended to firms exposed to the 2013 flooding in Germany was not accompanied by higher lending margins. Importantly, the estimated flood risk premium remains unchanged compared to the baseline model specification without realised risk.

The indicator for loans originated after flooding in column (3) considers only flood episodes with reported economic losses, and redefines the *Flood* dummy accordingly. Since the economic impact of floods on firms differs across contexts and events (Fatica et al., 2022a), so might also their potential implications for bank lending. Arguably, reported economic losses are indicative of more severe disasters (Roth Tran and Wilson, 2020), which in turn might translate into significantly different pricing strategies for bank loans. The estimates in column (3) corroborate the previous findings that loan pricing is unrelated to recent flooding. Moreover, the size and significance of the premium estimated on prospective risk remain stable.

Finally, we consider also the occurrence of multiple disasters in the semester before loan origination. Repeated flood episodes in such a short time frame provide relevant information

Table 6: **Realised flood risk and loan pricing.**

The table reports estimation results for different variants of Equation (2). The dependent variable is the interest rate at loan origination (in bps). *High risk* is an indicator variable equal to one for counties at high risk of flooding, and zero otherwise. *Flood prone* is an indicator variable equal to one in counties above the median of the empirical distribution of cumulated flood events in the sample, and zero otherwise. *Flood* is an indicator variable equal to one if there has been at least one flood episode in the six months before loan origination, and zero otherwise. Column (3) considers only floods with reported economic losses for the definition of the *Flood* indicator. Column (4) considers only multiple floods for the definition of the *Flood* indicator. *Panel b* adds the effect of a flood occurring in a high-risk county. The regressions include loan level controls, macroeconomic controls, and sets of fixed effects as specified. Standard errors, robust for heteroskedasticity and clustered at the county level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Panel a				
High risk	5.797***	5.687***	5.700***	5.689***
	(1.678)	(1.672)	(1.676)	(1.674)
Flood prone	-1.349			
	(1.251)			
Flood		1.038	1.424	1.654
		(1.146)	(1.654)	(6.406)
Loan term	26.374***	26.372***	26.372***	26.372***
	(1.989)	(1.989)	(1.989)	(1.990)
Loan balance	3.927**	3.932**	3.932**	3.930**
	(1.991)	(1.991)	(1.992)	(1.992)
Collateralised	-4.785***	-4.786***	-4.788***	-4.789***
	(0.971)	(0.972)	(0.972)	(0.972)
Macroeconomic controls	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes
Lender X Time FE	No	No	No	Yes
Adjusted R-squared	0.731	0.732	0.809	0.823
Observations	1,045,110	1,045,110	1,045,110	1,045,110
Panel b				
High risk		5.778***	5.640***	5.714***
		(1.695)	(1.668)	(1.677)
Flood		1.498	0.487	6.424
		(1.421)	(2.340)	(13.730)
High risk x Flood		-0.850	1.728	-6.696
		(2.105)	(3.286)	(15.281)
Loan term		26.373***	26.370***	26.373***
		(1.988)	(1.989)	(1.990)
Loan balance		3.931**	3.932**	3.930**
		(1.991)	(1.992)	(1.992)
Collateralised		-4.787***	-4.786***	-4.789***
		(0.971)	(0.972)	(0.972)
Macroeconomic controls		Yes	Yes	Yes
Borrower FE		Yes	Yes	Yes
Lender X Time FE		Yes	Yes	Yes
Adjusted R-squared		0.823	0.823	0.823
Observations		1,045,110	1,045,110	1,045,110

on the frequency of climate-related disasters and, hence, in our framework, they may affect loan pricing. Therefore, we redefine the indicator for *Flood* as taking unit value only for loans originated in the 6 months after multiple flood events, and 0 otherwise. The results are in column (4). The coefficient for the flood indicator is not estimated with precision, thus lending support to the notion that realised risk over the short term does not affect loan pricing. Moreover, the inclusion of this alternative measure of realised risk leaves the estimated premium for prospective flood risk unaffected.

While the actual occurrence of flood damage in itself is not incorporated into the price of small business loans, it may in principle alter the perception of the associated prospective flood risk. Chen et al. (2012) highlight the 'latent' nature of disaster risk, and predict its surge in the aftermath of actual disasters, which reduces agency problems, as well as disagreement by facilitating inference on both the likelihood and severity of hazards. Along the same line of reasoning, in our framework, recent flood episodes may indeed increase the salience of physical climate risk (Correa et al., 2022), as, arguably, they reduce uncertainty over the frequency of disasters. We test this hypothesis by introducing an interaction term between the high risk indicator and the dummies for recent floods in the model already augmented with the former variable. The estimates are reported in panel *b* of Table 6. In all cases considered, the interaction term is not statistically significant. This indicates that recent flooding does not change the perception of prospective flood risk (column (2)), even when only severe floods (i.e., floods with economic losses) as in column (3), or multiple flood episodes are considered, as in column (4). Overall, these findings suggest that the interest rate mark-up charged to borrowers in counties at high risk of flooding reflects considerations unrelated to the short-term cost of realised water damage. As such, this is suggestive of physical climate risk being already salient for lenders exposed to at-risk borrowers.

4 Flooding and loan performance

In this section, we study the effects of flooding on loan performance. Specifically, we aim to assess whether realised flood risk has a bearing on the occurrence of late payments and, eventually, of loan default. We consider two different instances when flooding can impair loan performance. First and foremost, there is a direct effect, whereby firms' capacity to service debt obligations deteriorates in the aftermath of the disaster (Noth and Schuewer, 2018). In this case, the analysis focuses on loan impairment occurring after flooding. Second, we consider also an indirect effect that may materialise for loans originated after a disaster. Here we capture risk-taking by banks or potential loosening of lending standards in the wake of increased loan demand for reconstruction purposes in the aftermath of the hazard (Bos et al., 2022).

We employ survival analysis, which models the likelihood of loan i to default before it reaches its final maturity or the observation period ends. Compared to standard binary models, such as the logit, a time-varying duration model allows us to account also for implicit measures of risk-taking. The hazard rate in a duration model has the intuitive interpretation as the probability of default in each period, conditional on surviving until that period.[19] As such, the hazard rate can be considered a per-period measure of risk and, hence, it is comparable between loans with different maturities.

Formally, let $S(t) = Pr(T > t)$ be the probability of survival beyond time t, also known as survival function. We define the hazard function, also known as hazard rate, as:

$$h(t) = \lim_{\Delta t \longrightarrow 0} \frac{Pr(t < T < t + \Delta t | T > t)}{\Delta t}. \tag{3}$$

Given a p-dimensional vector of covariates $\boldsymbol{x}$, we can model the survival time as $h(t|\boldsymbol{x}) = \exp(\phi_o + \phi'\boldsymbol{x})$, where the exponent imposes the non-negativity of $h(\cdot)$. In the Cox's propor-

[19] We refer to Gupta et al., 2018 for an overview of the application of hazard models in predicting SMEs failures and to Dirick et al., 2017 for an introduction to survival analysis.

tional hazard model (Cox, 1972) the hazard function is:

$$h(t|\boldsymbol{x}) = h_0(t)\exp(\phi'\boldsymbol{x}), \tag{4}$$

where $h_0(t)$ is an unknown non-negative function that incorporates the baseline hazard when the vector of covariates $x_{i1} = \ldots = x_{ip} = 0$. The associated survival function is:

$$S(t|\boldsymbol{x}) = \exp\left(-\exp(\phi'\boldsymbol{x})\int_0^t h_o(u)\mathrm{d}u\right) = \exp(-\exp(\phi'\boldsymbol{x})H_0(t)), \tag{5}$$

where $H_0(t)$ is the cumulative of the baseline hazard function $h_0(t)$.

Let y_{it} be a binary variable indicating whether the i^{th} loan in time t is defaulted or not. For each loan i, we define the survival time T as the time at which the default (i.e., $y_{iT} = 1$) occurs, and the censoring time C as the end of the observation period or the loan's final maturity. We compute the time variable t as the difference in months between the cut-off date (i.e., the date when the updated information about the loan is observed) and the loan's origination date.

The vector $\boldsymbol{x}$ includes a binary variable that indicates whether the county where loan i was extended experienced at least a flood in the previous q months. This allows us to test the impact of recent flood events on the deterioration of performance. As disasters and their economic consequences may have a delayed effect on firms' financial fragility, we estimate variants of the proportional hazard model for different time horizons, that is, we consider, alternatively, $q = 6,\ 12$, and 24 months. As a second test, we verify whether flooding at origination matters for loan performance. We do so by augmenting the model with a binary variable that indicates the occurrence of at least a flood event in the q months before loan origination. As before, we consider, alternatively, $q = 6,\ 12,\ 24$. As an additional flood-related variable, we control for projected risk by using the dummy *High risk*, which equals 1 for the counties that have a normalised risk indicator above the median value of the empirical distribution of food risk, and 0 otherwise. In addition, the vector $\boldsymbol{x}$ includes loan-level regressors, namely the current interest rate, as well as the logs of the loan balance (in euros), the residual loan term (in months), and a dummy variable for highly collateralised loans.[20] We also include fixed effects specific to the lender and to the sector of the borrower, as well as controls for local macroeconomic conditions, namely the growth rates of GDP and employment. The choice of variables follows Barbaglia et al. (2023), who investigate the delinquency of residential mortgages in Europe using data from the EDW. Their results indicate that interest rates and local economic conditions as the most important drivers of mortgage default.

To define the dependent variable, we exploit the information on the loan payments schedule in the EDW database. We classify a loan as defaulted if it is in arrears for more than 90 consecutive days. If a loan is labelled as defaulted, we discard all updates of the loan status following the date when it first appears in prolonged delinquency. Hence, we do not consider the possibility of defaulted loans returning to a performing status. While the focus of this section is on loan default, we also estimate the duration model for late payments, considering as dependent variable a binary variable that indicates when the loan first enters arrears status (see Appendix B).[21] In our sample, the fraction of loans in arrears is 4.9%, and the average default rate is 1.5%. Thus, even compared to temporary delays in payments, defaulting is a rare event in our sample. This is consistent with the overall good quality of the securitised loans in the EDW database (Ertan et al., 2017).

Table 7 reports the results of the Cox's proportional hazard model. To simplify the discussion, Table 7 displays the estimated hazard rates, instead of the underlying coefficients. A hazard ratio higher than 1 for a covariate indicates that loans with that feature or risk factor have a shorter survival than loans without that feature. If the hazard ratio is lower than 1, it would mean that the hazard was less in loans with the potential risk factor. Columns (1)-(3) in the table focus on the direct impact of flooding on loan default using the

[20]The indicator takes the value of 1 if the value of pledged collateral is above 50% of the loan amount, and 0 otherwise.

[21]We consider arrears on principal or interest payments.

Table 7: **Flooding and loan default.**
The table reports the hazard ratios from a Cox's proportional hazard model for loan survival. *Flood* is an indicator variable equal to one if there has been at least one flood episode in the 6, 12, or 24 months before loan default, and zero otherwise. *High risk* is an indicator variable equal to one for counties belonging to the top two quartiles of the country-specific distributions of the flood risk measure, and zero otherwise. *Flood before origination* is an indicator variable equal to one if there has been at least one flood episode in the 6, 12, or 24 months before loan origination, and zero otherwise. Columns (1)-(3) focus on the direct impact of flooding on loan default using the occurrence of flood events before the observation date. Columns (4)-(6) focus on the impact of flooding on loan default using flood events occurred before the origination date of the loan. All regressions control for industry, lender, region (NUTS2) and business type fixed effects, as well as growth rates of GDP and employment. ***, **, and * indicate that the hazard estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Realised flood risk before default			Realised flood risk at loan origination		
	6 months	12 months	24 months	6 months	12 months	24 months
Flood	0.898***	1.203***	1.544***	0.898***	1.201***	1.538***
	(0.024)	(0.023)	(0.026)	(0.024)	(0.023)	(0.026)
High risk	1.039**	1.040**	1.046**	1.040**	1.041**	1.046**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Flood before origination				1.173***	1.228***	1.042**
				(0.025)	(0.021)	(0.017)
Interest rate	1.110***	1.113***	1.116***	1.111***	1.113***	1.116***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Loan balance	0.868***	0.870***	0.874***	0.869***	0.871***	0.874***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Residual loan term	1.044***	1.040***	1.036***	1.045***	1.042***	1.037***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Collateralised	1.941***	1.943***	1.905***	1.928***	1.919***	1.901***
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Region (NUTS2) FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,516,457	13,516,457	13,516,457	13,516,457	13,516,457	13,516,457

occurrence of flood events before the observation date. The results in column (1) indicate that, if any, the impact of flooding on loan default does not significantly materialise in the 6 months after the disaster. The hazard ratio associated with the occurrence of flooding in the previous 6 months is 0.898, which suggests a protective effect of flood on outstanding loans, ceteris paribus . This counter-intuitive effect might be due to the short time span considered, in comparison with the definition of default. Indeed, we define a default as 3 consecutive delinquent months, thus making the 6-month window arguably too short to assess the impact of the natural disaster on the SME financial performance.[22] The estimated hazard for the flood risk variable is larger than 1, but rather small from an economic perspective, and significant at 5% level. This suggests that loans in high-risk counties have a shorter survival probability than loans extended to firms that do not face a high risk of flooding. As for the other explanatory variables in the survival model, all the estimated effects are highly statistically significant and economically meaningful. A 1-basis point rise in the interest rate increases the hazard rate by one-tenth. A higher residual balance decreases the probability of loan default. By contrast, loans that have higher residual duration and are highly collateralised are more likely to enter default status than other loans, ceteris paribus. With an estimated hazard of 1.94, the effect of collateralisation is sizeable.

The second and third columns of Table 7 consider the occurrence of at least one flood in, respectively, the 12 and 24 months before the observation date. Focusing on the longer horizons, the estimated hazards associated with the *Flood* variable are larger in magnitude and highly statistically significant. Loans to flooded borrowers are 1.2 times more likely to default in the 12 months following the disaster than credit facilities to firms that did not experience water damage in the previous year (column(2)). Considering the 2-year window (column (3)), the estimated hazard reaches 1.5. As the loans in our sample are of relatively high quality (Ertan et al., 2017), our estimates are likely conservative with respect to the impact of flooding on the performance of the universe of credit extended to SMEs in Europe.

[22] The estimates for entering into arrears show that late payments on outstanding loans materialise already in the 6 months after a flood event. See Appendix B.

Moreover, our results indicate that the impact of flooding on loans' probability of default is more pronounced at longer horizons. While in the first months after the flood exposed firms may still rely on their cash holdings and other financial buffers to cushion the negative shock (Joseph et al., 2022), they are likely to encounter liquidity and solvency issues in the medium term, as water damage disrupt firm operations in a significant and persistent way (Fatica et al., 2022a). In fact, the results on loan arrears show that flooding increases the probability of late payments on outstanding loans already in the first six months after the event, with these signs of financial fragility persisting for our two-year observation period (see Appendix B).

There is a second, indirect way through which flooding may have a bearing on loan performance. The need to rebuild in the aftermath of climate hazards brings about an expansion of credit on the back of increased demand (Berg and Schrader, 2012; Koetter et al., 2020). However, in a context where the timely availability of funds is crucial for firms' operations, banks might increase risk-taking when they provide recovery lending to disaster-stricken SMEs. To test whether banks incur systematically more credit risk in their recovery loans than in other credit, we introduce an indicator variable for post-disaster credit in the survival model. Specifically, following the approach taken in the analysis of pricing at origination, we use a dummy (*Flood before origination*) that takes value 1 for loans originated in the q months after flooding, and 0 otherwise. As before, we consider, alternatively, $q = 6,\ 12,\ 24$. The results are reported in columns (4)-(6) of Table 7. As the hazard ratios of the other explanatory variables are practically unchanged with respect to the baseline specification, we focus our comment on the variable of flooding at origination. Loans originated up to 1 year after a flood event are on average 1.2 times more likely to default than other loans, all other factors being equal. Hence, the hazard rate increases by one-fifth for post-disaster loans. Importantly, the result holds while keeping other observable loan characteristics, such as the interest rate, the residual duration, the balance and the fraction of the loan that is collateralised, constant. The fragility of recovery loans materialises also for credit extend 2 years after the disaster, although is expectedly much more muted (column (6)). Overall, these findings indicate that the cohorts of loans extended in the aftermath of flooding perform worse than other credit facilities, pointing to an additional vulnerability factor arising from realised physical climate risk for the default of loans to SMEs.[23]

5 Risk pricing and loan default: a discussion

The results in Section 3 indicate that banks price flood-related climate risk into new loans to small and medium-sized firms. While there is substantial heterogeneity across borrower and lender types, the average risk premium appears rather small in size. Section 4 shows that flood episodes are an important risk factor for firms' ability to service their debt as they significantly increase the relative likelihood of loan default. Hence, the question of whether projected risk is adequately priced against realised risk naturally arises.

In this section, we attempt to provide a first answer to this question resorting to a very stylised framework inspired by the valuation of Credit Default Swaps with a constant hazard rate model (Hirsa and Neftci, 2014). The standard equation takes the form:

$$S = PD(1 - R), \tag{6}$$

where S is the interest rate spread, PD is the loan default probability, and R is the recovery rate in case of loan default, so that $(1 - R)$ is the loss given default (LGD) associated to the loan, or $LGD = (1 - R)$. Defining S_0 the average loan spread observed in the sample (233.96 bps, as in Table 1), and with $\hat{S}_f$ the spread in the case the realised flood risk is fully priced, we can retrieve the corresponding risk premium by plugging the relevant observed

[23]The results in Appendix B show that recovery loans are also more likely to enter into arrears than loans not originated in the aftermath of flood events. The effects are milder than in the case of default, presumably reflecting the fact that short-term late payments are relatively more likely to occur than prolonged arrears.

variables and the estimated parameters into the ratio $\hat{S}_f/S_0$, or:

$$\hat{S}_f/S_0 = \hat{h}(L\hat{G}D_f/LGD_0). \tag{7}$$

In equation 7, $\hat{h}$ is the estimated hazard ratio obtained from the survival model estimated in Section 4.[24]

As for the calibration of the loss given default, we exploit the information available in the EDW database, which reflects banks' internal assessment of the LGD on the loans in their portfolios. Also in this case, we need values for the LGD in the different scenarios with and without flood risk accounted for. To this purpose, we formally test whether the estimated loss given default that the banks report on each loan is affected by disaster risk and flooding occurrence both during the lifetime of the loan and when it is originated. We find that banks adjust their estimated LGD on existing loans upwards in the 6 months following flooding, but not at longer time horizons, notwithstanding the deterioration of loan performance uncovered in the survival model. By contrast, the occurrence of floods before loan origination increases the ex-ante assessment of the LGD, although the adjustment rather small in size .[25] The empirical model and the full set of results are reported in Appendix C,

In line with the analysis of loan default, we assess loan pricing against flood risk that is realised at different points in time, that is both during the lifetime of the loan and before its origination. We refer to them as *ex-post realised risk* and *ex-ante realised risk*, respectively. In the case of ex-post realised risk, our back-of-the-envelope calculations give an hypothetical optimal risk premium of roughly 50.5 bps.[26] This is almost 9 times the size of the average risk premium estimated in Section 3. To evaluate the pricing of ex-ante realised risk, we

[24]We calculate the optimal risk premium as $\hat{S}_f - S_0$, where $\hat{S}_f$ is obtained from the formula in Equation (7).

[25]Interestingly, estimates of the LGD are not significantly affected by the projected flood-related physical risk in the county where the loan is granted (see Appendix C).

[26]We have 284.47-233.96=50.5, where we obtain 233.96*1.21*1.00=284.47 from Equation (7), with 1.21 the average estimated hazard ratio on the *Flood* indicator (see columns 1-3 in Table 7), and 1.00 the ratio in LGD obtained applying the average of the estimated coefficient on the *Flood* indicator (see columns 1-3 in Table C.1).

use the estimated parameters associated with the dummy variables defined considering the occurrence of flood episodes before loan origination. The average ex-ante risk premium is in the range of 36 bps, or 6 times the estimated risk premium in our pricing model in Equation (2).[27] All in all, even in this very simple setup, it appears that the pricing of projected flood risk does not adequately reflect the increased credit risk associated with water hazards.

6 Floods and loan securitisation

The analysis in Section 4 shows that small and medium-sized firms in flooded areas are more likely to incur delays in debt-servicing and to eventually default on their loans in the aftermath of the disasters than borrowers not exposed to flooding, ceteris paribus. Such increased financial fragility is also persistent, as substantially higher loan default probabilities materialise even 2 years after flooding. The surge in impaired loans in banks' portfolios and the higher risk of credit extended in flooded areas may affect banks' lending behaviour (Chavaz, 2016; Schuewer et al., 2018), depending on their ability to transfer risk through securitisation. For instance, Ouazad and Kahn (2022) find evidence of a pass-through of climate risk in the initiation of mortgages that can be securitised in areas hit by natural disasters. In a similar vein, in this section we consider the volume of newly originated loans at the county level, and ask whether it is impacted by recent flooding. This aggregate analysis sheds light on who ultimately bears localised climate-related risks. Moreover, in a setup where we only observe securitised loans, it gives indications of the potential geographic re-composition of securitisation activities as climate hazards intensify in frequency and severity.

We use a staggered difference-in-differences methodology to study the average effect of flooding on the aggregate amount of new securitised small business lending in the local areas, that is, at the NUTS3 level. As before, time periods are indexed by t and counties

[27] We obtain 270.10-233.96=36.1. From Equation (7), we get 233.96*1.15*1.00=270.10, with 1.15 the average estimated hazard ratio on the *Flood before origination* indicator (see columns 1-3 in Table 7), and 1.00 the ratio in LGD obtained applying the average of the estimated coefficient on the *Flood before origination* dummy (see columns 1-3 in Table C.1).

by $j \in \mathbb{T}, \mathbb{C}$, where $\mathbb{T}$ and $\mathbb{C}$ identify the sets of flooded and non-disaster counties, which constitute the treated and the control group, respectively. Let $D_{j,t} = \mathbb{1}\{j \in \mathbb{T}\}$ denote the treatment status, which equals 1 for flooded counties. Furthermore, let the actual outcome be $y_{j,t} = Y_{j,t}(D_{j,t})$, depending on the treatment state. The county-time average treatment effect (ATT) is then defined as follows:

$$ATT_t = \mathbb{E}[y_{j,t}(1) - y_{j,t}(0)|D_{j,t} = 1; Z_{j,t}], \tag{8}$$

where $Z_{j,t}$ is a set of control variables on which the ATT is also conditioned. We perform the analysis at the quarterly frequency, and calculate aggregate new lending at the county level in each quarter t.[28] We use both the total volume of newly extended credit and the number of new credit lines at the county level. To account for the potential effects of few large loans on total lending volumes, we also consider the average amount of new credit. In equation 8, the treatment dummy $D_{j,t}$ takes the value 1 in the quarter where the county has been flooded. The vector $Z_{j,t}$ contains GDP per capita, and the growth of GDP and of employment, defined at county-quarter level.[29] We use the ATT estimator proposed by de Chaisemartin and D'Haultfœuille (2020).

Figure 4 reports the estimated ATTs, for up to 8 quarters after the floods, alongside their 95% bootstrap-based confidence bands. A few interesting patterns emerge. First, no pre-trends are apparent in the half-year before the hazard. Second, the volume of new securitised lending to small businesses steadily decreases in the aftermath of flooding (panel *a* of Figure 4). The negative evolution is persistent and statistically significant over the observation horizon of 2 years. The same downward dynamic is apparent for the total number of loans (panel *b*), although the large standard errors do not make the effect statistically significant. The average loan balance is also declining, while turning statistically insignificant

[28]In practice, we obtain quarterly aggregates by summing up the monthly observations for loans at origination that we use for the pricing analysis in Section 3.

[29]We obtain quarterly values applying the Denton method (Di Fonzo and Marini, 2012) to the annual accounts for NUTS3 counties available from Eurostat.

at the longer time horizons. Overall, these results point to reduced risk sharing through securitisation in the aftermath of flood events, suggesting that physical climate risk is, at least partly, borne by banks lending to borrowers more exposed to natural hazards. Given the overall high quality of securitised loans that comprise our sample (Ertan et al., 2017), the decrease in volumes of securitised lending in flooded counties may also indicate a general deterioration of the quality of the loans in these areas.

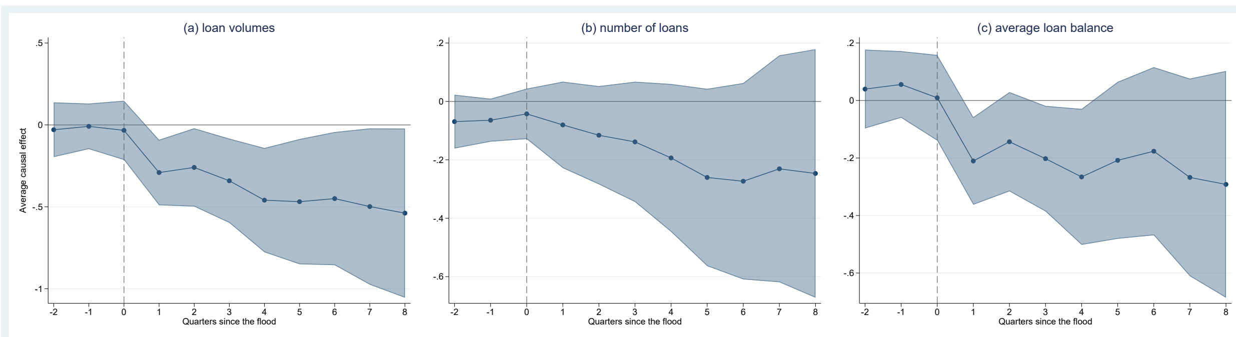

Figure 4: **Average treatment effect of flooding.** Plot of the average treatment effect of floods on new credit for up to 8 quarters, alongside the 95% confidence bands. Panel (a) shows the impact on the total new lending, panel (b) the average loan balance, and panel (c) the number of new loans.

7 Conclusion

Extreme weather events and climate-related natural hazards are becoming more frequent and severe with the rise in global temperatures. While floods are already among the most damaging hazards at the European scale and the increase in the associated risk is substantial, their financial implications are still far from being fully understood. In this paper, we use a large cross-country data set of securitised loans to study the impact of flooding on small business lending in Europe.

First, using detailed information on interest rates at origination, we find that banks charge higher interest rates on new loans originated in counties that are at high risk of flooding. The risk premium, rather small on average, turns sizeable for smaller borrowers, and in the case of local specialised lenders, i.e. cooperative and savings banks. Moreover, flood risk appears already salient for lenders, as we do not find evidence of pricing being affected by recent flood events.

Second, we find that flood events are an important risk factor for loan performance. Using survival analysis, we uncover two distinct channels through which realised risk affects loan default. First, firms exposed to a flood are more likely to default on their loans than firms in non-disaster areas, by up to 1.5 times in the second year after the water hazard. Second, loans originated in the aftermath of flooding are also more likely to enter delinquency status than loans with otherwise similar financial characteristics. Using a stylised version of a standard credit model, we show that the average climate risk premium estimated in our pricing analysis does not adequately account for the deterioration in loan performance that occurs once flood risk is realised, either before origination or during the lifetime of the loan.

Finally, through a staggered difference-in-differences model we document that floods decrease the volumes of securitised small business lending in local markets. This points to reduced risk sharing possibilities, and supports the notion that physical risks are still borne within the banking sector.

Taken together, our results suggest that the intensification of natural disasters due to climate change may become an important source of financial vulnerability for European small and medium-sized businesses, and for the banks that finance them. From a financial stability perspective, the fact that climate-related developments impact standard financial risk suggests that they need to be addressed by prudential policies, ideally in a framework that accounts for their specificity in terms of systemic effects. More broadly, our findings point to the importance of policies that mitigate the disruptive effects of physical risks on the real economy, including by adequately addressing adaptation to climate change.

In this perspective, future research might investigate whether physical risk similarly impacts other loan terms, such as collateral and covenants (Mabille and Wang, 2023). The study of non-price terms could bring further insights on the financial implications of climate change for bank finance to smaller businesses.

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Appendix

A Data cleaning

This section illustrates the data cleaning steps performed on the loan-level data from the European DataWarehouse (EDW) more in detail, as a complement to the data description provided in the main text. (i) Consistent with the time period for which we have information of flood events, we select only loans originated in between January 1^{st} 2008 and December 31^{st} 2019. (ii) We exclude all items with a pool-cut-off date prior to January 1^{st} 2015, on the grounds of better overall reporting quality thereafter. (iii) We drop all observations with no geographic indication at NUTS3 level, and convert all entries following the 2013 NUTS classification[30]. (iv) We exclude all loans with non-positive values for the relevant loan characteristics. (v) To ensure that only loans to profit-maximizing entities are included in our sample, we drop all credit lines extended to borrowers with a Nomenclature of Economic Activities (NACE) in sectors beginning with "S" (*Other services activities*, including of membership organization), "T" (*Activities of households as employers; undifferentiated goods - and services - producing activities of households for own use*) or "U" (*Activities of extraterritorial organisations and bodies*). Moreover, we do not consider inter-banking financing operations by excluding borrowers in the NACE 2-digit sector "64" (*Financial service activities*). (vi) To filter out outliers, we winsorize the interest rate, loan balance and loan term variables at the 1.5 and 98.5 percentiles.

The EDW reports loan-level information including static (i.e., features observed at loan origination, for instance, the loan origination date or the NUTS3 county where the borrowing SME is located) and dynamic variables (i.e., updated information about the loan as observed at the latest pool-cut-off-date, for instance, the current interest rate or the loan status). In the main paper, we assess the impact of flood risk on the cost of borrowing by analyzing a data set of unique loans with information at their origination. It might be that the information at the loan origination provided by EDW differs across pool cut-off dates due to

[30] Conversion tables are available at `https://ec.europa.eu/eurostat/web/nuts/correspondence-tables/postcodes-and-nuts`.

reporting errors. To address the concern of potential measurement error in the variables due to misreporting, we consider information at loan origination as reported in the most recent pool cut-off date. Finally, the interest rate at loan origination is not a mandatory variable to be reported in the securitisation disclosure, and therefore is not normally provided by the EDW. There is a mandatory requirement for disclosing the current interest rate, which is therefore observed at the different pool-cut-off dates. In the main paper, we are interested in studying the interest rate when the loan is issued. Therefore, we first select only loans with a fixed interest rate. Then, we add floating-rate credit lines that have been observed within one year after their origination.

B Flooding and loan arrears

Section 4 in the main paper documents a significant and persistent effect of flooding on loan default probabilities. Here we complement that evidence by considering more broadly arrears on loan payments as a first indication of the deterioration of firms' ability to servicing their debt. Hence, we estimate the Cox's proportional hazard model in Section 4 using an alternative definition of the dependent variable that captures the occurrence of loan entering into arrears for either interest payments or principal repayment. As before, we investigate both the direct and the indirect effect of flooding on loan performance. In other words, we consider the impact of flood events occurring during the lifetime of the loan as well as that of floods taking place before loan origination.

The results are reported in Table B.1. Columns (1)-(3) focus on the direct impact of flooding on loan default using the occurrence of flood events during the loan lifetime. The hazard ratios associated with recent flooding indicate a sizeable and statistically significant direct impact of realised flood risk on SMEs' financial fragility in terms of late payments on their debt obligations. Firms in flooded areas are more likely to experience delays in loan payments even two years after the disaster: the relevant hazard ratios are in the range of 1.1 at the shorter time horizons and increase to 1.2 in the second year. The indirect effect of flooding, while still highly statistically significant, is milder. Being originated in the aftermath of flood events is itself a risk factor for loans. The estimated hazard ratios imply that loans granted 6 or 12 months after a flood are almost 1.1 times more likely to experience late payments than other loans. The effect fades away at the longer time horizon. As for the analysis of loan default, the estimated hazard for the flood risk variable is larger than 1, but rather small from an economic perspective, and significant at 5% level. All in all, these results are not surprising since temporary late payments are relatively more frequent than episodes of prolonged delinquency, and hence potentially less influenced by flooding.

Table B.1: **Flooding and loan arrears.**
The table reports the hazard ratios from a Cox's proportional hazard model for loan survival. The dependent variable is the number of months in arrears. *Flood* is an indicator variable equal to one if there has been at least one flood episode in the months before the date the loan first enters into arrears, and zero otherwise. *High risk* is an indicator variable equal to one for counties belonging to the top two quartiles of the country-specific distributions of the flood risk measure, and zero otherwise. *Flood before origination* is an indicator variable equal to one if there has been at least one flood episode in the months before loan origination, and zero otherwise. Columns (1)-(3) focus on the direct impact of flooding on loan entering into arrears using the occurrence of flood events before the observation date. Columns (4)-(6) focus on the impact of flooding on loan entering into arrears using flood events occurred before the origination date of the loan. All regressions control for industry, lender, region (NUTS2) and business type fixed effects, as well as growth rates of GDP and employment. ***, **, and * indicate that the hazard estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Realised flood risk before arrears			Realised flood risk at loan origination		
	6 months	12 months	24 months	6 months	12 months	24 months
Flood	1.100***	1.098***	1.190***	1.100***	1.097***	1.186***
	(0.015)	(0.012)	(0.012)	(0.015)	(0.011)	(0.012)
High risk	1.023**	1.023**	1.022**	1.023**	1.022**	1.022**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Flood before origination				1.075***	1.079***	1.030***
				(0.012)	(0.010)	(0.009)
Interest rate	1.148***	1.148***	1.149***	1.148***	1.149***	1.149***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Loan balance	0.947***	0.947***	0.948***	0.947***	0.948***	0.949***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Residual loan term	1.014***	1.013***	1.013***	1.014***	1.014***	1.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Collateralised	1.039***	1.040***	1.036***	1.035***	1.034***	1.035***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Region (NUTS2) FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,395,676	13,395,676	13,395,676	13,395,676	13,395,676	13,395,676

C Banks' expected losses from loan default

Section 4 in the main paper documents a significant and persistent effect of flooding on loan default probabilities. On average, flooded firms are more likely to default on their loans in the aftermath of the disaster. The higher default probabilities recorded after flooding open the way for a negative supply channel, as banks facing higher credit risk need to write off impaired loan facilities. This entails that banks are incurring losses on their loan portfolios, which, in turn, could hamper their capacity to expand lending to meet demand for recovery financing in flooded areas. In this section, we study the implications of loan default for banks' balance sheets. In particular, we model the linear relationship between risk, flooding and the estimated loss given default reported by banks on their credit lines, as follows:

$$lgd_{ibj,t} = \alpha + \beta Flood_{j,t-q} + \gamma X_{ij,t} + \mu_{bl,t} + \varepsilon_{ibj,t}. \tag{9}$$

The dependent variable, $lgd_{ibj,t}$, is the loss given default, that is the fraction of loan i that the bank estimates will not be recovered if borrower b defaults on the loan, expressed as a percentage of the current loan balance. As before, $Flood_{j,t-q}$ is a dummy variable equal to 1 if there has been at least one flood episode in county j in the q months before the time of observation t, and 0 otherwise. The time variable t is defined at the year-quarter level. $X_{ij,t}$ is a vector that includes loan-level variables, i.e., the loan term, expressed in (log) months, the (log) loan balance, and the portion of securitised loan, and county-level controls, such as the growth rates of GDP and employment. Further, $\mu_{bl,t}$ denotes sets of fixed effects. In particular, we use borrower fixed effects to control for unobserved heterogeneity in the demand for credit. In addition, we interact lender fixed effects with the year-quarter dummies to take care of time-varying supply factors that may be correlated with the banks' estimates of the loss given default on their loans. Finally, $\varepsilon_{ibj,t}$ is the remainder stochastic disturbance. In the estimation, we cluster standard errors at the county level.

The results are reported in Table C.1. The coefficient for the flood dummy at the 6-month horizon is positive and highly statistically significant (column (1)). The economic magnitudes are negligible, though. The point estimate implies that the recent occurrence of flooding increases the estimated loss given default of loans in the flooded counties by

Table C.1: **Floods and losses from loan default.**

The table reports the hazard ratios from a Cox's proportional hazard model for loan survival. The dependent variable is the loss given default, expressed as a percentage of the current loan balance. *Flood* is an indicator variable equal to one if there has been at least one flood episode in the months before the date the loan first enters into arrears, and zero otherwise. *High risk* is an indicator variable equal to one for counties belonging to the top two quartiles of the country-specific distributions of the flood risk measure, and zero otherwise. *Flood before origination* is an indicator variable equal to one if there has been at least one flood episode in the months before loan origination, and zero otherwise. Columns (1)-(3) focus on the direct impact of flooding on loan default using the occurrence of flood events before the observation date. Columns (4)-(6) focus on the impact of flooding on loan default using flood events occurred before the origination date of the loan. The regressions include loan-level variables - the interest rate, residual loan term, loan balance and a dummy for highly collateralised loans -, macroeconomic controls, and borrower and reporting quarter fixed effects interacted with lender fixed effects. Standard errors, robust for heteroskedasticity and clustered at the county level, are reported in parentheses. ***, **, and * indicate that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Realised flood risk before default			Realised flood risk at loan origination		
	6 months	12 months	24 months	6 months	12 months	24 months
Flood	0.098***	0.054	0.039	0.099***	0.057	0.038
	(0.030)	(0.037)	(0.049)	(0.030)	(0.037)	(0.049)
High risk	-0.419	-0.419	-0.419	-0.418	-0.420	-0.416
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.501)
Flood before origination				0.116**	0.176***	0.109***
				(0.045)	(0.052)	(0.041)
Interest rate	-0.143***	-0.143***	-0.143***	-0.142***	-0.140***	-0.138***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Residual loan term	0.043	0.043	0.043	0.043	0.042	0.042
	(0.029)	(0.029)	(0.029)	(0.029)	(0.028)	(0.029)
Loan balance	-0.592***	-0.592***	-0.592***	-0.592***	-0.592***	-0.592***
	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)
Collateralised	0.292***	0.292***	0.292***	0.292***	0.289***	0.286***
	(0.085)	(0.085)	(0.085)	(0.085)	(0.084)	(0.084)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender X Reporting quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.905	0.905	0.905	0.905	0.905	0.905
Observations	15,233,921	15,233,921	15,233,921	15,233,921	15,233,921	15,233,921

around 0.1 percentage points, that is approximately 0.5% of the sample average value of the loss given default (22.5% of the current loan balance). When longer time horizons are considered, as in columns (2) and (3), the coefficients on the flood variable are not estimated with precision, indicating that past disasters do not significantly alter banks' valuation of the potential losses on their loan portfolios. Moreover, the coefficient on the variable for high risk counties is not statistically significant throughout. Hence, seemingly banks do not account for prospective physical risks in the estimation of the losses they may incur on loans to borrowers more exposed to such risks.

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