Flooded credit markets: physical climate risk and small business lending

Luca Barbaglia Serena Fatica Caterina Rho

Working paper no. 186

July 2024

Flooded credit markets: physical climate risk and small business lending

Luca Barbaglia[a], Serena Fatica[a,b], Caterina Rho[a]

[a] European Commission, Joint Research Centre (JRC), Ispra (VA), Italy
[b] Money and Finance Research Group

Revised: June 2024

Abstract

We document that banks charge higher interest rates on loans granted to European small and medium-sized firms located in areas at high risk of flooding. The risk premium, at 6.4 basis points on average, rises with loan duration, and in the case of smaller borrowers and local specialised banks. By contrast, at-risk firms that rely heavily on intangible and movable assets do not face a higher cost of credit, reflecting lower vulnerability to physical risk. Realised flood risk increases SMEs' financial vulnerability, as firms in flooded counties are more likely to default on their loans than non-disaster borrowers.

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

We thank two anonymous reviewers, Viral Acharya, Andrea Bellucci, Andreas Joseph, Steven Ongena, Oliver Rehbein, Markus Wintersteller, as well as the participants to the IAAE 2023 conference, the weekly seminar of the International Economics Department of the Graduate Institute in Geneva, the Research Progress Group of Banco de Mexico, the 2022 Paris Sustainable Finance Forum, the 2022 Econometrics Model of Climate Change conference, the 2022 Italian Economic Association annual congress, the 2022 JRC Summer School on Sustainable Finance for insightful comments. We are grateful to Ferdinand Krebs for help with the data. This is a substantially revised version of a paper previously circulated under the title "Flooded credit markets: loans to SMEs after a natural disaster".
Disclaimer: The views expressed are purely those of the authors and should not, in any circumstances, be regarded as stating an official position of the European Commission. All remaining errors are our own.

E-mail: luca.barbaglia@ec.europa.eu, serena.fatica@ec.europa.eu, caterina.rho@ec.europa.eu.

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 the cost of small business credit. We find that banks charge higher interest rates on loans to firms in counties that are exposed to a high risk of flooding. Moreover, we do not find evidence that recent flooding change the perception and assessment of flood risk, except when severe episodes are considered. Thus, if flood risk appears already salient for lenders, the full extent of its implications for credit risk emerges in the case of disasters when significant direct economic losses are reported.

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. Climate risk is acting as an amplifier of existing SME vulnerabilities, stemming from both the lack of preparation to respond to change change and limited resources to weather the effects of natural hazards. For banks, climate risk compounds existing risk categories such as credit and market risks, and calls for adequate and comprehensive risk management frameworks. More broadly, our findings point to the importance of policies that mitigate the disruptive effects of climate change on the real economy and the financial sector, and help identify, monitor and report on the underlying risks.

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 fixed capital and business disruptions jeopardise the ability of borrowers to meet their debt obligations. Both physical damage and the deterioration of financing conditions are likely to turn out particularly costly for smaller firms (Davlasheridze and Geylani, 2017), 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. The risk premium, around 6.4 basis points (bps) on average, increases for loans with longer maturities, and in the case of smaller borrowers and local specialised banks, that is, cooperative and savings banks. By contrast, at-risk firms that are movable- and intangible-intensive do not face a higher cost of credit, reflecting lower vulnerability to physical risk. Moreover, we do not find evidence that recent flooding change the perception and assessment of flood risk, hence, the extent of the risk premium, except when severe episodes are considered. Thus, if flood risk appears already salient for lenders, the full extent of its implications for credit risk emerges in the case of disasters when significant direct economic losses are reported.

Next, as our data allows us to track loans during their lifetime, we use survival analysis to investigate whether the occurrence of flooding 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 1.6 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 and relax their lending stadards 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 increasing their cost of capital, and by jeopardising their ability to service their debt obligations. 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 disrupt 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 (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 for the banks financing them. In a simple setup, we show that different factors come into play when assessing whether climate risk premia accurately reflect the increased credit risk that banks face on the loans granted to borrowers impacted by natural disasters. The capacity to accurately evaluate climate risk exposure and vulnerabilities is crucial, particularly as rising temperatures exacerbate the impact of natural hazards also in the short and medium term. In this context, firms' preparedness and ability to weather the shocks can reduce the feedback loop to the cost of capital.

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; Javadi and Masum, 2021; Huang et al., 2022). 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 in 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., 2023). A number of studies document that natural hazards bring about an increase in the demand for credit for reconstruction purposes (Berg and Schrader, 2012; Cortés and Strahan, 2017; Koetter et al., 2020; Chavaz, 2016; Celil et al., 2022). Importantly, to meet increased demand, 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 flooding is 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. 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 accounts for the observed deterioration in loan performance. Finally, Section 6 concludes.

2 Data

2.1 Loan-level data

We obtain data on loans to SMEs from the European DataWarehouse (EDW), a centralised repository part of the European Central Bank (ECB) loan-level initiative that collects, validates, and distributes information on securitised loans backing asset-backed securities (ABS) pledged as collateral in the ECB repurchase agreement ("repo") financing operations. SME ABS deals are the second largest securitisation market in Europe, after residential mortgage-backed securities, in terms of both outstanding amounts and new issuances (Association for Financial Markets in Europe, 2023). By enhancing transparency, the ECB loan-level initiative aimed to restore confidence in the securitisation market in the aftermath of the global financial crisis. It was widely recognised that proper assessments of ABSs had been hindered by the lack of standardised, timely and accurate information on single loan exposures, paving the way for the crisis. 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 in a standardised format. We take advantage of these enhanced transparency requirements to build a loan-level dataset that covers three European countries - Belgium, Italy and Spain. Banks in these countries are among the most active in the securitisation of SME loans in Europe (Ertan et al., 2017 and Van Bekkum et al., 2018). In Appendix A.1 we provide more details on the EDW data and the underlying securitisation process, and assess their representativeness with respect to the universe of SME loans.

For each securitised credit facility, the EDW repository provides a number of loan characteristics, as well as information on the borrower and on the lending bank.[1] As for loan-level variables, we observe the original loan balance and the maturity date, and several 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 date of origination, which is also reported. Information on the lender is limited, but includes the bank name. As for the borrower, we know its legal form and business type, the sector of the activity , and its location. In particular, we have information on borrowers' location at the NUTS3 level, which identifies local units corresponding approximately to counties in the United States.[2] Borrowers' location is crucial 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. Such '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 districts in Belgium. 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 the interest rate, as well as the loan status, notably whether the credit facility is in delinquency. In that case, the delinquent amount and number of days in arrears are also reported. Consistent with the time coverage of the flooding data, our sample includes loans originated between 2008 and 2019. We refer to Appendix A.1 for a description of the data cleaning steps we use to build our sample.

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 provides harmonised 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 the recording and collection of granular data on climate-related hazards and losses, and physical 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 in two separate modules that cover 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 (H) for a specific area or community in a given period of time (t). As such, it compounds

[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.

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, and on layers for physical assets. Flood frequency at the local level is assessed starting from model simulations on the areas at risk of being inundated by floods with different return periods.[6] The simulated return periods are 10, 50, 100, 200 and 500 years.[7] Then, the associated potential impacts are determined based on land use at the local level. In other words, the indicator is calculated using information on the share of industrial and commercial, residential and agricultural areas at risk of being inundated by a flood with a specific return period occurring within each territorial unit. The average expected impacts are assessed at different projection horizons, namely for 1, 2, 5, 10, 15 and 25 years, by 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 levels weighted by the 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.[8] The vulnerability component intends to assess 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 (see Table A.1 in Appendix A.2).

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

[7]Return periods are estimates of the interval of time between events. For example, a return time of 10 years indicates that the event will occur once in 10 years on average, therefore the probability that a similar event could occur in the same interval of time is 1/10, or 10%. In this context, scenarios associated with increased hazard probabilities correspond to lower return periods.

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

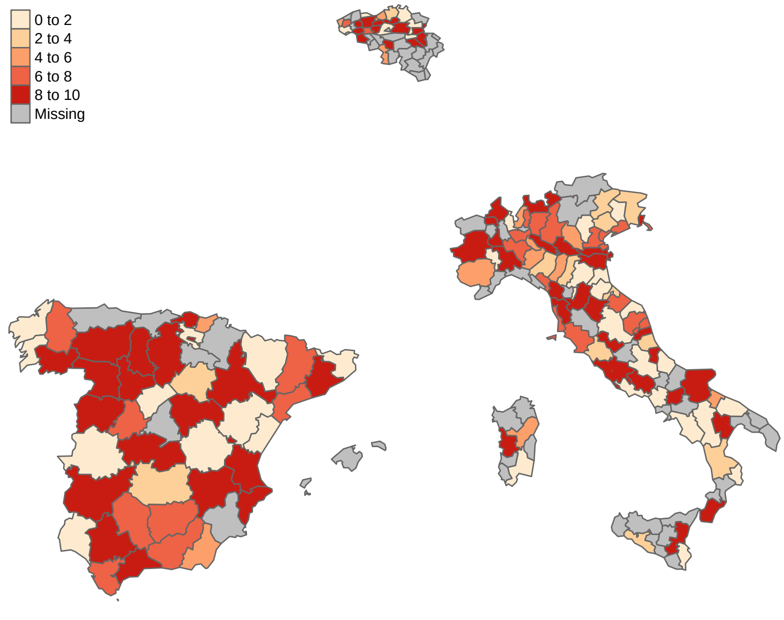

Figure 1: **Flood risk.** The figure shows the map of flood risk across counties (NUTS3 units). The flood risk indicator is averaged across the projections years (i.e., 1, 2, 5, 10, 15 and 25 years) and normalised within country over the $[0, 10]$ scale. Low (high) values indicate low (high) flood risk,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

By combining the metrics for exposure and vulnerability, the overall risk indicator provides a measure of the potential impacts of hazards on different assets in a specific location. We employ the risk indicator for industrial and commercial buildings, defined at county level and averaged across the different projection periods.[9] The values of the risk indicator are normalised within countries on a scale ranging from 0 to 10, which indicate, respectively, minimum and maximum risk.[10] Figure 1 maps the normalised flood risk across counties, with darker shades corresponding to higher levels of risk. In the empirical analysis, we consider counties at high (low) risk of flooding those counties for which the value of the flood risk indicators is above (below) the median value of the distribution of the normalised risk scores.

[9]Other assets for which the risk indicator is calculated are residential real estate and agricultural areas.

[10]In assessing the information content of the RDH risk indicator, European Central Bank and European Systemic Risk Board (2021) find that the resulting flood risk profiles of the local areas are broadly comparable to these obtained aggregating more granular metrics such as the one provided by Four Twenty Seven, an affiliate of Moody's. Four Twenty Seven assesses risks at the company level, and is available for approximately 1.5 million firms in Europe.

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.[11] 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 sample.[12] 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 is the least affected country, 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 loan-level data set to characterise the impact of flooding on local credit conditions. For

[11] 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. The use of different sources allows for a more comprehensive account of disasters compared to the standard sources alone, such as EM-DAT, which tend to underreport events characterised by minimal level of fatalities or those not requiring international aid, mainly in developed countries (Botzen et al., 2019)

[12] 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.

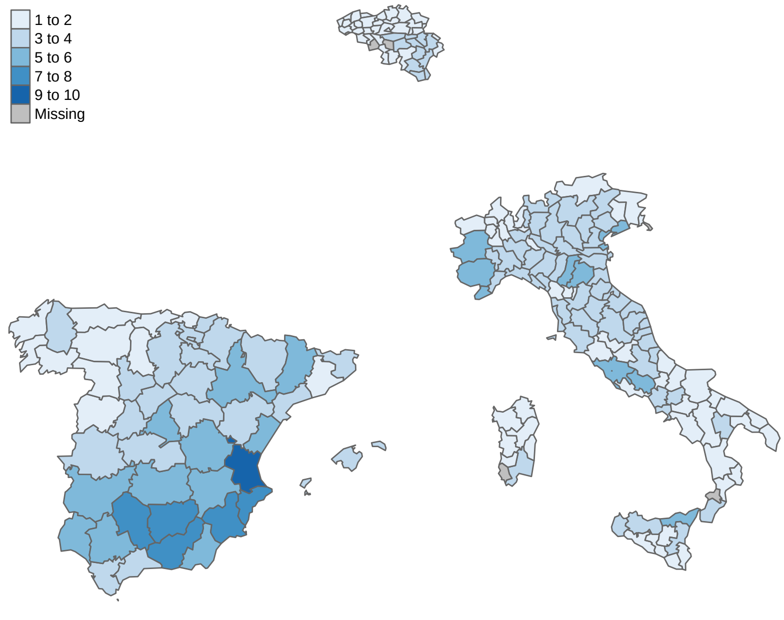

Figure 2: **Flood events.** The figure maps the number of flood events across counties (NUTS3 units) over the 2007-2018 period.

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 borrowing firm 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.

In the loan-level analyses, we account for the realisation of flood risk that may occur 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 which we compute flood occurrence is the date of loan origination. In the latter case, the reference time are the dates after origination when the loan is observed, i.e. the reporting dates.

3 Flood risk and the cost of SME credit

This section studies whether flood-related physical risk affects the cost of SME credit, focusing on loans at origination.

3.1 Descriptive evidence

Table 1 reports the descriptive statistics on the main loan-level characteristics recorded at the time of origination. Our final estimating sample contains approximately 1 million unique term loans. The avearge interest rate is 383.4 basis points (bps), and ranges from 90 to 790 bps moving from the 5th to the 95th percentile of the distribution.[13] The average loan term is around 5.5 years (66.5 months). The average loan balance is around EUR 145,000. The middle and lower panels of Table 1 report summary statistics for the sub-samples of loans extended in high-risk and in low-risk counties, i.e. those with a flood risk measure above (below) the median of risk scores, respectively. At 394.5 bps, the average interest rate on credit facilities to borrowers facing a high risk of flooding is higher than that in the sub-sample of firms in low-risk counties (363.8 bps). Also, the average loan balance is larger in high-risk counties than in low-risk areas (EUR 150,860 vs. EUR 134,550). By contrast, both the average loan term and the fraction of the loan value that is collateralised are lower in high risk counties than in low-risk ones. All the differences are statistically significant at 1% level.

Figure 3 displays the distribution of the balance 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-sized enterprises. We have only limited information on borrowers' characteristics. Roughly 84% of the firms in our sample are classified as limited companies, 8.3% are individual companies, and 2.2% are reported as

[13]The EDW database provides the interest rate type and the current interest rate observed at the different reporting dates. To obtain our dependent variable, we consider all loans with a fixed interest rate, assuming that the rate observed during the loan lifetime be equal to the one at origination. Further, 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 the loan value that is collateralised. All variables are as observed at origination. Summary statistics are provided for the full sample of loans (top panel), and for the sub-samples of loans originated in high-risk counties (middle panel) and in low-risk counties (bottom panel). (*) denotes that a one-sided t-test for the for mean equality across the sub-samples of loan in high-risk and low-risk counties has p value<0.001.

	Mean		Std. dev.	p5	p25	p50	p75	p95
Full sample								
Interest rate (bps)	383.45		224.19	90.00	215.00	350.00	515.00	790.00
Loan term (months)	66.55		46.16	12.03	37.02	60.03	72.07	180.13
Loan balance ('000 EUR)	145.00		420.39	5.00	16.00	31.00	80.52	536.00
Collateralised	72.80		24.66	22.61	58.60	79.58	92.47	100.00
High-risk counties								
Interest rate (bps)	394.49		229.58	90.00	225.00	366.30	532.70	800.00
Loan term (months)	65.70		45.07	13.02	37.02	60.03	72.07	180.10
Loan balance ('000 EUR)	150.86		441.87	5.00	15.50	30.00	80.00	600.00
Collateralised	72.18		24.77	21.83	58.24	78.86	91.97	100.00
Low-risk counties								
Interest rate (bps)	363.80	(*)	212.84	92.20	200.00	330.50	490.00	745.00
Loan term (months)	68.06	(*)	47.99	12.03	37.05	60.03	72.07	180.13
Loan balance ('000 EUR)	134.55	(*)	378.92	6.00	17.52	33.00	86.25	500.00
Collateralised	73.91	(*)	24.42	24.11	59.71	80.77	93.95	100.00

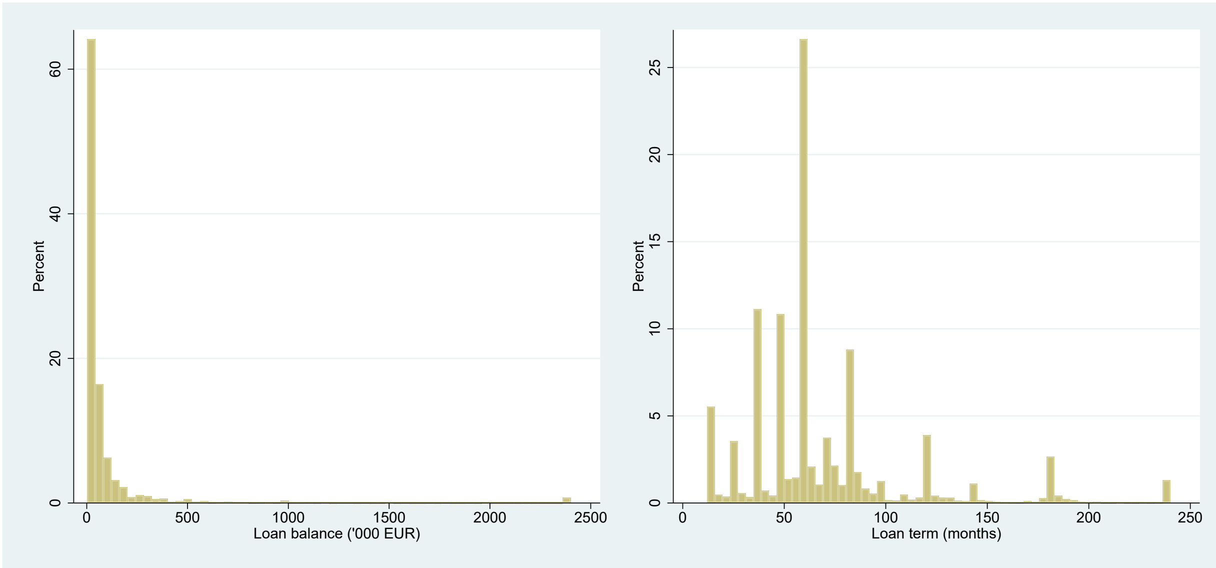

Figure 3: **Distribution of loan balance at origination and loan term.** The left panel reports the distribution of the loan balance (thousands of EUR). The right panel reports the distribution of the loan term (months).

partnerships.

Table 2 details the number of loans originated after flood events, in the full sample (top panel) and in the sub-sample that includes only counties at high risk of flooding (bottom panel). As discussed in Section 2, we consider the time windows of 6, 12, and 24 months following a flood episode. Approximately 131,074 individual SME loans, or 12% of the total number of loans in our sample, are originated within two quarters following a water hazard. When we consider a two-year window after flooding, the share reaches 42%. Conditional on being originated in the aftermath of flood episodes, about 38% of loans are extended after severe disasters, that is, floods with reported economic losses. Moreover, 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 0.4% when we focus on the half-year time span, to 7.2% in the 2-year period. At 0.6% and 8.1% respectively, the shares are practically unchanged when we consider only the high-risk counties. Flood frequency becomes compelling when we take a long-term perspective, however. For each month-year when we observe new loans, we calculate the cumulative sum of floods in each

Table 2: **Number of loans originated after flooding.**
Number of loans originated 6, 12, and 24 months after at least one flood (first row), a severe flood (i.e., 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 1,050,948, of which 673,067 in high-risk counties, and 748,447 in flood-prone counties.

	6 months	12 months	24 months
Full sample			
At least one flood	131,074	250,893	442,729
Severe flood	50,404	100,642	191,112
Multiple floods	4,603	16,253	75,913
Flood in flood-prone county	109,264	208,379	354,888
High-risk counties			
At least one flood	85,706	164,309	292,685
Severe flood	37,555	75,375	144,599
Multiple floods	3,918	12,302	54,606
Flood in flood-prone county	72,996	139,772	241,281

county from the year 2000, the first year when we have a comprehensive recording of flood episodes. Then, we define as flood-prone those counties exposed to a number of floods above the median value of the distribution of flood episodes. Overall, around 71% of all loans in our sample are originated in flood-prone counties.

3.2 The empirical model

The baseline regression model for the cost of credit takes the following form:

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

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 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 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 level and at the county level. 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 variable that captures the share of the loan value that is collateralised. Growth rates for the county GDP and employment are included to account for the general macroeconomic conditions at the local level. Further, $\varphi_{bsrl,y}$ denote sets of fixed effects defined at the borrower (b), industry (s) $\times$ region (r), lender (l) and year (y) levels, as detailed in the next section, aimed at tightening our identification strategy by controlling for demand and supply factors in credit developments (Jakovljević et al., 2020). Business type dummies take care of time-invariant heterogeneity across categories of borrowers, distinguishing among public companies, limited companies, partnerships, individual firms and other borrowers. Moreover, in the spirit of Degryse et al. (2019), we include the interaction between industry (NACE 2 digit classification) and region (NUTS2), and further also with time, to control for demand-related shocks that may affect the cost of SME credit. In this setup, the effect of flood risk is identified from the cross-sectional variability across counties within each region. The fixed effects defined at the lender and the year level account for unobserved heterogeneity on the supply side of credit and time varying shocks that could affect loan pricing. Finally, $\varepsilon_{ibj,t}$ is the stochastic disturbance term.

3.3 Results

3.3.1 Baseline results

Table 3 reports the results from estimating different versions of Equation (2).[14] The specification in column (1) includes fixed effects for business types and industry $\times$ region, in addition to the loan characteristics and the macroeconomic controls. The coefficient of the $High\,risk_j$ indicator is positive and statistically significant at 1% level. The point estimate indicates an average flood risk premium of around 9.5 bps. The coefficient on the loan term

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

is also positive and highly statistically significant, suggesting that the term structure of interest rates on SME loans is positively sloped. There is a negative and statistically significant correlation between the loan amount and its cost at origination. Finally, the interest rate declines with the fraction of the loan value that is collateralised, in line with the 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 10.8 bps, and is still highly 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 7.1 bps, without altering its high statistical significance. Finally, in column (4), we interact the industry $\times$ region and the lender fixed effects with the year dummies. This allows us to take care of time-varying demand and supply factors that may drive loan interest rates. The point estimate for the flood risk premium is around 6.4 bps, which is around 2% 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 other 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. As for debt capital markets, Acharya et al. (2022) find that exposure to local heat stress leads to municipal bond yield spreads that are higher by around 15 basis points per annum.

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.

Table 3: **Flood risk and the cost of SME credit: baseline results.**
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	9.4825***	10.8026***	7.0823***	6.3737***
	(3.5758)	(3.3630)	(2.3717)	(2.3315)
Loan term	39.2858***	40.2847***	11.9477***	16.6737***
	(5.8240)	(5.7128)	(4.1154)	(4.1759)
Loan balance	-18.9868***	-17.7309***	-21.3329***	-22.5675***
	(2.4547)	(2.0225)	(1.9221)	(1.9654)
Collateralised	-0.8536***	-0.9122***	0.4324***	0.3787***
	(0.1750)	(0.1910)	(0.0873)	(0.0787)
Macroeconomic controls	Yes	Yes	Yes	Yes
Business type FE	Yes	Yes	Yes	Yes
Industry × Region FE	Yes	Yes	Yes	No
Lender FE	No	Yes	Yes	No
Time FE	No	No	Yes	No
Industry × Region × Time FE	No	No	No	Yes
Lender × Time FE	No	No	No	Yes
Adjusted R-squared	0.309	0.334	0.402	0.451
Observations	1,050,948	1,050,948	1,050,948	1,050,948

In column (1) we use the spread of the loan interest rate over the 3-month monthly EURIBOR as the dependent variable. This allows us to account for money market conditions at the time the loan is extended. At 6.1 bps, the estimated risk premium is in line with the baseline estimates. The specification in column (2) redefines the granularity of the time fixed effects to address the concern of confounding demand and supply factors. Specifically, we introduce year-month fixed effects interacted both with industry × region dummies and with lender fixed effects to allow for shocks occurring at a higher frequency than in the baseline specification. Again, the coefficient estimate for the flood risk premium is quantitatively and qualitatively similar to the estimates from the baseline model in column (4) of Table 3 .

Table 4: **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 estimating equations include a high risk indicator 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	6.3352***	5.7210**	6.3463***
	(2.3248)	(2.4301)	(2.3477)
Bordering counties' risk			4.7139
			(2.8802)
Loan term	17.1625***	17.5812***	16.6283***
	(3.9856)	(4.4572)	(4.1761)
Loan balance	-23.2528***	-23.6188***	-22.4552***
	(1.8838)	(1.9943)	(1.9521)
Collateralised	0.3930***	0.4258***	0.3777***
	(0.0737)	(0.0811)	(0.0789)
Macroeconomic controls	Yes	Yes	Yes
Business type FE	Yes	Yes	Yes
Industry × Region × Time FE	Yes	Yes	Yes
Lender × Time FE	Yes	Yes	Yes
Adjusted R-squared	0.411	0.474	0.451
Observations	1,050,948	990,464	1,047,717

Finally, we test the adequacy of our risk measure and for the presence of spatial spillovers in the effect of local physical climate risk into SME overall financing costs (Bassetti et al., 2024). To address the concern that it may capture other unobserved characteristics in the broad geographic area, we consider the riskiness of the counties bordering the ones where each loan is extended. Hence, in column (3) we introduce another risk measure (*Bordering counties' risk*), an indicator variable that captures still above-median flood risk. It 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 on the bordering counties' risk indicator is indeed not statistically significant. By contrast, controlling for this additional source of risk does not affect the size and the statistical significance of the coefficient estimate for the *High risk* indicator, pointing to the relevance of the local flood risk measure, and to the absence of significant spatial spillovers, 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 affects the cost of credit to small businesses.

Table 5: **Flood risk and the cost of SME credit: 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) includes in the estimating sample borrowers from knowledge-intensive (KIA) sectors. Column (4) and (5) restrict the estimating sample to borrowers in industries with the highest intensity of intangible capital and movable capital, respectively (defined as those in the top quartile of the respective distributions). Column (6) uses only loans extended by cooperative and savings banks. Columns (7)-(8) 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)	(8)
High risk	7.4446*	6.9429**	3.7089	5.9776	4.1588	27.6288***	5.2626**	8.1248***
	(3.9230)	(2.9724)	(2.4319)	(4.2371)	(2.5460)	(6.6164)	(2.3123)	(2.5660)
Loan term	0.2420	-2.3475	16.0753***	13.0216***	11.4847	-22.1547***	20.5270***	-20.4398
	(5.2005)	(4.5446)	(4.4833)	(4.2125)	(8.1251)	(5.4804)	(1.5414)	(13.6697)
Loan balance	-20.6793***	-19.8656***	-18.1076***	-19.2653***	-24.4990***	-42.3969***	-11.4956**	-34.0404***
	(4.1780)	(3.2156)	(1.6030)	(1.6780)	(1.0203)	(2.1635)	(4.8414)	(1.4454)
Collateralised	0.6909***	0.5129***	0.3380***	0.5332***	0.4006***	0.7878***	-0.2152***	0.6369***
	(0.0786)	(0.0302)	(0.1059)	(0.0810)	(0.1187)	(0.1552)	(0.0674)	(0.0808)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Region × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.318	0.342	0.503	0.400	0.488	0.512	0.428	0.498
Observations	395,470	336,629	196,943	91,183	200,924	83,304	415,295	630,236

We first gauge the extent of the risk premium across different types of borrowers, based on characteristics that capture their broad financial vulnerability and, hence, arguably, their ability to weather climate-related shocks. 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 7.4 bps, the estimated risk premium is larger than the coefficient estimate in the full sample. It is statistically significant at the 10% level.

To formally test the implications of firm size, in column (2) we single out only borrowers classified as small or micro firms, according to the official definition of the European Commission.[15] This reduces the sample to roughly 337,000 unique loans. The flood risk premium on credit to small and micro firms is in the range of 6.9 bps, only marginally higher than the estimate for the full sample, and statistically significant at 5% level. Smaller borrowers face already a higher cost of credit. The average interest rate for smaller firms is around 428 bps, by roughly one-fifth larger than the average rate on loans to medium-sized firms in our sample. This gap presumably already reflects considerations on lower credit worthiness and financial fragility of small and micro businesses (Fatica et al., 2022b), which do not appear exacerbated by their vulnerability to the impact of physical climate risks, however.

We next explore whether the type of inputs used in production have a bearing on flood risk pricing. We focus on firms' reliance on production inputs that, in principle, should make them less vulnerable to physical damage, such as intangibles and movable assets. Moreover, when intangible assets result from R&D and similar activities, such as software, patents or licenses, they have the potential to enhance post-disaster firm performance and productivity. We implement this approach using different proxies defined at the sectoral level. First, we single out borrowers in sectors with predominating knowledge-intensive activities (KIA), according to the Eurostat classification.[16] The estimates are reported in

[15]Based on the European Commission guidelines, small and micro firms are firms with (i) fewer than 50 employees, and (ii) either annual sales below EUR 10 million or total assets below EUR 10 million. See `https://ec.europa.eu/growth/smes/sme-definition`.

[16]Knowledge-intensive activities (KIA) are identified on the basis of the share of skilled employment over

column (3). The flood risk premium for firms in KIA sectors is rather small, and statistically insignificant. Second, we consider categories of capital assets. We derive data on capital and investment at the sectoral level from the EUKLEMS and INTANProd databases, which provide harmonised estimates for capital inputs, including intangible assets, in Europe.[17] For each sector, we aggregate the estimated capital stocks (at current replacement prices) into intangible/tangible and movable/immovable assets, and then calculate their shares with respect to the value of the total capital stock used in production.[18] Then, we consider in the estimation only the borrowers in the sectors where the shares of intangible and movable assets over the total capital stock is in the top quartile of the respective empirical distributions.[19] The estimates in column (4) are on the sub-sample of firms in sectors at high intensity of intangible assets. The risk premium is not statistically different from zero, lending support to the hypothesis of limited implications of physical damage for the operations of firms that make an intensive use of tangible assets. Similar conclusions are reached for borrowers in sectors at high intensity of movable capital, since the flood risk premium in column (5) is not estimated with precision.

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.[20] Then, we retain only savings and cooperative banks in the estimating sample. The results reported in column (5) point to a significant

total employment.

[17]Data and methodolgical background are available from https://euklems-intanprod-llee.luiss.it/.

[18]As for tangible assets, we sum up computing equipment, communications equipment, transport equipment, other machinery and equipment, total non-residential structures, cultivated assets. Following the standard classification we consider research and development, computer software and databases, and other intellectual property products (IPP) assets as intangible assets. Further, other machinery and equipment and total non-residential structures are classified are immovable assets, whereas the remaining assets are considered movable.

[19]The distributions are rather skewed towards larger shares of tangible and immovable assets. For instance, the median share of tangibles over total capital assets across sectors is 93.5%, while that of immovable assets is 86.3%. Hence, to meaningfully disentangle high (low) reliance on intangibles or movables (tangibles or immovables) we use the quartiles as thresholds.

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

flood risk premium of 27.6 bps, a fourfold increase with respect to the baseline estimates obtained in the full sample that includes also commercial banks. Arguably, this result suggest that smaller lenders are aware of physical climate risk, and also that they need to price it, given their limited capacity to geographically diversify their loan portfolio.

Finally, we focus on loan duration. It is held that since the most disruptive consequences of climate change will fully materialise at longer horizons, pricing physical risk should be particularly compelling for loans with longer maturities. The argument is especially relevant for mortgage lending, which usually extends for several decades (Nguyen et al., 2022). Nonetheless, as flood risk is relevant also in the short and medium term, it is still an open question whether and how its pricing changes across loan maturities, especially because business loans, particularly those extended to SMEs, are characterised by relatively short duration (Chodorow-Reich et al., 2021). The median loan term in our sample is 5.5 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 in physical risk pricing, we run the baseline regression model on two sub-samples comprising credit facilities with 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, 5.3 vs 8.1 bps on average. This evidence corroborates the view that climate risk considerations become particularly compelling at longer horizons.[21]

3.4 Projected or realised risk?

The results from the analysis of SMEs' borrowing costs highlight that physical risk related to flooding is priced into small business credit. As it is based on probabilistic scenarios and modelling simulations, our measure of flood risk captures projected risks and impacts.

[21] 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.

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 model reflects lenders' considerations on the short-term damage from realised risk rather than concerns for current and prospective climate risk developments. In this section, we test this hypothesis using the information on historical flood events to build several measures of realised flood risk.

The results are reported in Table 6. First, we use a time-varying measure of flood frequency over the long term to pinpoint counties that have been most exposed to water hazards. Specifically, we calculate the cumulative sum of flood events for each county and month-year starting from 2000, the year since when flood episodes are comprehensively recorded in our data sources. 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 model in Equation (2), augmented with the indicator for flood-prone counties. The estimated coefficient for flood risk is qualitatively and quantitatively similar to the baseline case. By contrast, the coefficient on the flood-prone dummy is not estimated with precision. Hence, there is no evidence that SME bank credit is more expensive in flood-prone areas than in counties where flooding is less frequent.

Next, we test several alternative backward-looking measures of realised risk, with a focus on the short and medium term, that is, on the occurrence of flood episodes in the months before loan origination. In particular, using the information on the precise date of origination and flooding, for each loan in our sample we appraise whether it was extended in the aftermath of at least one flood episode. As the benchmark case, we consider the 6 months following the 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 estimated flood risk premium remains unchanged compared to the baseline model specification without realised risk. Thus, pro-

Table 6: **Realised flood risk and the cost of SME credit.**

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 cumulative flood events over the long run, 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 severe events 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	6.3643***	6.3709***	6.3106***	6.3795***
	(2.3073)	(2.3321)	(2.3112)	(2.3287)
Flood prone	0.8656			
	(5.7441)			
Flood		0.7746	2.9361	-4.7866
		(2.2549)	(3.1271)	(8.3332)
Loan term	16.6742***	16.6707***	16.6683***	16.6739***
	(4.1769)	(4.1743)	(4.1776)	(4.1760)
Loan balance	-22.5674***	-22.5673***	-22.5645***	-22.5663***
	(1.9653)	(1.9652)	(1.9653)	(1.9655)
Collateralised	0.3787***	0.3787***	0.3787***	0.3786***
	(0.0787)	(0.0787)	(0.0787)	(0.0787)
Macroeconomic controls	Yes	Yes	Yes	Yes
Business type FE	Yes	Yes	Yes	Yes
Industry × Region × Time FE	Yes	Yes	Yes	Yes
Lender × Time FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.451	0.451	0.451	0.451
Observations	1,050,948	1,050,948	1,050,948	1,050,948
Panel b				
High risk		6.6439***	5.7643**	6.3106***
		(2.3235)	(2.3036)	(2.3222)
Flood		2.1544	-6.8463	-28.5504
		(2.2530)	(4.8773)	(27.6648)
High risk × Flood		-2.1693	13.3647**	29.0074
		(3.6223)	(5.4209)	(27.6648)
Loan term		16.6693***	16.6747***	16.6690***
		(4.1747)	(4.1779)	(4.1754)
Loan balance		-22.5679***	-22.5660***	-22.5658***
		(1.9654)	(1.9648)	(1.9653)
Collateralised		0.3788***	0.3784***	0.3787***
		(0.0787)	(0.0787)	(0.0787)
Macroeconomic controls		Yes	Yes	Yes
Business type FE		Yes	Yes	Yes
Industry × Region × Time FE		Yes	Yes	Yes
Lender × Time FE		Yes	Yes	Yes
Adjusted R-squared		0.451	0.451	0.451
Observations		1,050,948	1,050,948	1,050,948

spective risk is taken into account also in the presence of realised risk. By contrast, the coefficient on the indicator for recent flooding is positive, but not statistically significant. Hence, while still reflecting flooding risk, 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 document that the recovery lending after the 2013 flooding in Germany was not accompanied by higher lending margins. In fact, evidence from the banking literature concurs on disasters acting as a positive shock to the demand for credit (Berg and Schrader, 2012; Koetter et al., 2020). At the same time, the expansion of credit supply to accommodate increased demand (Cortés and Strahan, 2017; Chavaz, 2016; Celil et al., 2022) dampens the effects on prices.

Physical features of flood episodes, including their severity, are an important source of heterogeneity in the impact of water hazards on firm performance (Fatica et al., 2022a). Likewise, disaster severity may have implications for the cost of SME credit. To test for this potential differential effect, the indicator for loans originated after flooding in column (3) considers only severe flood episodes, defined as those with reported economic losses (Roth Tran and Wilson, 2020). The *Flood* dummy is redefined accordingly. The estimates in column (3) corroborate the previous findings that the cost of credit is unrelated to recent flooding, even if the disaster is severe enough to cause (officially reported) economic losses. Moreover, the size and significance of the premium on prospective flood risk remain unchanged.

Finally, we consider the occurrence of multiple disasters in the semester before loan origination. Repeated flood episodes in a short time frame, by providing relevant information on the intensifying frequency of climate-related disasters, may worsen perceived credit risk at the local level, and, hence, increase the cost of credit. 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 realised flood indicator is negative, but not estimated with precision. This supports the notion that realised risk over the short term does not affect loan pricing. Moreover, once again, 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 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 latter variables. The estimates are reported in panel *b* of Table 6. In the baseline case where the recent occurrence of at least one flood episode is considered (column (2)), the interaction term is not statistically significant. Results are similar when only multiple events are accounted for, as in column (4). By contrast, in the case of severe floods (column (3)), the interaction term is estimated at 13.4 bps and is statistically significant at 5% level. Hence, the flood risk premium raises to almost 19 bps in high-risk counties recently stricken by severe flooding. Overall, this indicates that recent flooding, even if occurring frequently, does not change the perception of prospective flood risk, unless it is accompanied by significant economic losses. The short-term cost of realised water damage makes increases the salience of the implications of more severe disasters for lenders exposed to at-risk borrowers.

4 Flooding and loan performance

In this section, we study the effects of flooding on loan performance. 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 disasters (Noth and Schuewer, 2018). Second, we consider also an indirect effect that may materialise for loans originated after a disaster. This case captures risk-taking by banks or potential loosening of lending standards in the presence of increased loan demand for reconstruction purposes after the occurrence of water hazards (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.[22] 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 proportional 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

[22] 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.

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 dates (i.e., the dates when the 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 one flood in the previous q months. This allows us to test the direct impact of recent flood events on the deterioration of performance. As disasters and their economic consequences may induce firm distress with a delay, 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 one flood episode 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. The vector $\boldsymbol{x}$ includes also 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 variable measuring the share of loan value that is collateralised. We also include lender fixed effects, and fixed effects for the business type and the sector of the borrower, as well as the growth rates of GDP and employment at the county level to control for local macroeconomic conditions.[23]

[23]The choice of variables follows Barbaglia et al. (2023), who investigate the delinquency of residential

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 reported 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, in Appendix B 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.[24]

Table 7 reports the results of the Cox's proportional hazard model. To simplify the discussion, the table 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 occurrence of flood events before the observation date. The results in column (1) indicate that, if any, the negative 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 0.93, which suggests a protective effect of the hazard on outstanding loans, ceteris paribus. One possible explanation behind this counterintuitive result is the effect of emergency financial aid and relief measures enacted as immediate response to natural disasters. For instance, the emergency relief measures for flooded areas in Italy normally include direct transfer and subsidies, tax holidays and suspension of debt payments.[25] Evid-

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.

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

[25]As an example, several large banks pledged support after the September 2023 severe flash floods in the Marche region. Intesa Sanpaolo allocated EUR 200 million for emergency aid, including a 12-month loan repayment moratorium. UniCredit offered a suspension for a year of capital reimbursements on loans to customers based in the flood-stricken areas, while Credit Agricole promised loans on more favourable terms and fast-track procedures for their approval. See `https://www.reuters.com/business/finance/top-banks-italy-rush-help-clients-flood-stricken-marche-region-2022-09-16/`.

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
High risk	1.0021	1.0022	1.0052	1.0027	1.0030	1.0055
	(0.0182)	(0.0182)	(0.0183)	(0.0182)	(0.0182)	(0.0184)
Flood	0.9306***	1.1981***	1.6066***	0.9306***	1.1958***	1.6016***
	(0.0240)	(0.0230)	(0.0266)	(0.0240)	(0.0229)	(0.0266)
Flood before origination				1.1741***	1.2301***	1.0399**
				(0.0248)	(0.0206)	(0.0163)
Interest rate	1.1185***	1.1214***	1.1262***	1.1178***	1.1191***	1.1256***
	(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0057)
Loan balance	0.8653***	0.8662***	0.8681***	0.8651***	0.8660***	0.8680***
	(0.0070)	(0.0070)	(0.0070)	(0.0070)	(0.0069)	(0.0070)
Residual loan term	1.0203**	1.0169*	1.0155*	1.0219**	1.0199**	1.0160*
	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0090)	(0.0089)
Collateralised	1.0104***	1.0105***	1.0104***	1.0103***	1.0104***	1.0104***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Business type FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,328,791	6,328,791	6,328,791	6,328,791	6,328,791	6,328,791

ence from the US in Collier et al. (2024) indicates that government-provided recovery loans to small businesses following natural disasters reduce firm distress, increase employment and revenue, and reduce the share of firm debt that is delinquent and the duration of delinquent debt, which can be precursors to bankruptcy and exit. Similarly, Davlasheridze and Geylani (2017) find that small business administration disaster loans are effective in mitigating disaster aftereffects, including firm exit. While we do not have data on post-flooding emergency measures for the events in our sample, we conjecture that a similar mechanism may be at play here, whereby the rapid injection of liquidity and emergency measures enable firms to weather the shock, at least in the short run. The estimated hazard for the flood risk variable is statistically insignificant. Hence, loans in high-risk counties do not have per se a shorter survival probability than loans extended to firms that do not face a high risk of flooding. As expected, this suggests no separate effect of prospective risk on loan survival. As for the other explanatory variables, 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 roughly one-tenth. A higher residual balance decreases the probability of loan default. By contrast, loans that have higher residual duration and are more collateralised are more likely to enter default status than other loans, ceteris paribus, although the size of the effect is rather small form an economic perspective.

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. When longer horizons are considered, the estimated hazards associated with the *Flood* variable are larger in magnitude. Being located in a flooded county increases the probability of defaulting on debt repayment in a statistically significant way. In the 12 months following the disaster, loans to flooded borrowers face a hazard 20% greater than credit facilities to firms that did not experience water damage in the previous year (column(2)). Considering the 2-year window as in column (3), the estimated hazard ratio reaches 1.6. Our results indicate that the impact of flooding on loans' probability of default is more pronounced and turn sizeable at longer horizons.

While in the first months after the flood exposed firms may still rely on their cash holdings and different form of financial aid 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 during our two-year observation period (see Appendix B).

There is a second, indirect way through which flooding may affect loan performance. Rebuilding efforts after natural disasters increase the demand for credit (Berg and Schrader, 2012; Koetter et al., 2020). However, in a context where the timely availability of funds is crucial for the continuity of firms' operations, banks might increase risk-taking or relax their credit standards when they provide recovery lending to disaster-stricken SMEs. To test whether banks incur systematically more credit risk in their recovery loans, we augment the survival model with an indicator variable for post-disaster lending activity. Specifically, in line with the loan pricing model in Section 3, we use a dummy (*Flood before origination*) that takes value 1 for loans originated in the q months after flooding, and 0 otherwise. We consider, alternatively, $q = 6, 12, 24$. The results are reported in columns (4)-(6) of Table 7. The hazard ratios of the variables for flood risk and the occurrence of recent water hazards are practically unchanged with respect to the baseline specification. Interesting results emerge when turning to the variable that captures flooding at origination. The hazard ratio associated with origination 6 month after flooding is 1.17 (column (4)), and 1.23 for the 12 month-span (column (5)). Hence, 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. In other words, the hazard rate increases by one-fifth for post-disaster loans compared to loans extended in normal times. 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 extended 2 years after the disaster, although it is, expectedly, much more muted. The estimated hazards ratio in column (6) is 1.04. 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 channel through which realised physical climate risk affect SMEs' financial vulnerability and distress.[26]

5 The pricing of flood risk: a back-of-the-envelope assessment

The results in Section 3 indicate that flood-related climate risk is priced into new loans to small and medium-sized firms. Moreover, there is substantial heterogeneity in the size of the risk premium across borrower and lender types. 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 flood 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, and with $\hat{S}_f$ the spread in the case the realised flood risk is fully priced, we can retrieve the

[26]The results in Appendix B show that recovery loans are also more likely to enter into arrears than loans originated in normal times. 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, and hence flooding has worsens only marginally existing financial fragility.

corresponding risk premium by plugging the relevant observed variables and the estimated parameters into the ratio $\hat{S}_f/S_0$, or:[27]

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

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

As for the calibration of the loss given default, we exploit the information available in the EDW data, 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. The empirical model and the full set of results are reported in Appendix C. We find that banks do not adjust their estimated LGD on existing loans in the aftermath of flooding, notwithstanding the deterioration of loan performance uncovered in the survival model. Similarly, the occurrence of floods before loan origination does not increase the ex-ante assessment of the LGD. By contrast, estimates of the LGD are not significantly affected by the projected flood-related physical risk in the county where the loan is granted, although the effect is rather small in magnitude.

Following the analysis of loan default, we assess the pricing of climate risk against flooding occurring at different points in time, that is during the lifetime of the loan and before its origination. Let us consider first the case of flooding occurring before loan origination. Factoring in the hazard ratio corresponding to the 12-month time window, we obtain an optimal interest rate of around 438 bps. This corresponds to a risk premium for the indirect

[27] We calculate the optimal interest rate, $\hat{R}_f$ from the spread in Equation (7), defined over the EURIBOR as $\hat{S}_f = \hat{R}_f -$EURIBOR. S_0 is computed using the average interest rate in the sample of 383.45 bps (see Table 1). The average value of the 3-month EURIBOR over our sample period is 144 bps.

effect of flooding of around 55 bps over the average interest rate in the sample, that is almost 9 times the estimated risk premium in our empirical model in Section 3.[28] Turning to the 24-month horizon, and using the corresponding hazard ratio of 1.04 (see column (5) of Table 7), gives a hypothetical optimal risk premium of 9.5 bps, which is rather close to our baseline estimates. This reflects the fact that the intrinsic fragility we uncover for post-disaster loans fades at longer time spans.

In the case of realised risk during the loan's lifetime, we need to account also for the probability of the occurrence of flooding in the future, which is not known when the loan is priced at origination. We use the simulations of the probabilistic scenarios underlying the flood risk risk indicator, which factor in the potential occurrence of events of different severity, i.e. for floods with different return periods (see Appendix A.2).[29] As a plausible scenario that matches ordinary levels of risk, instead of extreme events which are relatively rare, we focus on simulated flood episodes with a 10-year return period. Figure 4 plots the corresponding hypothetical level of the interest rate that accounts for that risk, over different projection periods.[30]

The patterns of hypothetical optimal prices appears roughly in line with the sample average interest rate for current flood risk projections over a 10-year horizon. This suggests the pricing of projected flood risk appears to adequately reflect the increased credit risk associated with water hazards at the median loan term in our sample (around 6 years). Considering projection periods below (above) the decade would imply an overestimation (underestimation) of the risk premium.

Admittedly, this is a very simple and stylised exercise, which we do not purport has the validity and robustness of a fully fledged multi-period dynamic optimisation process.

[28] We calculate 438.54-383.45=55.1, where we obtain (383.45 - 144)*1.23*1.00+144=438.54 from Equation (7), with 1.21 the estimated hazard ratio on the *Flood before origination* indicator (see column 5 in Table 7), and 144 is the average 3-month EURIBOR over the sample period. We set the ratio of LGDs to 1 as the estimated coefficients on the *Flood* indicator in Table C.1 are not statistically different from zero.

[29] The simulated probabilities are reported in Table 3 of Antofie et al. (2020).

[30] We use the hazard ratio associated with the default that accounts for flood episodes in the 24-month time span before loan delinquency (see the *Flood* dummy in column (6) of Table 7).

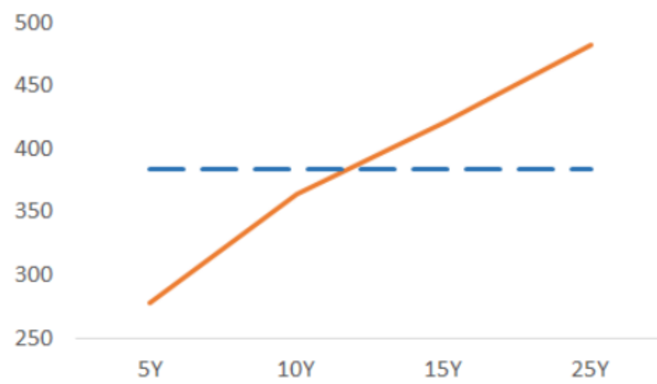

Figure 4: **Simulated interest rate values accounting for flood risk.** The solid line plots the hypothetical optimal interest rate (in bps) from equation 7, augmented for the probability of flood occurrence, for projection periods ranging from 5 to 25 years (solid line). The dashed line is the average interest rate in the sample.

Nonetheless, it allows us to make some important general considerations on flood risk, and its pricing. First and foremost, climate risk is already compelling at longer horizons. This calls for potentially marked adjustment in the price of longer-lived assets, all other things being equal. Second, the increase in frequency and severity of flooding induced by climate change implies that correspondingly higher risk levels are materialising also at shorter time horizons, affecting the valuation of shorter-lived financial assets as well. Against this background, adaptation measures that address SMEs' financial fragility, besides reducing the direct cost of water hazards, have also important implications in preventing a negative feedback loop through increased financing costs. Moreover, SMEs' ability to correctly evaluate and disclose their climate risk exposure is crucial. At the same time, on the supply side of credit, climate-related risks need to be integrated in banks' overall risk management process.

6 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 credit to European small and medium-sized businesses.

First, we document that banks charge higher interest rates on new loans originated in counties that are at high risk of flooding. The risk premium is heterogeneous across borrower types, and increases substantially in the case of credit facilities extended by cooperative and savings banks. Moreover, severe events make flood risk more salient for lenders, arguably as they unveil the full extent of its implications for credit risk when significant direct economic losses are reported.

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. The effect is sizeable, and persists even in the second year after the water hazard. Second, for given financial characteristics, loans originated in the aftermath of flooding are also more likely to enter delinquency status than loans extended otherwise. Both this intrinsic fragility and the deterioration in loan performance in the aftermath of flooding needs to be adequately accounted for in the pricing of flood risk.

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. Climate risk is acting as an amplifier of existing SME vulnerabilities, stemming from both the lack of preparation to respond to change and limited resources to weather the effects of natural hazards. For banks, climate risk compounds existing risk categories such as credit and market risks, and calls for adequate and comprehensive risk management frameworks. More broadly, our findings point to the importance of policies that mitigate the disruptive effects of climate change on the real economy and the financial sector, and help identify, monitor and report on the underlying risks.

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. Moreover, important policy indications may be derived from research addressing the impacts of adaptation measures, including insurance, to mitigate climate-related risks.

References

Acharya VV, Johnson T, Sundaresan S, Tomunen T. 2022. Is physical climate risk priced? evidence from regional variation in exposure to heat stress. Working Paper 30445, National Bureau of Economic Research.

Alfieri L, Feyen L, Salamon P, Thielen J, Bianchi A, Dottori F, Burek P. 2016. Modelling the socio-economic impact of river floods in europe. Natural Hazards and Earth System Sciences **16**: 1401–1411.
URL https://nhess.copernicus.org/articles/16/1401/2016/

Altavilla C, Boucinha M, Pagano M, Polo A. 2023. Climate risk, bank lending and monetary policy. CEPR Discussion Paper No. 18541 .

Antofie T, Luoni S, Eklund S, Marin Ferrer M. 2020. Update of risk data hub software and data architecture. EUR 30065 EN, Publications Office of the European Union **25**.

Antofie T, Luoni S, Marin Ferrer M, Faiella A. 2019. Risk data hub: a web platform to facilitate management of disaster risks. EUR 29700 EN, Publications Office of the European Union **25**: 2189–2224.

Association for Financial Markets in Europe. 2023. Securitisation Report - European Structured Finance.
URL https://www.afme.eu/Portals/0/DispatchFeaturedImages/Securitisation%20Data%20Report%20Q4%202023%20and%202023%20Full%20Year.pdf

Baldauf M, Garlappi L, Yannelis C. 2020. Does climate change affect real estate prices? only if you believe in it. The Review of Financial Studies **33**: 1256–1295.

Barbaglia L, Manzan S, Tosetti E. 2023. Forecasting loan default in Europe with machine learning. Journal of Financial Econometrics **21**: 569–596.

Barbaglia L, Manzan S, Tosetti E. 2024. Household debt and economic growth in Europe. Macroeconomic Dynamics : 1–19.

Barth S J, Zhang. 2019. Banks and natural disasters. SSRN Working Paper **3438326**.

Bassetti T, Dal Maso L, Pieroni V. 2024. Firms' borrowing costs and neighbors' flood risk. Small Business Economics .

Bates PD, Horritt MS, Fewtrell TJ. 2010. A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling. Journal of Hydrology **387**: 33–45. ISSN 0022-1694.
URL https://www.sciencedirect.com/science/article/pii/S0022169410001538

Berg G, Schrader J. 2012. Access to credit, natural disasters, and relationship lending. Journal of Financial Intermediation **21**: 549–568.

Bernstein A, Gustafson MT, Lewis R. 2019. Disaster on the horizon: The price effect of sea level rise. Journal of Financial Economics **134**: 253–272.

Bos JW, Li R, Sanders MW. 2022. Hazardous lending: The impact of natural disasters on bank asset portfolio. Economic Modelling **108**: 105760. ISSN 0264-9993.

Botzen WW, Deschenes O, Sanders M. 2019. The economic impacts of natural disasters: A review of models and empirical studies. Review of Environmental Economics and Policy **13**: 167–188.

Campiglio E, Daumas L, Monnin P, von Jagow A. 2023. Climate-related risks in financial assets. Journal of Economic Surveys **37**: 950–992.

Celil HS, Oh S, Selvam S. 2022. Natural disasters and the role of regional lenders in economic recovery. Journal of Empirical Finance **68**: 116–132. ISSN 0927-5398.

Chavaz M. 2016. Dis-integrating credit markets: diversification, securitization, and lending in a recovery. Bank of England Working Paper **617**.

Chen J, Joslin S, Tran K. 2012. Rare disasters and risk sharing with heterogeneous beliefs. Review of Financial Studies **25**: 2189–2224.

Chodorow-Reich G, Darmouni O, Luck S, Plosser M. 2021. Bank liquidity provision across the firm size distribution. Journal of Financial Economics **144**: 908–932.

Collier BL, Howell ST, Rendell L. 2024. After the storm: How emergency liquidity helps small businesses following natural disasters. Working Paper 32326, National Bureau of Economic Research.
URL `http://www.nber.org/papers/w32326`

Correa R, He A, Herpfer C, Lel U. 2022. The rising tide lifts some interest rates: Climate change, natural disasters and loan pricing. International Finance Discussion Papers 1345. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/IFDP.2022.1345. .

Correia S. 2014. Reghdfe: Stata module to perform linear or instrumental-variable regression absorbing any number of high-dimensional fixed effects. Statistical Software Components S457874, Boston College Department of Economics, 2014 .

Cortés KR, Strahan PE. 2017. Tracing out capital flows: How financially integrated banks respond to natural disasters. Journal of Financial Economics **125**: 182–199. ISSN 0304-405X.

Cox DR. 1972. Regression models and life-tables. Journal of the Royal Statistical Society: Series B (Methodological) **34**: 187–202.

Davlasheridze M, Geylani PC. 2017. Small business vulnerability to floods and the effects of disaster loans. Small Business Economics **49**: 865–888.

Degryse H, De Jonghe O, Jakovljević S, Mulier K, Schepens G. 2019. Identifying credit supply shocks with bank-firm data: Methods and applications. Journal of Financial Intermediation **40**: 100813. ISSN 1042-9573. Bank-firm relationships in the post-crisis

era.
URL https://www.sciencedirect.com/science/article/pii/S1042957319300154

Dirick L, Claeskens G, Baesens B. 2017. Time to default in credit scoring using survival analysis: a benchmark study. Journal of the Operational Research Society **68**: 652–665.

Dottori F, Alfieri L, Bianchi A, Skoien J, Salamon P. 2022. A new dataset of river flood hazard maps for Europe and the Mediterranean Basin. Earth System Science Data **14**: 1549–1569. ISSN 1866-3508.

Eklund LG, Sibilia A, Salvi A, Antofie TE, Rodomonti D, Salari S, Poljansek K, Marzi S, Gyenes Z, Corban C. 2023. Towards a european wide vulnerability framework. JRC Technical Report JRC118850 .

Ertan A, Loumioti M, Wittenberg-Moerman R. 2017. Enhancing loan quality through transparency: Evidence from the european central bank loan level reporting initiative. Journal of Accounting Research **55**: 877–918.

European Central Bank. 2017. Guidance to Banks on Non-Performing Loans.
URL https://www.bankingsupervision.europa.eu/ecb/pub/pdf/guidance_on_npl.en.pdf

European Central Bank, European Systemic Risk Board. 2021. Climate-related risk and financial stability - Data Supplement.
URL https://www.ecb.europa.eu/pub/pdf/other/ecb.climateriskfinancialstability202107_annex~4bfc2dbc5e.en.pdf

European Environment Agency. 2022. Economic losses from weather and climate-related extremes in Europe reached around half a trillion euros over past 40 years. Publications Office of the European Union.
URL https://data.europa.eu/doi/10.2800/530599

Faiella A, Antofie TE, Luoni S, Rios Diaz F, Ferrer MM. 2020. The risk data hub loss datasets-the risk data hub historical event catalogue. JRC Technical Report JRC116366 .

Fatica S, Katay G, Rancan M. 2022a. Floods and firms: vulnerabilities and resilience to natural disasters in Europe. JRC Working Paper in Economics and Finance **2022/13**.

Fatica S, Oliviero T, Rancan M. 2022b. On the determinants of corporate default in the eu-27: Evidence from a large sample of companies. JRC Technical Report, EUR 31342 EN, Publications Office of the European Union, Luxembourg, 2022, ISBN 978-92-76-60449-5, doi:10.2760/580733. **JRC131613**.

Giglio S, Kelly B, Stroebel J. 2021. Climate finance. Annual Review of Financial Economics **13**: 15–36.

Gupta J, Gregoriou A, Ebrahimi T. 2018. Empirical comparison of hazard models in predicting SMEs failure. Quantitative Finance **18**: 437–466.

Hirsa A, Neftci S. 2014. Chapter 23 - credit spread and credit derivatives. In Hirsa A, Neftci S (eds.) An Introduction to the Mathematics of Financial Derivatives (Third Edition). San Diego: Academic Press, third edition edition. ISBN 978-0-12-384682-2, 373–399.

Hoffmann M, Maslov E, Sørensen BE. 2022. Small firms and domestic bank dependence in Europe's great recession. Journal of International Economics **137**.

Huang HH, Kerstein J, Wang C, Wu FH. 2022. Firm climate risk, risk management, and bank loan financing. Strategic Management Journal **43**: 2849–2880.
URL `https://onlinelibrary.wiley.com/doi/abs/10.1002/smj.3437`

Iyer R, Peydró JL, da Rocha-Lopes S, Schoar A. 2013. Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007–2009 crisis. The Review of Financial Studies **27**: 347–372.

Jakovljević S, Degryse H, Ongena S. 2020. Introduction to the symposium on contemporary banking research: The use of fixed effects to disentangle loan demand from loan supply. Economic Inquiry **58**: 917–920.
URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/ecin.12875`

Javadi S, Masum AA. 2021. The impact of climate change on the cost of bank loans. Journal of Corporate Finance **69**: 102019. ISSN 0929-1199.
URL `https://www.sciencedirect.com/science/article/pii/S0929119921001401`

Jiang F, Li W, Qian Y. 2023. Do costs of corporate loans rise with sea level? Mimeo, University of Buffalo .

Joseph A, Kneer C, van Horen N. 2022. All you need is cash: Corporate cash holdings and investment after the financial crisis. CEPR Discussion Paper No. 14199 .

Kara A, Marques-Ibanez D, Ongena S. 2016. Securitization and lending standards: Evidence from the european wholesale loan market. Journal of Financial Stability **26**: 107–127. ISSN 1572-3089.
URL `https://www.sciencedirect.com/science/article/pii/S1572308916300572`

Keys BJ, Mukherjee T, Seru A, Vig V. 2010. Did Securitization Lead to Lax Screening? Evidence from Subprime Loans. The Quarterly Journal of Economics **125**: 307–362. ISSN 0033-5533.
URL `https://doi.org/10.1162/qjec.2010.125.1.307`

Keys BJ, Seru A, Vig V. 2012. Lender Screening and the Role of Securitization: Evidence from Prime and Subprime Mortgage Markets. The Review of Financial Studies **25**: 2071–2108. ISSN 0893-9454.
URL `https://doi.org/10.1093/rfs/hhs059`

Koetter M, Noth F, Rehbein O. 2020. Borrowers under water! rare disasters, regional banks, and recovery lending. Journal of Financial Intermediation **43**: 100811.

Kraemer-Eis H, Botsari A, Gvetadze S, Lang F, Torfs W. 2023. The european small business finance outlook 2023. Working Paper 96, European Investment Fund.
URL https://www.eif.org/news_centre/publications/eif_working_paper_2023_96.pdf

Mabille P, Wang O. 2023. Intermediary-based loan pricing: Price and non-price terms across markets. INSEAD Working Paper No. 2023/37/FIN .

Nadauld TD, Weisbach MS. 2012. Did securitization affect the cost of corporate debt? Journal of Financial Economics **105**: 332–352. ISSN 0304-405X.
URL https://www.sciencedirect.com/science/article/pii/S0304405X12000396

Nguyen DD, Ongena S, Qi S, Sila V. 2022. Climate change risk and the cost of mortgage credit. Review of Finance **26**: 1509–1549.

Noth F, Schuewer U. 2018. Natural disaster and bank stability: Evidence from the u.s. financial system. SAFE Working Paper **167**.

OECD. 2024. Financing SMEs and Entrepreneurs 2024.
URL https://www.oecd-ilibrary.org/content/publication/fa521246-en

Pörtner RD H-O, Tignor M, Poloczanska E, Mintenbeck K, Alegría A, Craig M, Langsdorf S, Löschke S, Möller V, Okem A, Rama B. 2022. IPCC, 2022: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press (in press).

Rehbein O, Ongena S. 2022. Flooded through the back door: The role of bank capital in local shock spillovers. Journal of Financial and Quantitative Analysis **57**: 2627–2658.

Roth Tran B, Wilson D. 2020. The local economic impact of natural disasters. Federal Reserve Bank of San Francisco Working Paper 2020-34 .

Skouloudis A, Tsalis T, Nikolaou I, Evangelinos K, Leal Filho W. 2020. Small & medium-sized enterprises, organizational resilience capacity and flash floods: Insights from a literature review. Sustainability **12**: 7437.

Van Bekkum S, Gabarro M, Irani RM. 2018. Does a larger menu increase appetite? collateral eligibility and credit supply. The Review of Financial Studies **31**: 943–979.

Wang Y, Xia H. 2014. Do Lenders Still Monitor When They Can Securitize Loans? The Review of Financial Studies **27**: 2354–2391. ISSN 0893-9454.
URL https://doi.org/10.1093/rfs/hhu006

Appendix

A Data

A.1 Loan data

A.1.1 The securitisation process

SME loan securitisation is a structured finance practice that allows banks to diversify and transfer their SME credit risk exposures. Securitisation is administered through special purpose entities (SPE) that are originated by banks ("originators"). These entities pool a large portfolio of SME loans from banks' balance sheets and use the derived cash flows (i.e., the principal and interest payments) as collateral to issue new debt (asset-backed securities or ABS). These ABS are then sold to institutional investors or are purchased by the originator and retained on its balance sheet to be used as repo collateral. The securitised SME loan portfolio is static, thus the bank cannot change its structure over time. ABS tranches are rated by credit rating agencies based on specific criteria, including notably diversification of the pool and credit enhancements, which hedge ABS deals from borrowers' idiosyncratic credit risks. Consequently, the majority of ABS tranches have high ratings (i.e., usually AAA or AA rated), reflecting higher credit quality that the average quality of the underlying securitised loans. The originating bank is normally responsible for servicing and tracking the performance of the securitised loan portfolio, including notably the reporting of relevant portfolio-level information. Especially after the global financial crisis (GFC), many European banks started retaining their ABS deals in order to place them as repo collateral. This practice has also positive impacts on banks' liquidity coverage ratio.

While remaining much smaller than its US peer, the European securitisation market has grown steadily from the beginning of the previous decade until the outbreak of the GFC. SME loan-backed ABS deals constitute the second largest securitisation market in Europe (after residential mortgage-backed securities), in terms of both the amounts outstanding and new issuances (Association for Financial Markets in Europe, 2023). During the financial crisis, ABS issuance remained initially at high levels in Europe, but these volumes were almost exclusively driven by their eligibility as collateral for ECB liquidity operations. Afterwards, while the overall market activity decreasing to the levels recorded in 2003/2004, the composition of deals placed with institutional investors versus those retained changed significantly. The share of SMEs ABS transactions retained by originators reached 100% in 2022, while constantly hovering above 90% in the post-crisis era, when the ECB has served as the primary investor in the majority of ABS deals in the Eurozone (Kraemer-Eis et al., 2023). Importantly, with very high amounts at below market level interest rates being available for repo backed by ABS, this facility became a very important source of liquidity for Eurozone banks in the post-crisis era.

The GFC revealed structural inefficiencies in loan securitisations, stemming from the lack of transparency about the quality of the underlying loans and banks' loan screening and monitoring activities. Agency problems in loan underwriting and monitoring were documented also by the economic literature. In the years preceding the crisis, in the US, loan securitisations led to banks' lowering their credit standards as well as their screening and monitoring efforts (see e.g., Keys et al., 2010, 2012; Wang and Xia, 2014). There is also evidence that securitisation caused the mispricing of credit risk (see e.g., Nadauld and Weisbach, 2012; Kara et al., 2016).

To correct for the perverse incentives from risk transfer and restore confidence in the market, after the crisis there was a global call for greater transparency in loan securitisation processes. In this context, in 2013 the ECB introduced the first ABS loan level reporting standards in Europe, requiring comprehensive and recurring information collection and disclosure by banks about their ABS portfolio structure and performance. Ertan et al. (2017) provide a thorough assessment of the implications of the ECB loan-level reporting initiative for the SME securitisation market in Europe. They document that enhanced transparency not only improved the quality of reporting, but had also real effects by incentivising banks to improve their credit practices. Moreover, the greater information set available enabled banks to make more informed credit decisions, resulting in stronger market discipline, and strengthened screening efforts and underwriting standards, correcting for perverse incentives in securitisation. Importantly for our purposes, they do not find evidence of strategic behaviour in securitisation. In other words, banks do not appear to have strategically selected better loans to securitise and retained worse quality loans on their balance sheets, which would have led them to face increased riskiness in their operations.

A.1.2 Data representativeness

We draw our loan-level data from the European Data Warehouse (EDW), a third party agency that administers the data collection, monitoring and control process under the reporting regime introduced by the ECB in 2013. In the light of the discussion in the previous section, a relevant question to address is whether our data is representative of the population of loans granted to European SMEs. Indeed, there could be concerns that the securitised loans might not be representative of the underlying population. On the one hand, securitised loans need to meet the credit quality standards, which might induce banks to include in the pool high quality loans and retain lower quality ones on their balance sheet. This would result in EDW containing loans of significantly higher credit quality and under-represent low credit quality ones. While the results in Ertan et al. (2017) do not find of strategic securitisation, we cannot rule out this hypothesis a priori for our sample. On the other hand, by transferring risk, securitisation market might increase banks' risk appetite and encourage laxer lending standards. Also, lenders that are more active on the securitisation market might be those with a more difficult access to capital markets. In this sense, the pool of EDW loans might prove of lower quality relative to the population of SME credit. While working in opposite directions, both of these effects could potentially bias our results.

When it comes to other securitised loans under the loan-level initiative, Barbaglia et al. (2024) find that EDW data for residential mortgages reflect quite closely the underlying population of mortgages along a number of dimensions. In evaluating the representativeness of our sample of SME loans we face important challenges stemming from the limited availability of comparable data derived from national credit registries.

We first consider the cost of credit. We extract information from the OECD Financing SMEs and Entrepreneurs scoreboard (OECD, 2024).[31] Figure A.1 reports the evolution of

[31] The Scoreboard is a collection of indicators on SME access to finance derived from data supplied by financial institutions, statistical offices and other government agencies. This is supplemented by national and regional demand-side surveys in order to provide a more comprehensive view of the evolution of financing trends and needs.

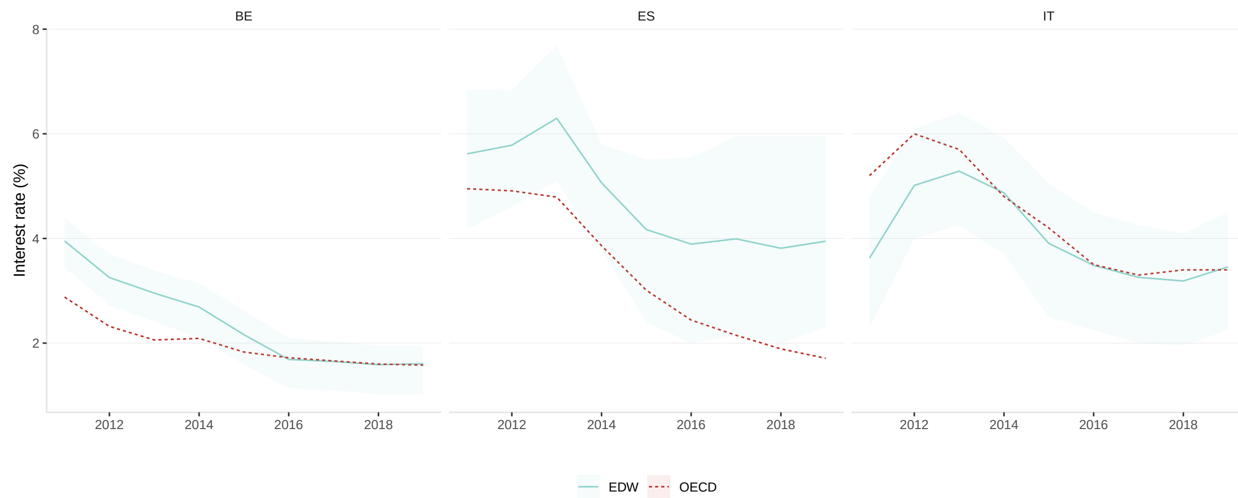

Figure A.1: **Interest rate.** The solid line plots the average interest rate from EDW, with the confidence bands corresponding to the observed inter-quartile range. The dashed line is the interest rate reported by the OECD Financing SMEs and Entrepreneurs scoreboard.

the observed average interest rate in EDW by country and year, alongside the figure obtained from the OECD Scoreboard. To gauge heterogeneity at the geographical and industrial levels in our data, we also plot confidence bands representing the inter-quartile range calculated from the loan-level information. The EDW and OECD series show a reasonably good match, with similar dynamics over time, across the three countries in our sample. The series for Belgium and Italy practically overlap in the most recent years of our sample period. Some differences are apparent for Spain. The two series follow a similar pattern, with the gap seemingly widening in the latest sample years. Nevertheless, the OECD interest rate is still comprised within the inter-quartile range from our microdata. Importantly, consistent with the findings in Kara et al. (2016) for syndicated loans, we do not find evidence of securitised loans being priced more aggressively compared to the rest of SME loans in a systematic way.

We also evaluate the representativeness of EDW data with respect to loan performance comparing the default rates in our sample to official data on non-performing loans (NPLs) as a share of gross loans.[32] The OECD Scoreboard provides data on the SME NPLs ratio

[32] As a caveat to bear in mind, the definition of NPL closely follows, but does not perfectly match the definition of default adopted in the paper. The regulatory categorisation of non-performing loans (NPLs) varies across jurisdictions. The 90-day past due criterion is most widely used by countries, and in line with the Basel criteria for problem asset or establishing default, and the European Banking Authority's (EBA) criteria for non-performing exposures (European Central Bank, 2017). The Basel and EBA criteria also include loans that are less than 90 day overdue but are deemed unlikely to be repaid. Guidelines on

only for Belgium. For Spain and Italy, we obtain the share of NPLs loans to total gross loans from the World Bank Group (WBG).[33] An important caveat to bear in mind in the comparison is that a composition effect is at play for these two countries, where NPLs ratios are calculated on total outstanding loans for the entire baking sectors, without differentiating borrowers by size. Figure A.2 plots the evolution of the observed percentage default rate in EDW by country and year, alongside the figures obtained from the OECD and the WBG. The evolution of the default rate in the EDW data matches well the dynamics of NPLs reported by the OECD and the WBG. When looking at the levels, the series are rather close for Belgium. By contrast, some discrepancies emerge for Spain and, especially, Italy, although the gap is widening in the more recent years. Overall, the default rate in EDW is lower than the NPL ratios reported by OECD and WBG. Given the methodological caveats spelled out above, including the different categorisation underlying the different aggregates, we cannot draw strong conclusions from the comparison about the EDW loans being of higher quality than the whole population of SME loans. In fact, even if that were the case, our results from the analysis of loan performance would be rather conservative, and we would be underestimating the actual impact of flooding on loan default.

A.1.3 Data cleaning

This section illustrates the cleaning steps performed on the loan-level information to obtain the estimating sample. (i) For consistency with the time period covered by the data on flood episodes, we retain only loans originated between January 1^{st} 2008 and December 31^{st} 2019. (ii) We drop all observations with no geographic indication at NUTS3 level, and convert all entries following the 2013 NUTS classification[34]. (iii) We exclude all loans with non-positive values for the relevant loan characteristics. (iv) 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*

statistical data reporting on NPLs suggest similar criteria.

[33]The WBG indicators are available at `https://data.worldbank.org/indicator/FB.AST.NPER.ZS`.

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

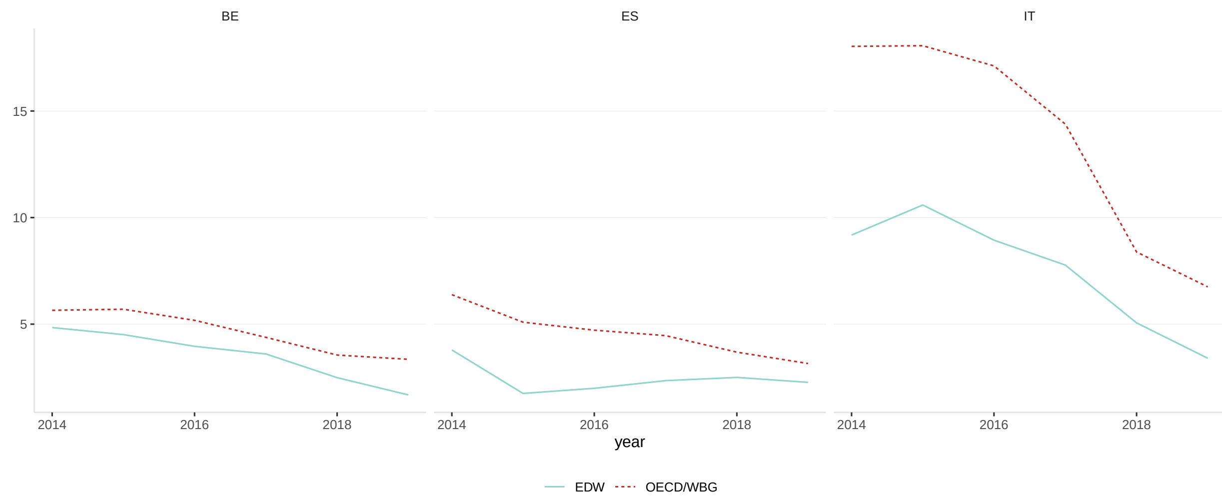

Figure A.2: **Default rate.** Plot of the percentage observed default rate in EDW (solid) and the ratio of non-performing loans (NPLs) to gross loans reported from official sources (dashed): for Belgium, we plot the NPL ratio from the OECD Financing SMEs and Entrepreneurs scoreboard; for Spain and Italy, we plot the NPL ratio from the WBG, which refers to the aggregate volumes of NPLs for the whole banking sector.

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 interbank financing operations, thus we exclude borrowers in the NACE 2-digit sector "64" (*Financial service activities*).

A.2 The flood risk indicator

The RDH risk indicator gauges the potential impact of flooding for a specific area in a given period of time. It compounds two different metrics associated to the occurrence of a flood: exposure and vulnerability. Exposure is assessed by combining geolocalised information on relevant flood metrics, such as frequencies and intensities, and on layers for different types of physical assets (i.e., residential buildings, industrial and commercial buildings, and land). To obtain a measure of the areal extent of the flooded areas, European inundation maps derived from the two-dimensional high-resolution hydrological model LISFLOOD (Bates et al., 2010; Alfieri et al., 2016) are used.[35] The presence of the assets in the 'footprint' of the hazard, as in

[35]LISFLOOD is a grid-based hydrological rainfall-runoff-routing model that simulates the full water cycle, including transport of water in horizontal and vertical directions through the landscape and soil, from rainfall to water in rivers, lakes and groundwater. Hydrological processes simulated under the combined effects of weather and climate changes, land use, socio-economic changes on water demand, as well as policy measures

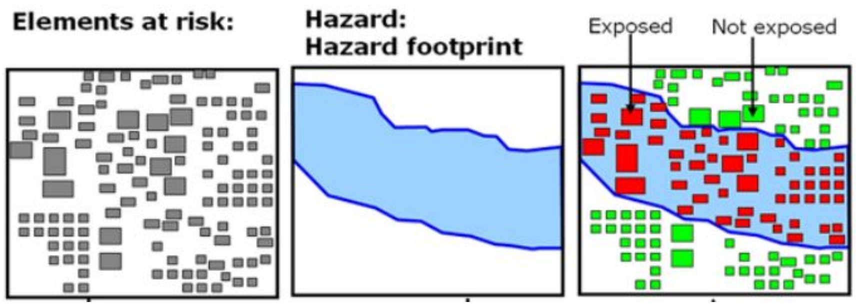

Figure A.3: **Hazards and assets at risk in RDH exposure component.**
Source: JRC Risk Data Hub.

Figure A.3, is considered exposure. For tractability, the exposure is then aggregated within administrative units, according to European administrative boundaries (Eurostat/GISCO), at the level of country (NUTS 0), regions (NUTS 2), provinces (NUTS3) and LAU (Local Administrative Units).

The hazard layers are probabilistic, with flood intensities assessed at different return periods, as follows (Antofie et al., 2020):

1. Calculation of the probability of exceedance P_{e,T_n} in a given year, which indicates the probability that a flood with a given return period T_n (in years) takes place, $P_{e,T_n} = 1/T_n$. The return periods are T_n, with $n = \{10, 50, 100, 200, 500\}$.

2. Calculation of the probability of occurrence of an event with a return period T_n in one year, P_n:
$$P_n = 1 + \frac{P_{e,T_n} - 1}{\prod_{n=T_1}^{T_n-1}(1 - p_n)}. \tag{8}$$

3. Calculation of the probabilities of occurrence for each event over a selected time interval of m years:
$$p_n(m) = 1 - (1 - P_n)^m, \tag{9}$$
where $n = \{500, 200, 100, 50, 10\}$ are the returning periods in years, and $m = \{2, 5, 10, 15, 25\}$ are the projection horizons, in years.

Finally, the calculation of the overall average loss expected for all events in different time

for water savings or flood control.

periods is:

$$U_m = \sum_{i=T_1}^{T_n} p_{i,m} L_i, \tag{10}$$

where L_i is the expected loss associated to a single event. The expected loss for a given event combines the exposure component and the vulnerability component. The potential impacts are not expressed in monetary values, but are normalised on a 0-to-10 scale.

Overall, the composite vulnerability component encompasses 43 unique indicators split across three geographic levels: country, NUTS2 and NUTS3 (see Table A.1). The vulnerability index is calculated by aggregating all unique indicators for the dimensions considered, i.e. social, economic, political, environmental and physical, at each geographic level. Hence, sub-indices for all areas and levels are created. Subsequently, the sub-indices are aggregated at the relevant geographic level. Eklund et al. (2023) develops the RDH vulnerability framework and describes the underlying methodology. In general, several data cleaning steps may be needed for the sub-indicators, in line with the standard approach for composite indicators, for instance treatment of missing data, e.g. by linear regression for indicators in which a clear pattern can be detected; winsorisation, and potential log-transformation to reduce excess skeweness and kurtosis of the distribution. Finally, values are finally normalised in a scale from 0 to 10 to make them comparable across different indicators.

Table A.1: **Variables used to compute the vulnerability component of the flood risk indicator.**

Level	Dimension	Hazard-independent Indicator	Vulnerability	Data Provider
Country	Social	Projected population change (increase)	(+)	Eurostat
Country	Social	Children at-risk-of-poverty	(+)	Eurostat
Country	Social	Disabled people with need for assistance	(+)	Eurostat
Country	Social	Long-term care (health) expenditure	(-)	Eurostat
Country	Social	Change in Age-dependency	(+)	Eurostat
Country	Social	Self-reported unmet need for medical care	(+)	Eurostat
Country	Social	Perceived Good Health	(-)	Eurostat
Country	Economic	Gross National Saving	(-)	WBG
Country	Economic	GDP per capita	(-)	Eurostat
Country	Economic	Income Inequality	(+)	Eurostat
Country	Economic	Cultural heritage	(+)	UNESCO
Country	Political	Governmental efficiency	(-)	WGI
Country	Political	Political Stability	(-)	WGI
Country	Political	National Adaptation Strategies	(-)	Climate-Adapt
Country	Environment	Environmental protection expenditure	(-)	Eurostat
Country	Environment	Climate related economic losses	(+)	Eurostat
Country	Environment	Common farmland bird index	(-)	Eurostat
Country	Environment	Natura 2000 protected areas	(-)	Eurostat
NUTS2	Social	Life expectancy	(-)	Eurostat
NUTS2	Social	Hospital beds per 100'000 population	(-)	Eurostat
NUTS2	Social	Participation in Social Networks	(-)	Eurostat
NUTS2	Social	Information (Frequency of internet access: once a week (including every day))	(-)	Eurostat
NUTS2	Social	People at risk of poverty or social exclusion	(+)	Eurostat
NUTS2	Social	People with tertiary education	(-)	Eurostat
NUTS2	Economic	Severe material deprivation rate	(+)	Eurostat
NUTS2	Economic	Household income	(-)	Eurostat
NUTS2	Economic	Motorways	(-)	Eurostat
NUTS2	Economic	Railways	(-)	Eurostat
NUTS2	Economic	Employment rate	(-)	Eurostat
NUTS2	Political	Regional Quality of Government index	(-)	GU
NUTS2	Environment	Urban area classified as green space	(-)	CORINE
NUTS2	Environment	Urban land cover	(+)	CORINE
NUTS3	Social	Population density	(+)	Eurostat
NUTS3	Social	Net migration	(+)	Eurostat
NUTS3	Social	Young dependency	(+)	Eurostat
NUTS3	Social	Old dependency	(+)	Eurostat
NUTS3	Economic	NUTS3 GDP per capita vs country average	(-)	Eurostat
NUTS3	Economic	Gross Value Added (at basic prices)	(-)	Eurostat
NUTS3	Economic	Power plants per 100'000 inhabitants	(-)	WRI
NUTS3	Economic	Patent applications to the EPO	(-)	Eurostat
NUTS3	Environment	Soil erosion	(+)	Eurostat

B Flooding and loan arrears

Section 4 in the 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. 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 flooding occurring 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 effect of realised flood risk on SMEs' 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 estimated at 1.13 for the 6-month period (column (1)), at 1.06 after 1 year (column (2)) and increase to 1.15 in the second year (column (3)). The indirect effect of flooding, while still highly statistically significant at the shorter horizons, is milder. Origination in the immediate aftermath of flood events is itself a risk factor for loan repayment. The estimated hazard ratios in columns (4) and (5) 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, when the estimated hazard loses statistical significance. 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. As for the analysis of loan default, the estimated hazard for the flood risk variable is not estimated with precision.

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
High risk	0.9873	0.9872	0.9887	0.9990	0.9991	0.9998
	(0.0152)	(0.0152)	(0.0152)	(0.0156)	(0.0156)	(0.0156)
Flood	1.1307***	1.0613***	1.1515***	1.0838***	1.0479***	1.1446***
	(0.0286)	(0.0204)	(0.0194)	(0.0277)	(0.0169)	(0.0207)
Flood before origination				1.0576***	1.0479***	1.0128
				(0.0216)	(0.0169)	(0.0145)
Interest rate	1.1741***	1.1742***	1.1758***	1.1839***	1.1836***	1.1853***
	(0.0051)	(0.0051)	(0.0051)	(0.0056)	(0.0056)	(0.0056)
Loan balance	1.0608***	1.0611***	1.0614***	1.0395***	1.0399***	1.0406***
	(0.0069)	(0.0069)	(0.0069)	(0.0069)	(0.0069)	(0.0069)
Residual loan term	0.9620***	0.9617***	0.9611***	0.9649***	0.9645***	0.9637***
	(0.0072)	(0.0072)	(0.0072)	(0.0073)	(0.0073)	(0.0072)
Collateralised	0.9978***	0.9978***	0.9977***	0.9993**	0.9993**	0.9992**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Business type 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	3,584,382	3,584,382	3,584,382	3,584,382	3,584,382	3,584,382

C Banks' expected losses from loan default

Section 4 in the 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:

$$lgd_{ibj,t} = \alpha + \beta HighRisk_j + \gamma Flood_{j,t-q} + \delta X_{ij,t} + \mu_{brsl,y} + \varepsilon_{ibj,t}. \tag{11}$$

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, $High\,risk_j$ is an indicator variable that takes value one if the normalised flood risk indicator for the county where the loan is extended is above the median of the empirical distribution of risk scores, and zero otherwise. $Flood_{j,t-q}$ is a dummy variable equal to one if there has been at least one flood episode in county j in the q months before the time of observation t, and zero otherwise. The time variable t is defined at the year-quarter level. As before, we also augment this baseline equation with an additional variable for realised flood risk, $Flood\,before\,origination$, which equals one if there has been at least one flood episode in the 6, 12, or 24 months before loan origination, and zero otherwise. $X_{ij,t}$ is a vector that includes loan-level variables, i.e., the loan term, expressed in (log) months, the (log) loan balance, and the share of collateralised loan, and county-level controls, such as the growth rates of GDP and employment. Further, $\mu_{brsl,y}$ denotes sets of fixed effects. We use business type and interacted industry, region and time 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' valuations of the loss given default on their loans. Finally, $\varepsilon_{ibj,t}$ is the remainder stochastic disturbance term. In the estimation, we cluster standard errors at the county level.

The results are reported in Table C.1. The coefficient on the high risk dummy are positive and significant at 10% statistical level throughout the different model specifications. Hence, seemingly banks account for prospective physical risks in the estimation of the losses they may incur on loans to borrowers more exposed to such risks. 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 around 0.23 percentage points, that is approximately 1% of the sample average value of the loss given default (22.5% of the current loan balance). The coefficients on the variables that capture recent realised flood risk are statistically insignificant. Hence, the occurrence of flooding does not significantly alter banks' valuation of the potential losses on their loan portfolios. The same holds for the indicator of flooding before loan origination. The estimated coefficients in all model specifications in columns (4)-(6) are positive, but not estimated with precision.

Table C.1: **Floods and bank 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. *Highrisk* 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
High risk	0.2324*	0.2326*	0.2327*	0.2334*	0.2344*	0.2386*
	(0.1262)	(0.1262)	(0.1254)	(0.1261)	(0.1261)	(0.1257)
Flood	-0.1243	-0.0510	0.0004	-0.1261	0.0690	-0.0533
	(0.1820)	(0.1514)	(0.1891)	(0.1816)	(0.1499)	(0.1777)
Flood before origination				0.2308	0.2592	0.3195
				(0.2186)	(0.2635)	(0.3181)
Interest rate	0.1231	0.1231	0.1231	0.1221	0.1204	0.1215
	(0.1366)	(0.1366)	(0.1367)	(0.1363)	(0.1357)	(0.1363)
Residual loan term	-0.9962***	-0.9962***	-0.9962***	-0.9951***	-0.9945***	-0.9967***
	(0.1992)	(0.1992)	(0.1992)	(0.1986)	(0.1983)	(0.1992)
Loan balance	-2.0360***	-2.0360***	-2.0361***	-2.0364***	-2.0364***	-2.0359***
	(0.1726)	(0.1727)	(0.1726)	(0.1726)	(0.1728)	(0.1730)
Collateralised	0.0581***	0.0581***	0.0581***	0.0579***	0.0578***	0.0580***
	(0.0045)	(0.0045)	(0.0045)	(0.0046)	(0.0047)	(0.0046)
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Region × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Business type FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.603	0.603	0.603	0.603	0.603	0.603
Observations	6,543,723	6,543,723	6,543,723	6,543,723	6,543,723	6,543,723