A climate stress testing exercise on loans to European small and medium enterprises

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Abstract: We develop a micro-level climate stress testing framework to evaluate the financial performance of small business loans under diverse climate scenarios. Focusing on European small and medium-sized enterprises (SMEs), we estimate the impact of coastal, flash, and river floods on loan default risk using a discrete-time survival model. Our analysis reveals that flood events significantly increase SME loan default probabilities in countries such as Spain and France. However, this effect is notably reduced in regions with strong infrastructure or effective support mechanisms. To complement the empirical findings, we conduct a forward-looking stress testing exercise that projects default probability trajectories under varying flood severity scenarios. This approach enables financial institutions and regulators to quantify the loan-level credit risk associated with climate-related flooding, offering valuable insights for risk management and policy design.

Keywords: climate change, loan default, natural disasters, risk modelling, stress testing
JEL codes: C55, G21, Q51, Q54

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1 Introduction

In recent years, the intersection between climate change and credit risks has attracted the attention of regulators and financial institutions. For example, the Basel Committee on Banking Supervision issued 18 principles aimed at effective management and supervision of financial risks associated with climate change (BCBS, 2022). These principles underscore the importance of banks recognising the distinctive nature of risks linked to climate (as highlighted in Principle 8) and the necessity for banks to integrate physical and transitional risks into their strategic business planning processes (as outlined in Principle 12).

While previous studies and supervisory exercises have advanced the understanding of climate stress testing, they have primarily focused on system-wide assessments of banks and large corporations at an aggregate level (Alogoskoufis et al., 2021; Battiston et al., 2017; de Bandt et al., 2025). This approach is typically of a top-down nature, with climate risks affecting primarily macro-financial variables, and usually relies on an analytical toolkit spanning from general equilibrium models (Hallegatte et al., 2022) to financial risk assessment methodologies that leverage long-term climate scenarios. In contrast, this paper adopts a micro-level approach that assesses the impact of forward-looking climate shocks on the default probability of individual loans.

Our study is novel in two key respects. First, we develop a micro-level stress testing framework that directly models the default risk of individual loans, capturing borrower- and region-specific heterogeneity in exposure to physical climate risk. Previous studies (Battiston et al., 2017) and financial supervisors usually follow instead a climate stress testing approach at the financial institution level, such as the European Central Bank (ECB) climate stress testing exercise (ECB, 2022a,b). Second, our analysis focuses specifically on small and medium-sized enterprises (SMEs), a sector that is significantly more vulnerable to physical risks such as flooding and is under-represented in current regulatory stress tests. In contrast, all climate stress testing exercises performed on firm-level data consider only large corporations for data availability (Battiston et al., 2023). By doing so, we provide the first climate stress testing exercise for SME loan portfolios in Europe, offering new insights into how climate shocks translate into credit risk for this critical segment of the economy.

We achieve this by estimating six discrete-time survival models on securitised SME loans from six European countries: Belgium, Spain, the Netherlands, France, Italy, and Portugal. This discrete survival approach is in line with the inherent characteristics of credit risk analysis, as loan-level data are commonly observed at fixed intervals, making events inherently discrete. To implement the models, we combine loan-level information from the European DataWarehouse with granular flood event data at the regional level. The European DataWarehouse provides detailed information on securitised loans to European SMEs. This data set includes both the characteristics of SMEs at the time of loan application

and their behavioural variables throughout the loan life, which we further enrich by incorporating local macroeconomic indicators (Bellotti and Crook, 2013) and data on natural disasters. For the latter, flood event data and future projections across different return periods are sourced from the Risk Data Hub of the Joint Research Centre of the European Commission. Relying on the estimates of the survival model, we provide a quantitative assessment of the evolution of SMEs' financial performance under different climate scenarios. This data-driven approach allows for the identification of the most vulnerable European regions. It can also be used by regulators and banks to estimate the default probability under a stressed scenario.

Our results show that flooding has a statistically significant impact on the default probability of SMEs, highlighting their vulnerability to physical climate risks, particularly in flood-prone areas. In countries such as France and Spain, flood events significantly increase the probability of SME loan defaults, suggesting the need for financial institutions to incorporate climate risk evaluations into their lending assessments. However, in countries with strong flood management systems, like the Netherlands, or those offering considerable disaster assistance, such as Italy, the negative effects of flooding on SME loan defaults are mitigated. Looking at the results of the stress testing exercise, we showcase the projected trajectory of default probabilities under various flood severity scenarios, revealing the significant impact of increased climate risk on loan defaults. This corresponds to an economically meaningful increase in default probabilities, up to 24 basis points in Spain and 18 basis points in France.

Our findings highlight the significant impact of physical climate risks on the financial stability of the SME loan market. They also underscore the need for targeted policy measures to strengthen financial systems against climate-induced economic disruptions, such as flooding. This analysis has significant policy implications for central banks (Chen et al., 2021; Wang et al., 2025) and macroprudential regulators, highlighting the critical role of granular spatial data availability on extreme weather events and forward-looking climate scenarios in assessing physical climate risks. While existing financial regulations predominantly focus on the corporate sector (Tan et al., 2025), our findings show the pressing need to extend regulatory attention to the SME lending market, which is relatively underexplored due to the limited data availability.

The remainder of this paper is structured as follows. Section 2 discusses the related literature, and Section 3 presents the data. The methods and results are presented in Sections 4 and 5, respectively. Finally, Section 6 concludes.

2 Literature review

As awareness of the economic and social impacts of climate change increases, a growing body of research investigates the potential risks it presents to key aspects of the financial system, particularly credit risk (Gourdel et al., 2024). Campiglio et al. (2023) provided an overview of the main studies focused on the impact of climate-related risks to financial assets. Chen et al. (2024) developed an Extreme Weather Index to assess weather risks in China and found significant negative effects of weather shocks on firm-level loans. Lu et al. (2024) analysed the impact of climate change on credit spreads among listed companies issuing corporate bonds. There are different transmission channels between weather events and the lending market. The destruction of capital assets, such as buildings and infrastructure, caused by severe natural disasters reduces the return on capital, labour productivity, and knowledge productivity, ultimately leading to lower overall output (Dietz et al., 2016). Dafermos et al. (2018) showed that physical risks trigger economic contraction and capital destruction, negatively impacting firms' profitability and liquidity. Consequently, rising default rates increase bank leverage and reduce capital adequacy, leading to tighter credit conditions and a negative feedback loop that hampers economic growth and intensifies business difficulties.

All the previous studies are focused on corporate lending. However, the impact of extreme weather events on the SME lending market remains underexplored, largely due to limited data availability. Aguilar-Gomez et al. (2024) obtained that extreme heat increases credit delinquency rates for SMEs in Mexico. Barbaglia et al. (2024) examined the impact of flooding on credit to European SMEs and highlighted a significant effect on loan delinquency. Their study found that firms affected by flooding are up to 1.6 times more likely to default on existing loans compared to firms in non-disaster areas. We build on their work, extending the analysis both in terms of time coverage and country scope, and introducing a novel stress testing framework for climate risk.

Climate change has also emerged as a significant risk to financial stability, prompting financial supervisors worldwide to adopt climate stress tests as a central tool to assess the resilience of the financial system. These methodologies simulate adverse but plausible climate scenarios to identify systemic vulnerabilities and guide regulatory responses (Hansen, 2022). Institutions such as the European Systemic Risk Board (ESRB) and the Basel Committee on Banking Supervision (BCBS) have called for the incorporation of climate-related risks into the strategic planning, risk governance, and supervision frameworks of banks (ECB/ESRB, 2023; de Bandt et al., 2025). Most of these efforts have so far focused on system-wide assessments at the macroprudential level, evaluating aggregate exposures of financial institutions and sectors to climate risks (Battiston et al., 2017; Grippa and Mann, 2020; Bank of England, 2021; FRB, 2021; Acharya et al., 2023).

However, recent research and supervisory initiatives increasingly highlight the need for micro-level

analysis, that is, assessing physical climate risk at the level of individual loans or borrowers (de Bandt et al., 2025; Anastasiou et al., 2025). This asset-level perspective captures heterogeneity across obligors, locations, and sectors that is often masked in aggregate analyses. It is particularly critical for SMEs, which are more vulnerable due to their localised operations and limited access to capital markets. Micro-level stress testing enables the identification of specific obligors or properties most exposed to climate risk, revealing that even loans with similar observable features can differ substantially in their climate sensitivities (Denton and Perrella, 2023).

A leading example of this approach is the ECB 2021 economy-wide climate stress test, which combined macroeconomic modelling with firm-level data for 2.3 million companies in Europe (Alogoskoufis et al., 2021; ECB, 2022a). The ECB assessed both non-financial corporations and euro area banks over a 30-year time horizon, finding that firms exposed to high physical risks could see a 25% increase in default probability by 2050 under a "hot house world" scenario. These results underscore the long-term threat posed by unmanaged physical risks and demonstrate the value of micro-level data in informing macroprudential stress-testing frameworks.

Moreover, insights from micro-level assessments are essential for informing macroprudential policy. They help supervisors identify channels of risk transmission, target interventions more effectively, and refine regulatory guidance. For example, studies have shown that extreme events can significantly increase the probabilities of mortgage default, even after accounting for insurance coverage (Zanin et al., 2024), and that SMEs exposed to increased climate risk and uncertainty are more likely to become discouraged borrowers (Anastasiou et al., 2025). These findings support the integration of climate considerations into credit risk modelling, loan approval processes, and supervisory evaluations.

Despite their importance, micro-level stress testing efforts face substantial data and methodological challenges. As noted by the ECB and others, detailed loan and borrower-level data remain limited, particularly for households and SMEs, even as coverage for large non-financial corporations improves (ECB, 2022b). This data gap presents a key barrier to developing robust, bottom-up climate risk assessments at scale. However, stress testing remains a critical tool for supervisors to monitor vulnerabilities, assess progress in risk management, and develop targeted macroprudential instruments (ECB, 2022b; de Bandt et al., 2025; ECB/ESRB, 2023).

Our study contributes to this growing literature by conducting a novel micro-level climate stress testing exercise focused on European SMEs. We assess changes in loan default probabilities under scenarios involving natural disasters with long return periods (up to 25 years). To our knowledge, this is the first climate stress test specifically targeting SME loan portfolios in Europe, helping to fill a critical gap in both academic research and regulatory practice.

3 Data

3.1 Loan-level data

We acquire loan-level data from the European DataWarehouse (EDW), a centralised securitisation repository providing data within the ECB loan-level initiative to collect, validate, and distribute standardised data for European countries. This data set covers a variety of loan types, including residential mortgages, credit card loans, automobile financing, and loans to SMEs in various European countries. Our research focuses on SME loans observed from the first quarter of 2013 to the end of 2022 and covers six European countries, namely Belgium, France, Italy, Portugal, Spain, and the Netherlands.

The EDW offers static and dynamic data that includes obligor information, loan characteristics, and loan performance metrics. The borrower details are collected at the beginning of the loan and, therefore, are static, including the business segment, type, and geographic location. The latter is reported following the Nomenclature of Territorial Units for Statistics (NUTS) classification. In particular, we have information on borrowers' location at the NUTS3 level, that is, local units corresponding approximately to US counties. Loan characteristics encompass both static elements (origination date, maturity date, original loan balance, and amortisation type) and dynamic elements (current loan balance and current interest rate). Loan performance metrics, such as arrears amounts and days in arrears, are dynamic and usually updated at least every quarter at pool cut-off dates. In this paper, we define a loan as being in *default* when it is recorded as 90+ days delinquent or more, which is a common definition in the industry and follows the guidelines set forth by BCBS (2017).

We merged the data obtained from the EDW with macroeconomic variables to capture the business cycle. In particular, we include quarterly growth rates of national Gross Domestic Product (GDP), Consumer Price Index (CPI), and Harmonised Unemployment Rate (HUR) available in Eurostat. Appendix A details the cleaning steps used to create the loan-level dataset. Table B.1 and B.2 in the Appendix report the descriptive statistics of continuous and categorical variables used in this paper, respectively. Table 1 reports some summary information about the loan-level dataset. The dataset consists of 13 million loan-quarter observations associated with 2 million unique loans. We observe large differences across countries. In particular, loan default rates range from a high of 7.92% in Spain to a low of 0.96% in France.

While these cross-country heterogeneities could arise from differences in securitisation practices, it is important to underline that the EDW plays a pivotal role in mitigating these disparities by enforcing standardised data templates and rigorous validation protocols across EU jurisdictions. The adoption of harmonised definitions and reporting formats significantly enhances the comparability of securitisation data, supports regulatory compliance, and ensures analytical consistency for both market participants

Table 1: *Loan-level data summary by country*

This table presents the number of loan-quarter observations, number of unique loans, number of defaulted loans, and default rate. The default rate is computed as the number of defaulted loans over the number of distinct loans in the sample. Note: We exclude those NUTS where the risk indicator is not available for the stress testing part.

Country	Nr. of observations	Nr. of loans	Nr. of default loans	Default rate (%)
Belgium	4,852,035	490,971	13,258	2.70
Portugal	474,366	111,949	3,181	2.84
France	1,079,110	311,437	3,004	0.96
Spain	4,569,405	610,556	48,357	7.92
Netherlands	104,648	32,749	388	1.18
Italy	2,655,423	453,797	18,005	3.97

and supervisory authorities. For a comprehensive assessment of the representativeness of securitised SME loans within EDW relative to the broader loan population, we refer to the Appendix of Barbaglia et al. (2024).

3.2 Disaster data

We use disaster data from the Risk Data Hub (RDH), a web-based platform administered by the European Commission's Joint Research Centre (Faiella et al., 2020)[1]. The RDH serves as a standardised repository of risk data and methodologies specifically targeted toward assessing disaster risks across Europe. Notably, the RDH is envisioned as the central European hub for collecting and recording detailed climate risk and loss data, aligning with the new European Strategy on climate change adaptation (ECB/ESRB, 2021). The data aim is to inform further European financial supervisors' analysis of climate risks and the development of relevant stress testing methodologies.

In this study, we focus on three types of flood disasters: coastal floods, flash floods, and river floods. These flood occurrences are recorded at the NUTS3 level, with some floods potentially affecting multiple areas simultaneously. Since loan-level data are available only at the NUTS3 level, a limitation of our analysis is that it cannot capture potential heterogeneity in flood exposure within NUTS3 regions. Figure 1 shows the number of floods that occurred from 2013 to 2022 at the NUTS3 level in the six EU countries included in this study. Over the past decade, it is evident that 2021 had the highest number of flood occurrences across the six countries, while 2022 had the fewest. When comparing the countries, France experienced the most flood disasters over the ten years, followed by Italy. Spain also had a significantly higher number of floods compared to the other three countries, with Portugal experiencing the fewest flood disasters.

To evaluate the impact of floods on credit risk, we construct a variable called *Flood_Indicator*. This dummy variable indicates whether a flood occurred in a NUTS3 region during a specific quarter (Yes

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

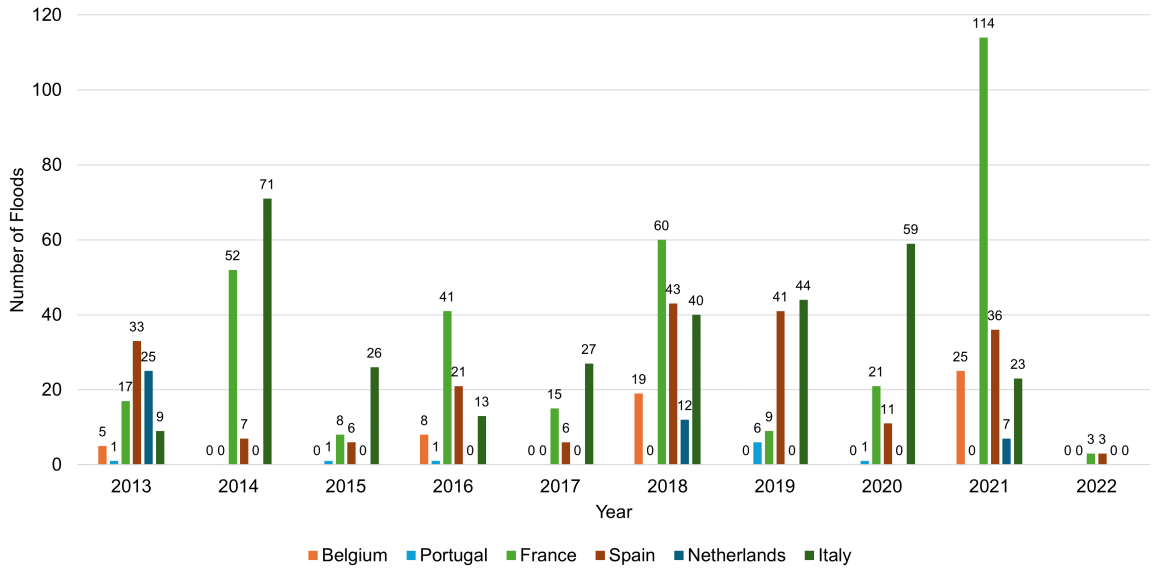


Figure 1: *Flood occurrences by year at the NUTS3 level for six EU countries.*

= 1, No = 0). We then merge the *Flood_Indicator* with the loan-level dataset described in the previous section, aligning by dates (at a quarter level) and NUTS3 regions to create the final dataset.

4 Methodology

4.1 Discrete-time survival model

We use a discrete-time survival model to estimate the probability of default over time. This approach is well-suited to credit risk analysis, where account records are typically observed at fixed frequencies - in this study, quarterly - making default events fundamentally discrete in time. Intuitively, the model answers a repeating question for each loan in each quarter: given that this loan has survived (not defaulted) so far, what is the probability it will default in this specific quarter? This quarterly conditional probability is known as the discrete-time hazard rate, which we denote as h_{ij} for loan i in time period (quarter) t_j. Because the data are organised as repeated loan–quarter observations, the discrete-time survival model can be approximated to a logistic regression on these binary outcomes (default vs. non-default in each quarter) with a duration function. This approximation allows the inclusion of time-varying covariates, such as flood occurrences, macroeconomic indicators, and evolving loan characteristics, while preserving the familiar interpretation of coefficients as log-odds ratios of default.

Formally, let the random variable T be the number of quarters since a loan originated (duration time), and T takes values t_j $(j = 1, \ldots, J_i)$ at distinct $t_1 < t_2 < \ldots < t_{J_i}$ for each loan i $(i = 1, \ldots, N)$. The variable Y_{ij} indicates whether loan i defaults at time t_j (0 = non-default or censored; 1 = default).

Once a loan is identified as defaulted, we discard any further status updates after the initial date of its prolonged delinquency. Moreover, we use x as the *Flood_Indicator* to represent whether at least one flood has occurred in the specific quarter in the NUTS3 region of the borrower. $\boldsymbol{b}$ represents a vector of time-varying variables collected across the lifetime of the loan (e.g., current interest rate), $\boldsymbol{c}$ represents a vector of time-invariant variables obtained at the time of loan origination (e.g., original loan balance), and $\boldsymbol{w}$ represents a vector of macroeconomic variables based on the national level, which is the same for all accounts on the same observation date (e.g., GDP). Finally, the conditional default probability, or hazard, is $h_{ij} = Pr(Y_{ij} = 1 \mid Y_{is} = 0 \text{ for all } s < j)$. Assuming a logit link function, we can add all variables as follows:

$$h_{ij} = logit^{-1}(\alpha + \boldsymbol{\varphi}(d)^\top \boldsymbol{\beta}_0 + x_{ij-l}\beta_1 + \boldsymbol{b}_{ij-l}^\top \boldsymbol{\beta}_2 + \boldsymbol{c}_i^\top \boldsymbol{\beta}_3 + \boldsymbol{w}_{ij-l}^\top \boldsymbol{\beta}_4), \tag{1}$$

where l is a fixed lag and $\boldsymbol{\varphi}$ is a vector transformation function of duration time d that is used to build a parametric survival model. Following Bellotti and Crook (2013), we use $\boldsymbol{\varphi}(d) = (d, d^2, log(d), (log(d)^2)$, where α is an intercept, and $\boldsymbol{\beta}_0$, β_1, $\boldsymbol{\beta}_2$, $\boldsymbol{\beta}_3$, and $\boldsymbol{\beta}_4$ are vectors of coefficients to be estimated.

The probability of surviving beyond a particular time t can be obtained as the product of the conditional survival probabilities for all time points up to t_j, such that $t_j \leq t$. Thus, the survival probability representing the probability of non-default up to t_j is given by:

$$S_{ij} = \prod_{j:t_j \leq t} (1 - h_{ij}), \tag{2}$$

and the probability of default up to t_j is given by:

$$PD_{ij} = 1 - S_{ij} = 1 - \prod_{j:t_j \leq t} (1 - h_{ij}). \tag{3}$$

It should be noted that the EDW data used in this study are left-truncated because a large number of loans originated before the observation period started. The left-truncated loans sampled at the beginning of the observation period tend to overrepresent low-risk loans among all SME loans and lead to biased estimates. To handle the left-truncated data, we refer to Guo (1993) to use a conditional likelihood approach. Let t_p be the number of quarters since a loan originated until the start of the observation period. Conditioning the likelihood of having survived to t_p, we can obtain the conditional log-likelihood for the discrete-time survival model:

$$\log L = \sum_{i=1}^{n} \sum_{j=1}^{J_i} Y_{ij} \log \left(\frac{h_{ij}}{1 - h_{ij}} \right) + \sum_{i=1}^{N} \sum_{j=p+1}^{J_i} \log(1 - h_{ij}). \tag{4}$$

The conditional log-likelihood in Equation (4) remains a binomial log-likelihood, which can be estimated by the maximum likelihood estimation for logistic regression.

4.2 Scenario analysis

Section 4.1 outlines a discrete survival model designed to estimate the probability of default for European SMEs, factoring in the impact of floods. By leveraging the model's estimates, we can conduct stress tests on the credit performance of SMEs under various climate scenarios, each characterised by different levels of flooding exposure.

While many climate scenarios are available and have been used in financial stress testing applications (Acharya et al., 2023), localised projections of the natural hazards investigated are not directly available. To this end, we rely on the risk scores provided by the RDH risk analysis module. These indicators allow for a multi-sector assessment of potential risks and losses from natural hazards for European regions at the NUTS3 level (Antofie et al., 2019). The risk score comprises two metrics, namely *exposure* and *vulnerability*. The *exposure* component joins localised hazard-specific metrics with layers for physical assets, while the *vulnerability* component combines hazard-independent information about the geographical unit impacted, like socio-economic factors. Finally, the flood risk score used in this paper represents the proportion of assets at risk relative to the total assets for each NUTS3 region. This is measured as the number of people at risk divided by the total population and the square meters of assets at risk divided by the total area of assets within the region. Consequently, the score ranges from 0 to 1.

The flood risk scores include projections for the next 1, 2, 5, 10, 15, and 25 years for each NUTS3 region. To construct various flooding exposure scenarios, we first pool the flood risk scores for all regions and projection horizons within each country. Using the distribution of these pooled scores, we define different flood-event thresholds. Specifically, we create seven scenarios based on seven thresholds, corresponding to the 90^{th}, 80^{th}, 70^{th}, 60^{th}, 50^{th}, 40^{th}, and 30^{th} percentiles of the pooled distribution, respectively. For each scenario, if the flood risk score of a region meets or exceeds the threshold, it is considered likely to experience flooding within the corresponding projection horizon. Scenario 1, defined by the 90^{th} percentile, represents the least stressed scenario, where only the NUTS3 regions with flood risk scores above the 90^{th} percentile of the pooled score distribution are associated with flood events. In contrast, Scenario 7, set at the 30^{th} percentile, represents the most stressed scenario, where the NUTS3 regions are considered flooded when their scores are above the 30^{th} percentile of the pooled score distribution. We stop at the 30^{th} percentile because, beyond this point, projected flood events (especially for 10-, 15-, and 25-year horizons) converge, suggesting that more extreme scenarios would lack meaningful differentiation.

Based on the previous steps, we can identify the NUTS3 regions projected to experience floods over different time horizons (1, 2, 5, 10, and 25 years). As flood risk scores increase with longer projection periods, more NUTS3 regions will be included in the longer-term projections. Similarly, because the thresholds from the 90^{th} to 30^{th} percentiles represent increasing levels of flooding exposure, a greater number of NUTS3 regions will be included in more severe scenarios. Table 2 illustrates the number of NUTS3 regions expected to experience floods across various projection horizons and scenarios, respectively, for each country. Although not directly based on NGFS or IPCC scenarios, our framework aligns with their core principles: it is forward-looking (up to 25 years), explores "plausible but adverse" futures, and spans multiple severity levels. Scenario 1 represents a mild stress event affecting only the most exposed areas, while Scenario 7 reflects a severe, widespread flooding case - conceptually similar to NGFS's "Hot House World" or "Disorderly Transition narratives". The scenarios we propose are primarily designed for a bottom-up approach, whereas the NGFS and IPCC scenarios are typically employed within top-down frameworks for macro-level assessments, which are unable to capture the spatial heterogeneity at the NUTS3 level that our approach provides.

We then apply a consistent method to map these NUTS3 regions to specific years. Specifically, the NUTS3 regions expected to experience floods in the second year are those included in the two-year projection horizon, but not in the one-year projection horizon. Similarly, the NUTS3 regions expected to experience floods from the third to fifth years are those included in the five-year projection horizon but not in the two-year projection horizon. We then sequentially assign these NUTS3 regions to year 3, year 4, and year 5. If the total number of NUTS3 regions is exhausted before reaching the last year, the remaining years will not be assigned any NUTS3 regions. If there are still NUTS3 regions remaining, a second round of allocation continues from year 3 to year 5 until all regions are assigned. This method is also used to allocate NUTS3 regions for periods between 5 and 10 years, 10 and 15 years, and 15 and 25 years. In the end, we obtain a series of NUTS3 regions for each year over the next 25 years. Based on this, we can construct a dummy variable indicating whether a flood event is projected to occur in a specific quarter[2] in a NUTS3 region, which aligns with the *Flood_Indicator* as explained in Section 3.2.

Finally, we obtain seven sets of *Flood_Indicator* corresponding to the seven stress scenarios for each country. To construct the scenario-specific datasets, we use loan information from the last observed quarter of each non-defaulted loan and merge it with the respective *Flood_Indicator* based on the quarter and NUTS3 region.

[2]If a NUTS3 region is assigned to a specific projected year, we assume it will experience floods in all 4 quarters of that year.

Table 2: *Number of NUTS regions expected to experience floods across country, projection horizons (Years) and scenarios.*

Country	Years	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Belgium	1	0	0	0	1	9	14	16
	2	0	0	1	8	10	15	17
	5	1	3	9	11	15	16	18
	10	2	9	10	15	15	17	19
	15	5	9	14	15	16	17	21
	25	9	12	15	15	16	18	22
France	1	0	0	2	5	12	20	30
	2	0	3	8	14	24	32	50
	5	4	14	24	30	39	59	70
	10	13	25	32	45	59	70	72
	15	14	30	41	58	65	71	76
	25	23	36	55	64	71	72	80
Italy	1	0	0	5	10	18	25	41
	2	0	7	11	19	25	37	51
	5	5	15	22	28	42	51	59
	10	11	21	30	42	50	59	63
	15	15	27	37	48	53	60	64
	25	19	29	43	50	58	63	66
Netherlands	1	0	1	2	3	5	10	13
	2	1	2	3	7	11	12	18
	5	2	3	10	13	14	17	25
	10	3	9	13	15	18	25	26
	15	5	11	13	17	23	25	26
	25	9	13	17	22	25	26	26
Portugal	1	0	0	2	2	2	3	4
	2	0	2	2	3	3	4	5
	5	1	2	3	4	5	7	9
	10	2	3	4	5	7	9	10
	15	2	4	5	7	9	10	11
	25	3	4	6	8	10	10	11
Spain	1	0	1	2	2	10	17	23
	2	1	2	2	11	15	23	28
	5	2	7	13	20	24	29	32
	10	5	12	20	26	28	32	35
	15	9	15	23	26	32	33	39
	25	12	20	25	28	32	35	40

5 Empirical results

5.1 The impact of flood risk on SME lending market across Europe

Table 3 reports the coefficient estimates of the discrete-time survival model for the six European countries. As indicated in Equation (1), in addition to *Flood_Indicator*, we include a vector transformation function of duration time and control for country-specific macroeconomic variables. We also account for various fixed effects, including loan term type, industry, business type, and amortisation type. For simplicity, we report only the coefficients of the main variables of interest. All other coefficient estimates are reported in Appendix Table B.4.

It can be seen that the *Flood_Indicator* variable has a statistically significant positive effect on the outcome in France and Spain, which means that SMEs in France and Spain are more likely to default

when having experienced at least one flood in quarter of the observation date. Specifically, the odds of default after experiencing at least one flood event are 1.27 times greater in France and 1.12 times greater in Spain. The positive findings also align with a concurrent study by Barbaglia et al. (2024), where the authors show that firms experiencing at least one flood event within a one- or two-year window are more likely to default on their loans than firms located in non-flooded areas.

Table 3: *Coefficient estimates for Flood_Indicator in the survival model.*

Country	Estimates	Std. Error	Flood_Indicator (=1, %)	Loan-quarter observation (Nr.)
Belgium	-0.258 ***	0.076	1.99	4,852,035
France	0.242 ***	0.059	6.05	1,079,110
Italy	-0.143 ***	0.027	9.92	2,655,423
Netherlands	-1.040	1.012	1.82	104,648
Portugal	-0.692 **	0.274	1.48	474,366
Spain	0.114 ***	0.0131	14.46	4,569,405

Note: The fourth column represents the proportion of loan-quarter observations with $Flood_Indicator$ equal to 1. The fifth column represents the number of loan-quarter observations. Significance: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

We do not observe a statistically significant effect in the Netherlands. From column 4 in Table 3, the Netherlands has the fewest loan-quarter observations and the second-lowest percentage of periods in which the flood indicator equals one. Specifically, only 1.82% of loan-quarter observations in the Netherlands coincide with a flood event, compared to 14.46% in Spain, for instance. The rarity of flood events in the Netherlands may hint at the insignificant results. We find that SMEs in Italy, Belgium, and Portugal are less likely to default on their loans following a flood event. Our findings underscore the importance of building separate survival models for each country as they exhibit heterogeneous flood impacts. Finally, since the securitised loans analysed in this paper are of high quality (Ertan et al., 2017; Barbaglia et al., 2024), our estimates understate the impact of flooding on the performance of the broader universe of credit lines provided to SMEs in Europe.

The insignificant impact of flood risk on Dutch SME loans can be explained by the country's effective flood management infrastructure and its nature-based solutions. Key flood management elements in the Netherlands include: (i) the *Room for the River Project* which designates areas for rivers to safely overflow, preventing urban flooding, (ii) *Robust Engineering*, including dike systems and storm surge barriers to protect against sea level rise, and (iii) *Wetlands* used for water retention, which act as natural buffers that absorb and gradually release excess water and reduce flood risks (World Economic Forum, 2023).

Furthermore, the advanced flood risk management infrastructure in the Netherlands is encapsulated in the Delta Programme (Zevenbergen et al., 2018; Delta Programme, 2024). This comprehensive system integrates a network of dams, sluice gates, storm surge barriers, and dikes. The programme also fosters a collaborative framework involving experts from water management, civil society, and

the government. The robustness and effectiveness of this system likely contribute to the statistically insignificant impact on SME default probability observed in our results. This suggests that flood management measures effectively shield businesses from the financial disruptions typically caused by such events.

In Italy, the decrease in the probability of SME default after flood events can be largely explained by substantial post-disaster financial support, particularly from EU Solidarity Fund (EUSF), a key instrument for responding to major natural disasters in the EU and candidate countries. Between 2002 and 2022, Italy received approximately EUR 3 billion, or 36.6% of the total EUR 8.2 billion disbursed by the European Union Solidarity Fund (EUSF), making Italy the fund's largest beneficiary (EU Solidarity Fund, 2022). Given that floods are the most frequent natural disasters in Europe, this support plays a crucial role in SME resilience. To provide direct evidence, Table B.3 summarises key aid payments and recovery budgets for major flood events across the study countries. Italy stands out with frequent and substantial disbursements: between 2010 and 2023, it received over EUR 850 million in EUSF aid for flood recovery, complemented by national allocations such as the EUR 1 billion government package for the 2023 Emilia-Romagna and Tuscany floods.

In Belgium, the observed decline in SME default risk following flood events may be explained by strong national and EU-level recovery mechanisms. As shown in Table B.3, Belgium received extensive financial support after the 2021 floods in Wallonia, including EUR 87.7 million from the EUSF and an additional EUR 2 billion in government funds dedicated to reconstruction and prevention. Similarly, Portugal has benefited from substantial post-disaster assistance. Following the severe 2010 floods in Madeira, Portugal received over EUR 31 million from the EUSF. Moreover, the country's well-established institutional framework for disaster management—coordinated by the National Authority for Emergency and Civil Protection (ANEPC)—ensures effective crisis response and recovery operations. These efficient recovery mechanisms and targeted financial supports likely contributed to the reduced SME default probability observed in Portugal after flood events.

Empirical evidence shows that disaster loans significantly improve the survival of small firms: Davlasheridze and Geylani (2017) found that an additional dollar in subsidised disaster loans per establishment helps retain four small businesses. Government support also contributes to post-disaster firm survival. In countries like Italy and Germany, low demand for flood insurance is linked to the "charity hazard" - the expectation of public compensation for uninsured losses (Tesselaar et al., 2022). This helps explain our counterintuitive finding of reduced SME default risk in Italy following floods: government aid and subsidies may boost liquidity and reduce immediate financial stress. Supporting this, Lodi et al. (2023) showed that Italian municipalities tend to increase public investment after floods, largely funded by higher-level governments. Similarly, Coelli and Manasse (2014) found that

firms affected by the 2010 Veneto floods experienced short-term growth in value added, partially driven by public recovery funds.

We further assess the predictive performance of the discrete-time survival models both in-sample and out-of-time. Given the highly imbalanced nature of our dataset, we use the Area Under the Precision-Recall Curve (AUPRC) instead of the traditional AUC, as it emphasises performance on the positive class. We also report the H-measure (Hand, 2009), an alternative to AUC that incorporates misclassification costs. To reflect the greater importance of correctly identifying defaulted loans, we set the severity ratio to 0.01, assigning a higher cost to misclassifying defaults than non-defaults.

In addition to these discrimination metrics, we evaluate probability calibration using the Brier Score (BS) and Logarithmic Loss Score (LLS) (Barbaglia et al., 2021). For both BS and LLS, smaller values suggest better predictive accuracy. In-sample results reflect performance on the full dataset (as presented in Table 3), while out-of-time evaluation tests the model's temporal generalization. For this, we use data from Q1 2013 to Q4 2020 for training, and Q1 to Q4 2021 for testing.

Table B.5 in the Appendix presents in-sample and out-of-time performance metrics across six countries. Overall, the models demonstrate robust performance, with acceptable generalisation across time and countries, particularly when accounting for class imbalance. France shows the strongest performance, with the highest in-sample AUPRC (0.054) and H-measure (0.435), and solid out-of-time results. Spain and Portugal also show encouraging results out-of-time, especially in terms of H-measure, indicating that the models for these countries remain reliable despite the shift in time periods. Calibration metrics (BS and LLS) are uniformly low across countries and periods, indicating well-calibrated probability estimates. Notably, out-of-time BS remain below 0.011 for all countries, and LLS are consistent with good probabilistic forecasts.

5.2 Robustness checks

To further assess the robustness of our findings, we conduct several additional analyses.

5.2.1 Interaction with GDP growth

Table 4 reports the coefficient estimates for *Flood_Indicator*, *GDP Growth*, and their interaction term. This specification tests whether the impact of floods on SME default risk depends on the broader economic environment.

Results remain largely consistent with the original model. The *Flood_Indicator* remains positive and significant for France and Spain, confirming that SMEs in these countries are more likely to default after flood events, regardless of macroeconomic conditions. By contrast, the coefficients for Belgium and Italy become statistically insignificant once GDP growth and its interaction are included,

suggesting that part of their previously observed resilience may be captured by local economic recovery dynamics.

For Portugal and the Netherlands, the estimated coefficients are unusually large. In both countries, the share of observations with *Flood_Indicator* = 1 is extremely small (1.48% and 1.82%; see Table 3). This sparsity, combined with the inclusion of the interaction term, induces strong collinearity between *Flood_Indicator* and its interaction with GDP growth, which inflates standard errors and leads to unstable or exaggerated coefficient estimates. The large values therefore, likely reflect estimation noise rather than meaningful effects.

Overall, the interaction term is small and insignificant across countries, indicating that the effect of floods on SME default risk operates largely independently of short-run macroeconomic fluctuations.

Table 4: *Coefficient estimates for Flood_Indicator, GDP Growth, and their interaction term in the survival model.*

	Belgium	Portugal	France	Spain	Netherlands	Italy
Flood_Indicator	-0.150	-35.472 ***	0.290 ***	0.111 ***	20.245	-0.128 ***
	(0.110)	(12.849)	(0.067)	(0.014)	(284.621)	(0.028)
GDP Growth	0.020 ***	-0.035 ***	0.001	0.007 ***	0.150 ***	0.009 ***
	(0.003)	(0.007)	(0.006)	(0.001)	(0.054)	(0.002)
Flood_Indicator:GDP Growth	-0.037	12.459 ***	-0.023	0.002	-2.787	-0.020 **
	(0.029)	(4.575)	(0.016)	(0.003)	(40.143)	(0.008)

Note: Significance: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5.2.2 Alternative observation windows

We assess robustness to alternative definitions of flood exposure by expanding the look-back window anchored at the quarter one year before the default observation, which means we keep the four-quarter (one-year) lag structure fixed, as shown in Equation (1). In the original model (results shown in Table 3), *Flood_Indicator* = 1 if a flood occurred in that single quarter, the $j-4$ quarter. Therefore, a 0.5Y window includes the quarter at $j-4$ and the immediately preceding two quarters, while a 2Y window extends to the eight quarters preceding $j-4$, and so forth up to 5Y. As the window lengthens, the likelihood that at least one flood falls within the exposure period mechanically increases, raising the percentage of observations that experienced a flood. Table 5 reports the corresponding coefficient estimates, while Table 6 shows the percentage of observations with *Flood_Indicator* = 1.

The results reveal both consistent and time-dependent patterns across countries. France and Italy show remarkable stability: coefficients remain positive and highly significant for France and negative and significant for Italy across all window lengths, confirming the robustness of their baseline effects. The Netherlands also displays consistent results, with coefficients remaining negative but statistically insignificant, in line with its strong flood protection infrastructure and low exposure frequency.

By contrast, Portugal, Belgium, and Spain exhibit more variation across observation windows. In

Spain, the coefficient of *Flood_Indicator* is positive and significant for shorter windows, turns negative for intermediate horizons, and becomes positive again once the window exceeds three years. This non-monotonic pattern may reflect short-term liquidity stress immediately after floods, followed by temporary recovery, and later renewed deterioration as cumulative flood exposure compounds. Belgium and Portugal show similar sign reversals, although with weaker significance levels, suggesting that their estimated flood–default relationships are more sensitive to how exposure is temporally defined.

Overall, the results indicate that while the direction and significance of flood effects remain stable for France, Italy, and the Netherlands, other countries display moderate sensitivity to the length of the exposure window. These differences likely reflect cross-country variation in post-disaster recovery speed, credit market conditions, and the persistence of flood-related disruptions.

Table 5: *Coefficient estimates of Flood_Indicator based on various observation windows.*

Country	0.5Y	1Y	1.5Y	2Y	2.5Y	3Y	3.5Y	4Y	4.5Y	5Y
BE	-0.012	0.015	-0.029	-0.014	-0.093***	-0.092***	0.072***	0.021	-0.012	-0.052***
	(0.042)	(0.034)	(0.029)	(0.026)	(0.022)	(0.019)	(0.018)	(0.018)	(0.019)	(0.019)
ES	0.020*	-0.038***	-0.152***	-0.208***	-0.057***	-0.004	0.036***	0.044***	0.049***	0.004
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
FR	0.138***	0.167***	0.158***	0.130***	0.089*	0.135***	0.100**	0.076*	0.086*	0.074*
	(0.053)	(0.053)	(0.047)	(0.048)	(0.049)	(0.045)	(0.046)	(0.045)	(0.045)	(0.044)
IT	-0.122***	-0.154***	-0.134***	-0.113***	-0.103***	-0.153***	-0.189***	-0.228***	-0.244***	-0.237***
	(0.017)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.017)	(0.018)	(0.019)	(0.020)
NL	-0.091	-0.143	-0.072	-0.041	-0.047	-0.122	-0.193*	-0.193*	-0.193*	-0.193*
	(0.145)	(0.124)	(0.116)	(0.112)	(0.110)	(0.105)	(0.103)	(0.103)	(0.103)	(0.103)
PT	0.466***	0.155	-0.034	0.014	0.010	0.007	-0.161*	0.184***	0.079	-0.071
	(0.113)	(0.113)	(0.113)	(0.105)	(0.105)	(0.105)	(0.086)	(0.062)	(0.056)	(0.051)

Note: Significance: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 6: *Percentage of Flood_Indicator = 1 (%) based on various observation windows.*

Country	0.5Y	1Y	1.5Y	2Y	2.5Y	3Y	3.5Y	4Y	4.5Y	5Y
BE	5.35	8.15	11.18	14.43	21.73	28.42	33.62	38.52	44.22	50.20
ES	33.04	45.06	53.22	58.29	62.07	65.33	68.29	70.90	72.81	75.01
FR	23.45	37.39	49.45	56.23	61.79	67.42	70.58	74.90	78.57	79.76
IT	30.46	47.60	57.91	64.43	70.76	75.60	79.88	83.10	86.59	89.88
NL	12.45	19.57	25.76	31.03	35.49	45.15	53.72	53.72	53.72	53.72
PT	3.92	6.02	6.98	7.78	7.80	7.82	9.77	11.97	14.40	18.52

5.2.3 Accounting for spatial heterogeneity

To assess whether the observed flood-default relationship might be confounded by spatial clustering of vulnerable firms, such as those systematically more prone to default and disproportionately located in flood-prone areas, we re-estimate the survival model including NUTS2-level random effects. If latent regional heterogeneity were driving the association, we would expect the estimated flood effects to shrink or lose statistical significance once these unobserved factors are accounted for. However, as shown in Table 7, the results remain qualitatively similar or even stronger compared to the model without spatial random effects (Table 3). In particular, the *Flood_Indicator* remains statistically sig-

nificant for France, Italy, and Spain, with slightly larger effect sizes. The robustness of the results indicates that the relationship between flood exposure and SME default is unlikely to be driven by regional clustering of high-risk firms, but instead points to a substantive underlying causal effect.

Table 7: *Coefficient estimates for Flood_Indicator in the survival model with spatial random effects (NUTS2).*

Country	Estimates	Std. Error	Significance
Belgium	-0.283	0.077	***
France	0.265	0.062	***
Italy	-0.102	0.028	***
Netherlands	-1.038	1.012	
Portugal	-0.693	0.274	**
Spain	0.158	0.013	***

Note: Significance: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5.3 A climate stress testing exercise for flooding risk

We conduct a stress testing exercise using the estimates derived in Section 5.1 from the survival model. We focus on the loans granted to SMEs in Spain and France, given that for these countries we obtain positive and significant coefficient estimates for the *Flood_Indicator* variable. We follow the methodology presented in Section 4.2 and analyse the changes in the predicted mean probability of default (PD) when including climate-related information in our setup against the nested baseline model. We evaluate the changes in PD along two dimensions: the projection years and severity of the climate scenario. The latter is defined by setting a threshold on the distribution of the associated risk scores, with Scenarios 1 and 7 indicating the least- and most-stressed scenarios, respectively. Tables 8 and 9 present the results of our stress tests for France and Spain, respectively. The first row of each table reports the mean PD derived from the base model, which does not include the *Flood_Indicator* variable, and serves as a benchmark for other scenarios. The subsequent rows report the difference in basis points between the mean PD of the stressed scenarios and the base model PD.

Looking at the evolution of the predicted PD along the projection years for the baseline model, both tables show comparable trends. There is a monotonic increase in the mean default probability when moving from the 1-year to the 25-year scenarios. The default probability increases more than tenfold over the next 25 years compared to the next year for all scenarios in both countries in analysis[3].

Looking at the intensity of the stress scenario, we also observe a consistent increase in the mean default probability between the least and most stressed scenarios. For example, the differences in mean default probability between the most and least stressed scenarios for France and Spain in the next year are 18 basis points and 24 basis points, respectively.

[3]We highlight that the polynomial–logarithmic specification of baseline hazard captures the observed duration dependence well. However, for France, the projected baseline hazard shows a gradual upward trend at longer durations (after 20 years), whereas for Spain it displays a stable pattern. The extreme value observed for France in 25 projection years is therefore likely influenced by the extrapolation of this functional form.

Table 8: *Scenarios of mean default probability for various scenarios in France.*

		Projection year						
		1	2	5	10	15	20	25
	Base model	2.02	3.73	7.47	12.84	21.25	34.66	94.78
Scenario	1	0.00	0.00	1.32	3.01	0.79	1.61	0.28
	2	0.00	1.58	4.93	5.25	2.00	1.33	0.04
	3	0.94	3.02	8.76	6.58	2.69	2.03	2.08
	4	2.95	7.36	10.63	7.86	3.52	1.35	0.02
	5	7.41	13.16	13.34	10.16	3.79	0.95	0.04
	6	14.12	17.46	17.31	11.40	3.19	0.27	0.01
	7	17.94	22.87	19.86	11.88	3.85	0.72	0.02

Note: The first row reports the predicted mean PD (%) for the baseline model by projection year (in the columns). Following rows report the basis point difference with respect to the baseline PD by projection year and climate scenario (in the rows).

Table 9: *Scenarios of mean default probability for various scenarios in Spain.*

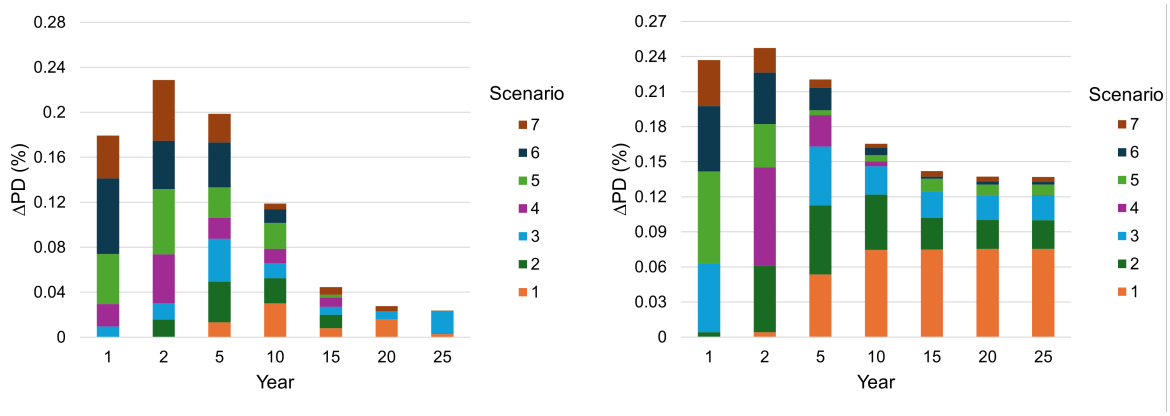
		Projection year						
		1	2	5	10	15	20	25
	Base model	4.02	7.92	19.97	38.28	46.41	47.72	47.78
Scenario	1	0.00	0.40	5.36	7.47	7.48	7.54	7.53
	2	0.42	6.08	11.28	12.20	10.21	10.03	10.01
	3	6.32	5.98	16.30	14.61	12.48	12.12	12.10
	4	6.32	14.44	18.99	15.04	12.45	12.17	12.15
	5	14.16	18.11	19.42	15.56	13.52	13.06	13.04
	6	19.77	22.53	21.32	16.20	13.69	13.30	13.28
	7	23.71	24.63	22.05	16.54	14.18	13.72	13.70

Note: The first row reports the predicted mean PD (%) for the baseline model by projection year (in the columns). Following rows report the basis point difference with respect to the baseline PD by projection year and climate scenario (in the rows).

The increased probability of default is economically significant. According to Ou et al. (2017), an increase in the average corporate default rate from 0 to 9 basis points would result in a substantial downgrade from Aaa to A ratings. With a 27 basis point increase in the default rate, the rating could be further downgraded to Baa, which separates investment-grade from speculative-grade borrowers. Our results provide empirical evidence that flood-related natural disasters may notably increase default probabilities. Even over short periods, flood risks can lead to substantial credit rating downgrades for SMEs. As the default risk of SMEs rises, banks may face higher levels of non-performing loans (NPLs), which can erode their capital buffers and profitability. The potential for credit rating downgrades underscores the economic significance of these risks, thereby weakening the financial stability of banks operating in the affected areas (Noth and Schüwer, 2023).

Figure 2 illustrates the cumulative percentage change in mean default probability (in basis points) as we move from the base model to the most-stressed scenario (Scenario 7) for France and Spain. Each segment within a bar, differentiated by colour, shows the incremental change in default probability from one scenario to the next. For example, Legend 1 in the plot represents the percentage increase in the average default probability from the base model to Scenario 1 with a 90^{th} percentile threshold; Legend 2 in the plot represents the percentage increase in the average default probability from Scenario

1 with a 90^{th} percentile threshold to Scenario 2 with an 80^{th} threshold. Initially, there are no significant differences in the mean default probability between the less stressed scenarios. However, differences begin to appear in the second year in Spain, and the fifth year in France. The total height of the stacked bar represents the change in the mean default probability between the most stressed scenario (Scenario 7) and the baseline model, highlighting the country-specific differences. In both countries, the difference initially peaks in the second year at around 24 basis points before declining. In Spain, it falls to about 14 basis points and stabilises after the 15th year, whereas in France it continues to decrease, dropping below 4 basis points. Additional descriptive statistics of the default probability distribution for various scenarios are provided in the Appendix.



(a) *France* **(b)** *Spain*

Figure 2: *Stacked column plots for percentage change in the mean default probability between every two adjacent thresholds by country. Scenarios from 1 to 7 are plotted in different colours.*

Finally, we explore the regional heterogeneity of the stress scenarios by plotting the maps in Figure 3. This figure consists of two sets of maps - the first row for France and the second row for Spain - and demonstrates the regional heterogeneity of flood risk and its impact on SME loan default probabilities. In the first column, we plot the maps of the predicted probability of default of the base model averaged across the projection years, without considering any climate stress scenarios.. In columns 2 to 4, we plot the maps of the predicted probability of default differences between the scenarios and the base model. For illustrative purposes, we only report Scenarios 1 (least stressed), 4, and 7 (most stressed). The colour intensity indicates the level of risk, with darker shades showing higher default probabilities.

Looking at the base model estimates in the first column, we can see that within-country regional heterogeneity plays an important role. France presents a highly heterogeneous risk profile, with the highest estimated probability of default concentrated in the Île-de-France and in the southeast regions. Although to a lesser extent than the French case, also Spain shows a high degree of variability in the estimated probability of default, with the highest rates in the capital region of Madrid and

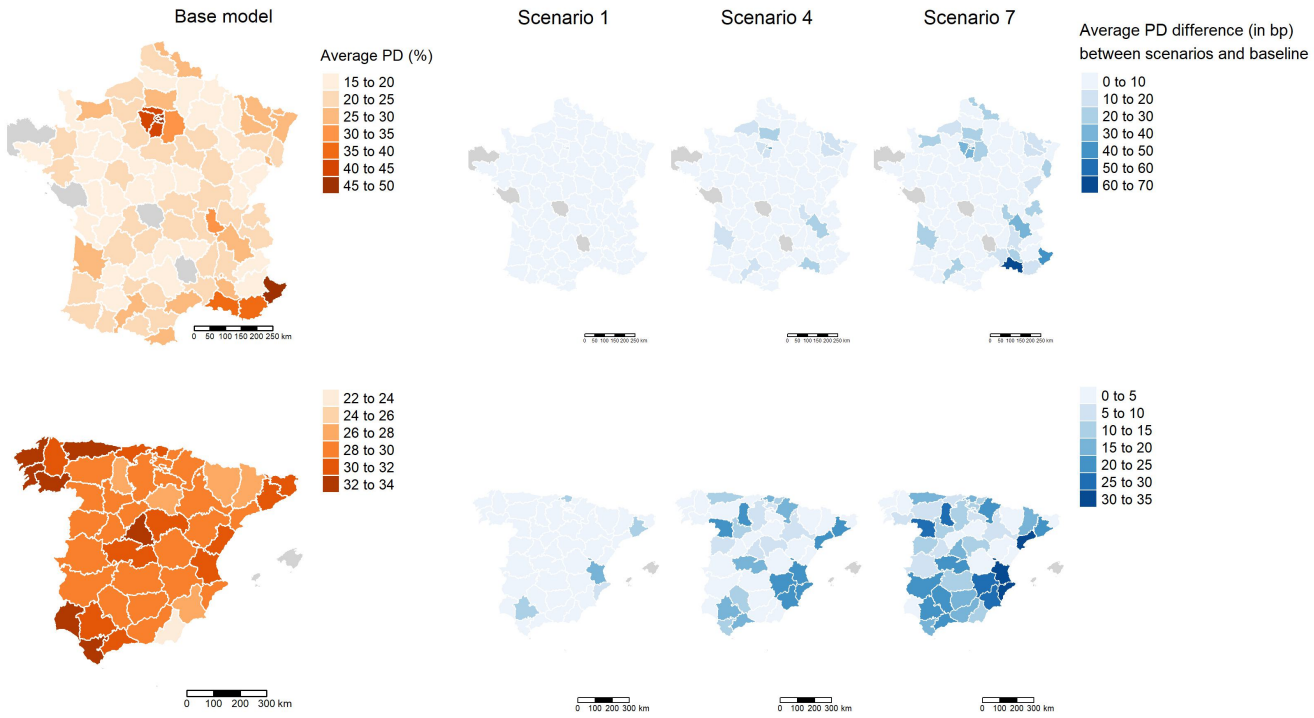


Figure 3: *In the first column, we plot the baseline model predicted PD (%) averaged across projection years by country. In columns two to four, we plot the average differences in predicted PD, in basis points (bp), averaged across projection years between Scenarios 1 (least stressed), 4 and 7 (most stressed), and the baseline model by country. The darker the colour, the higher the value. Regions in grey are missing because the risk indicator is not available.*

northwestern regions along the Atlantic coast. Looking only at country aggregates might not bring an accurate description of local dynamics; hence, the importance of relying on a modelling strategy that incorporates the regional dimension. The regional heterogeneity is a relevant factor also when looking at the scenarios. We observe that the French regions that would suffer the largest increase in default probabilities under a stressed scenario are the ones that actually started with the highest rates in the base model. On the other hand, this is not the case in Spain, where the regions that would suffer the highest relative increases in PD are the ones located on the Mediterranean coast, in particular within the Catalonia and Valencian communities. Under the most stressed scenario, these regions are expected to experience an increase of up to 35 basis points in PD, with more than 10 basis points larger than the average impact estimated at the country level.

Overall, our climate stress testing results, which indicate significant increases in default probabilities due to flood risks, highlight the urgent need for financial institutions to integrate climate risk into their decision-making frameworks. While exploratory in nature, our stress-test analysis can offer valuable guidance to policymakers by providing a preliminary outlook on the potential impact of climate risk. This outlook should be complemented by further quantitative and qualitative assessments, especially to refine long-term duration dynamics and to ensure that extended-horizon risk projections remain

informative and policy-relevant.

6 Conclusions

This paper presents a novel micro-level climate stress testing framework to assess the impact of natural disasters, particularly floods, on the default probability of SME loans across European countries. Leveraging detailed loan-level data and forward-looking hazard scenarios, we estimate a discrete-time survival model and simulate future default dynamics under increasingly severe flood conditions over a 25-year horizon.

Our results highlight a significant relationship between natural disasters - particularly flooding - and the default probability of SME loans across various European countries. In countries such as France and Spain, flood events lead to statistically and economically meaningful increases in SME loan default probabilities. In contrast, in countries with strong flood management infrastructure (Netherlands) or substantial post-disaster financial aid (Italy), the adverse effects appear mitigated. These findings highlight the role of national policy, infrastructure, and institutional support in shaping credit outcomes following climate shocks.

The stress testing exercise reveals potential long-term effects of climate change on loan performance, with the mean default probability showing a significant increase under more severe flood scenarios. This increase is economically significant, with quantifiable increases in default probability up to 24 and 18 basis points in Spain and France, respectively.

Our study is, to our knowledge, the first to conduct a climate stress testing exercise focused specifically on SME loans in Europe. By modelling default risk at the micro level, our approach captures risk heterogeneity that is often overlooked in macro-level assessments. This granularity is crucial for identifying vulnerable obligors, guiding risk-based capital allocation, and designing targeted regulatory responses.

These insights have important implications for financial institutions, supervisors, and policymakers. They underscore the urgency of integrating physical climate risk into credit risk modelling and stress testing frameworks, particularly for vulnerable sectors such as SME lending. We highlight that granular spatial data availability on extreme weather events and forward-looking climate scenarios are essential for central banks and regulators to perform accurate micro level climate stress testing exercises. More broadly, our findings support the development of a climate-resilient financial system that can better absorb the growing risks posed by climate change. Finally, our exercise shows the need to extend the focus of the financial regulation beyond the corporate sector to include also the SME lending market.

References

Acharya VV, Berner R, Engle R, Jung H, Stroebel J, Zeng X, Zhao Y. 2023. Climate stress testing. *Annual Review of Financial Economics* **15**: 291–326.

Aguilar-Gomez S, Gutierrez E, Heres D, Jaume D, Tobal M. 2024. Thermal stress and financial distress: Extreme temperatures and firms' loan defaults in mexico. *Journal of Development Economics* **168**: 103246.

Alogoskoufis S, Dunz N, Emambakhsh T, Hennig T, Kaijser M, Kouratzoglou C, Muñoz MA, Parisi L, Salleo C. 2021. ECB economy-wide climate stress test: Methodology and results. *ECB Occasional Paper* .

Anastasiou D, Ballis A, Kallandranis C, Lakhal F. 2025. Analyzing the effects of climate risk on discouraged borrowers: Deciphering the contradictory forces. *Risk Analysis* **45**: 223–239.

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.

Bank of England. 2021. Key elements of the 2021 biennial exploratory scenario: Financial risks from climate change. Technical report, Bank of England.

Barbaglia L, Fatica S, Rho C. 2024. Flooded credit markets: Physical climate risk and small business lending. *MoFiR Working Paper 186* .

Barbaglia L, Manzan S, Tosetti E. 2021. Forecasting loan default in europe with machine learning. *Journal of Financial Econometrics* **21**: 569–596. ISSN 1479-8409.

Battiston S, Mandel A, Monasterolo I, Roncoroni A. 2023. Climate credit risk and corporate valuation. *SSRN* **4124002**.

Battiston S, Mandel A, Monasterolo I, Schütze F, Visentin G. 2017. A climate stress-test of the financial system. *Nature Climate Change* **7**: 283–288.

BCBS. 2017. Prudential treatment of problem assets - definitions of non-performing exposures and forbearance. Technical report, Basel Committee on Banking Supervision.

BCBS. 2022. Principles for the effective management and supervision of climate-related financial risks. Technical report, Basel Committee on Banking Supervision.

Bellotti T, Crook J. 2013. Forecasting and stress testing credit card default using dynamic models. *International Journal of Forecasting* **29**: 563–574. ISSN 01692070.

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

Chen C, Pan D, Huang Z, Bleischwitz R. 2021. Engaging central banks in climate change? The mix of monetary and climate policy. *Energy Economics* **103**.

Chen Z, Li L, Tang Y. 2024. Weather, credit, and economic fluctuations: Evidence from China. *Journal of Economic Behavior & Organization* **221**: 406–422. ISSN 0167-2681.

Coelli F, Manasse P. 2014. The impact of floods on firms' performance. *Quaderni - Working Paper DSE 946* .

Dafermos Y, Nikolaidi M, Galanis G. 2018. Climate change, financial stability and monetary policy. *Ecological Economics* **152**: 29–234.

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

de Bandt O, Kuntz LC, Pankratz N, Pegoraro F, Solheim H, Sutton G, Takeyama A, Xia FD. 2025. The effects of climate change-related risks on banks: A literature review. *Journal of Economic Surveys* **39**: 1553–1594.

Delta Programme. 2024. The delta programme. Accessed: 2024-05-23.
URL `https://english.deltaprogramma.nl/#:~:text=The%20Delta%20Programme%20protects%20the,robust%20planning%20for%20our%20country.`

Denton MJ, Perrella J. 2023. Climate risk impacts on a lending portfolio; loan-level analytics. Technical report, Moody's.

Dietz S, Bowen A, Dixon C, Gradwell P. 2016. Climate value at risk' of global financial assets. *Nature Climate Change* **6**: 676–679.

ECB. 2022a. 2022 climate risk stress test - final results. Technical report, European Central Bank.

ECB. 2022b. ECB report on good practices for climate stress testing. Technical report, European Central Bank.

ECB/ESRB. 2021. Climate-related risk and financial stability - data supplement. Technical report, European Central Bank, and European Systemic Risk Board.

ECB/ESRB. 2023. Towards macroprudential frameworks for managing climate risk. Technical report, European Systemic Risk Board.

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.

EU Solidarity Fund. 2022. An overview of the eu solidarity fund 2002-2022. Accessed: 2024-05-23. URL `https://cohesiondata.ec.europa.eu/stories/s/An-overview-of-the-EU-Solidarity-Fund-2002-2022/qpif-qzyn/`

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* .

FRB. 2021. Pilot climate scenario analysis exercise. Technical report, Federal Reserve Board.

Gourdel R, Monasterolo I, Dunz N, Mazzocchetti A, Parisi L. 2024. The double materiality of climate physical and transition risks in the euro area. *Journal of Financial Stability* **71**: 101233. ISSN 1572-3089.

Grippa P, Mann S. 2020. Climate-related stress testing: Transition risks in Norway. *IMF Working Papers* **2020/232**.

Guo G. 1993. Event-history analysis for left-truncated data. *Sociological Methodology* **23**: 217–243.

Hallegatte S, Lipinsky F, Morales P, Oura H, Ranger N, Regelink M, Reinders H. 2022. Bank stress testing of physical risks under climate change macro scenarios: Typhoon risks to the philippines. *Working Paper International Monetary Fund WP/22/163* .

Hand DJ. 2009. Measuring classifier performance: a coherent alternative to the area under the ROC curve. *Machine learning* **77**: 103–123.

Hansen LP. 2022. Central banking challenges posed by uncertain climate change and natural disasters. *Journal of Monetary Economics* **125**: 1–15.

Lodi C, Marin G, Modica M. 2023. The public finance response to floods of local governments in italy. *Journal of Environmental Management* **332**: 117352.

Lu X, Hou X, Zeng W. 2024. Effects of climate change on firm credit risk: evidence from china. *Asia-Pacific Journal of Accounting & Economics* : 1–25.

Noth F, Schüwer U. 2023. Natural disasters and bank stability: Evidence from the us financial system. *Journal of Environmental Economics and Management* **119**: 102792.

Ou S, Irfan S, Liu Y, Kanthan K. 2017. Annual default study: Corporate default and recovery rates, 1920-2016. *Data Report-Moody's Investor Services* .

Tan R, Zhu W, Xu M, Zhang Z. 2025. From voluntary to mandatory implementation: The impact of green credit policy on de-zombification in China. *Energy Economics* **141**.

Tesselaar M, Botzen WW, Robinson PJ, Aerts JC, Zhou F. 2022. Charity hazard and the flood insurance protection gap: An eu scale assessment under climate change. *Ecological Economics* **193**: 107289.

Wang JZ, Narayan PK, Gunadi I, Hermawan D. 2025. Climate change and financial risk: Is there a role for central banks? *Energy Economics* **144**.

World Economic Forum. 2023. How the netherlands uses nature-based solutions for water security. Accessed: 2024-05-23.
URL `https://www.weforum.org/agenda/2023/08/netherlands-nature-based-solutions-water-security/`

Zanin L, Calabrese R, Thorburn CI. 2024. Climate stress testing for mortgage default probability. *International Review of Financial Analysis* **95**: 103497.

Zevenbergen C, Khan SA, van Alphen J, Terwisscha van Scheltinga C, Veerbeek W. 2018. Adaptive delta management: a comparison between the netherlands and bangladesh delta program. *International Journal of River Basin Management* **16**: 299–305.

Online appendix

A Data cleaning

This section delves into the data cleaning process applied to the loan-level data from the European DataWarehouse (EDW), complementing the data description in the main text. EDW can be reported following two templates. Initially, the EDW employed templates from the European Central Bank (ECB) for recording loan data. However, starting 2021 Q4, these were replaced by reporting templates from the European Securities and Markets Authority (ESMA)[4]. Our dataset, encompassing millions of loan observations across multiple European countries, includes data from both ECB and ESMA formats. We ensure consistency across templates by harmonising any discrepancies in the information. We implement the following main data cleaning steps:

1. Retained loan deals dated between January 1, 2013, and December 31, 2022, as per the loan cut-off dates.
2. Selected only the latest observation per quarter in cases of multiple observations for a single loan.
3. Prioritised ECB data over ESMA data for loans recorded in both datasets in the latest month.
4. Limited our analysis to loans originated between January 1, 2000, and December 31, 2019.
5. Excluded loans with a maturity date beyond December 31, 2045.
6. Omitted loans where the NUTS3 country code did not align with the deal's country code.
7. Generated a one-year lead (4 quarters) default status, discarding any missing values.
8. Removed subsequent observations following the first default record for each loan.

[4]ECB and ESMA templates are available at `https://www.ecb.europa.eu/paym/coll/loanlevel/transmission/html/index.en.html` and `https://www.esma.europa.eu/esmas-activities/markets-and-infrastructure/securitisation`, respectively.

B Additional tables

Table B.1: *Descriptive statistics for continuous variables.*

Country	Variables	Min	Max	Mean	Median	SD
	Loan characteristics					
	Duration	1	87	17.86	13	14.26
	Current Loan Balance (log)	0	17.73	10.55	10.41	1.38
	Current Interest Rate	0.61	6.45	3.01	2.87	1.44
Belgium	Original Loan Balance (log)	8.52	14.29	11.20	11.12	1.26
	Macroeconomic variables					
	CPI (%)	-0.39	6.36	1.41	1.35	1.05
	GDP (%)	-12.73	15.50	1.24	1.59	3.79
	HUR (%)	5.10	8.87	7.15	7.23	1.34
	Loan characteristics					
	Duration	1	84	10.67	8	9.99
	Current Loan Balance (log)	0	17.73	10.29	10.06	1.55
	Current Interest Rate	0.65	16	4.82	4.208	2.93
Portugal	Original Loan Balance (log)	8.52	14.68	10.87	10.46	1.22
	Macroeconomic variables					
	CPI (%)	-0.42	2.41	0.62	0.54	0.63
	GDP (%)	-17.78	17.20	1.18	1.88	3.25
	HUR (%)	6.13	18.10	11.75	12.30	3.26
	Loan characteristics					
	Duration	1	82	9.25	7	7.69
	Current Loan Balance (log)	0	20.09	9.49	9.86	2.45
	Current Interest Rate	0.36	5.35	1.57	1.25	1.02
France	Original Loan Balance (log)	3.76	13.69	10.31	10.24	1.13
	Macroeconomic variables					
	CPI (%)	-0.24	3.33	1.49	1.30	0.71
	GDP (%)	-18.01	17.82	0.13	1.96	6.39
	HUR (%)	7.33	10.47	8.75	8.80	0.77
	Loan characteristics					
	Duration	1	88	17.39	12	14.41
	Current LoanBalance (log)	0	18.42	9.93	9.90	1.50
	Current Interest Rate	0.56	14.11	4.16	3.90	2.57
Spain	Original Loan Balance (log)	7.67	13.92	10.60	10.55	1.31
	Macroeconomic variables					
	CPI (%)	-1.14	5.82	0.78	0.51	1.35
	GDP (%)	-21.67	19.44	0.94	2.21	5.48
	HUR (%)	13.40	26.33	19.24	18.20	4.47
	Loan characteristics					
	Duration	1	88	24.16	20	14.89
	Current Loan Balance (log)	0.41	18.59	12.52	12.62	1.40
	Current Interest Rate	0.85	7.10	3.38	3.15	1.34
Netherlands	Original Loan Balance (log)	9.46	15.82	13.03	13.07	1.22
	Macroeconomic variables					
	CPI (%)	-0.47	5.35	1.17	0.44	1.54
	GDP (%)	0.96	11.65	4.30	2.30	3.71
	HUR (%)	3.80	8.67	6.55	7.43	1.80
	Loan characteristics					
	Duration	1	87	16.15	13	11.50
	Current Loan Balance (log)	0	18.60	10.43	10.52	2.13
	Current Interest Rate	0.42	8.30	3.29	3.00	1.69
Italy	Original Loan Balance (log)	8.99	14.60	11.31	11.16	1.23
	Macroeconomic variables					
	CPI (%)	-0.39	3.74	0.72	0.40	0.87
	GDP (%)	-17.55	18.07	-0.58	0.34	6.57
	HUR (%)	8.57	12.93	10.64	10.37	1.35

Table B.2: *Descriptive statistics for categorical variables.*

	Belgium		Portugal		France		Spain		Netherlands		Italy	
Variable	Frequency	%	Frequency	%	Frequency	%	Frequency	%	Frequency	%	Frequency	%
Maturity												
<=3y	59562	12.13	29757	26.58	128646	41.31	171318	28.06	10035	30.64	153349	33.79
3-5y	199884	40.71	31178	27.85	30518	9.80	111548	18.27	49	0.15	43490	9.58
5-10y	111630	22.74	45099	40.29	117419	37.70	223214	36.56	1224	3.74	158427	34.91
+10y	119895	24.42	5915	5.28	34854	11.19	104476	17.11	21441	65.47	98531	21.71
Business Type												
Individual	65280	13.30	8074	7.21	3555	1.14	294299	48.20	569	1.74	126042	27.77
Limited	393644	80.18	94006	83.97	252856	81.19	298529	48.89	6504	19.86	164490	36.25
Other	28634	5.83	7377	6.59	49883	16.02	8948	1.47	25666	78.37	75133	16.56
Partnership	2640	0.54	45	0.04	4692	1.51	2186	0.36	8	0.02	68106	15.01
Public Company	773	0.16	2447	2.19	451	0.14	6594	1.08	2	0.01	20026	4.41
Amortisation Type												
Bullet or Partial Bullet	1207	0.25	18033	16.11	992	0.32	1061	0.17	6292	19.21	437	0.10
French	417992	85.14	22947	20.50	61501	19.75	396742	64.98	3876	11.84	397347	87.56
Linear	67218	13.69	11495	10.27	224282	72.02	203106	33.27	6152	18.79	40845	9.00
Other	4554	0.93	28855	25.78	19934	6.40	8960	1.47	16429	50.17	15154	3.34
Revolving			30619	27.35	4728	1.52	687	0.11			14	0.00
NACE Industry												
A	19833	4.04	4187	3.74	153327	49.23	53860	8.82	10276	31.38	27582	6.08
B	251	0.05	256	0.23	222	0.07	1131	0.19	16	0.05	619	0.14
C	33683	6.86	20868	18.64	14976	4.81	72034	11.80	2678	8.18	83321	18.36
D	464	0.09	136	0.12	281	0.09	3631	0.59	58	0.18	1467	0.32
E	1455	0.30	557	0.50	652	0.21	1935	0.32	104	0.32	2354	0.52
F	72560	14.78	8431	7.53	20233	6.50	37355	6.12	1729	5.28	57001	12.56
G	89319	18.19	40142	35.86	28783	9.24	148234	24.28	5902	18.02	109017	24.02
H	17510	3.57	4146	3.70	7270	2.33	44636	7.31	1826	5.58	18678	4.12
I	21057	4.29	5819	5.20	11785	3.78	60449	9.90	1547	4.72	41731	9.20
J	12240	2.49	2353	2.10	2130	0.68	13250	2.17	374	1.14	8727	1.92
K	10769	2.19	1101	0.98	6520	2.09	3715	0.61	675	2.06	3399	0.75
L	25003	5.09	3153	2.82	22570	7.25	20550	3.37	3203	9.78	32805	7.23
M	59290	12.08	8531	7.62	12400	3.98	45801	7.50	1461	4.46	18166	4.00
N	73568	14.98	3008	2.69	15373	4.94	14667	2.40	716	2.19	11718	2.58
O	45	0.01	1232	1.10	19	0.01	733	0.12	14	0.04	6770	1.49
P	1515	0.31	1207	1.08	1429	0.46	8247	1.35	135	0.41	1781	0.39
Q	36114	7.36	3784	3.38	7982	2.56	18288	3.00	1049	3.20	6613	1.46
R	5581	1.14	975	0.87	1417	0.45	10240	1.68	498	1.52	4506	0.99
S	10500	2.14	2061	1.84	4051	1.30	49949	8.18	488	1.49	16995	3.75
T	214	0.04	1	0.00	6	0.00	345	0.06			546	0.12
U			1	0.00	11	0.00	1506	0.25			1	0.00

Table B.3: *Regional flood aids since 2010.*

Country	Region	Year	Type	Aid
Italy	Veneto	2010	EU (EUSF)	16.9 million
Italy	Liguria &Tuscany	2011	EU (EUSF)	18.1 million
Italy	Sardinia	2013	EU (EUSF)	16.3 million
Italy	Multiple	2014	EU (EUSF)	56.0 million
Italy	Multiple	2018	EU (EUSF)	277.2 million
Italy	Marche	2022	EU (EUSF)	20.94 million
Italy	Emilia-Romagna	2023	EU (EUSF)	378.8 million
Italy	Tuscany	2023	EU (EUSF)	67.8 million
Italy	Emilia-Romagna & Tuscany	2023	Government	1 billion
Netherlands	Limburg	2021	EU (EUSF)	4.7 million
Netherlands	National	2011-	Delta Programme	NA
Belgium	Wallonia	2021	EU (EUSF)	87.7 million
Belgium	Wallonia	2021	Government	2 billion
Portugal	Madeira	2010	EU (EUSF)	31.3 million

Note: EUSF aid data is collected form Beneficiary States of the EU Solidarity Fund Interventions.Italian government support: Italy allocates €1b for flood recovery and prevention in Emilia-Romagna, Tuscany, and Marche. Belgian government support:The Case of the Summer2021 Floods in Wallonia. The Delta program details: Delta Programme 2011-2024.

Table B.4: *Coefficient estimates for the discrete-time survival model except Flood_Indicator.*

	Belgium	Portugal	France	Spain	Netherlands	Italy
Duration	-0.137 ***	0.063	-0.269 ***	0.381 ***	0.318	-0.076 ***
	(0.019)	(0.046)	(0.046)	(0.018)	(0.220)	(0.026)
Duration (square)	0.001 ***	-0.001 **	0.002 ***	-0.002 ***	-0.002	0.000 **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Duration (log)	0.344 ***	0.606 ***	-0.412 **	1.878 ***	3.454	-0.215
	(0.111)	(0.142)	(0.178)	(0.126)	(2.233)	(0.179)
Duration (log square)	0.103 *	-0.216 **	0.561 ***	-1.180 ***	-1.478	0.248 ***
	(0.062)	(0.110)	(0.121)	(0.061)	(0.919)	(0.088)
Original Loan Balance (log)	0.394 ***	-0.358 ***	-0.077 ***	-0.254 ***	0.178	-0.230 ***
	(0.027)	(0.034)	(0.020)	(0.012)	(0.164)	(0.013)
Maturity (+10y)						
<=3y	0.587 ***	-0.088	-0.137	0.275 ***	-13.402	0.001
	(0.051)	(0.103)	(0.107)	(0.029)	(499.172)	(0.043)
3-5y	0.192 ***	-0.452 ***	0.068	0.075 ***	-0.041	-0.212 ***
	(0.036)	(0.092)	(0.089)	(0.025)	(0.244)	(0.026)
5-10y	0.141 ***	-0.281 ***	0.160 **	0.026	-0.172	-0.184 ***
	(0.029)	(0.082)	(0.073)	(0.023)	(0.140)	(0.022)
Business Type (Individual)						
Limited	0.210 ***	-0.042	0.037	0.468 ***	0.000	0.370 ***
	(0.030)	(0.060)	(0.096)	(0.011)	(0.198)	(0.020)
Other	0.209 ***	-0.380 ***	0.337 ***	0.087 *	-0.598 *	0.185 ***
	(0.040)	(0.104)	(0.103)	(0.045)	(0.307)	(0.034)
Partnership	-0.060	0.660	-0.723 ***	0.197 **	-12.721	-0.031
	(0.123)	(0.456)	(0.204)	(0.100)	(651.889)	(0.025)
Public Company	-2.492 **	0.732 ***	0.977 ***	0.137 ***	-11.476	0.495 ***
	(1.001)	(0.106)	(0.370)	(0.047)	(1376.194)	(0.033)
Amortization Type (Bullet or Partial Bullet)						
French	0.087	0.357 ***	1.447 **	-0.159	0.275	-1.097 ***
	(0.210)	(0.068)	(0.716)	(0.148)	(0.415)	(0.165)
Linear	-0.012	-0.080	-2.863 ***	-0.290 *	-0.035	-0.930 ***
	(0.211)	(0.097)	(0.731)	(0.148)	(0.200)	(0.166)
Other	0.209 ***	-0.380 ***	0.337 ***	0.087 *	-0.598 *	0.185 ***
	(0.040)	(0.104)	(0.103)	(0.045)	(0.307)	(0.034)
Revolving		-0.043	2.456 ***	1.345 ***		-0.522
		(0.088)	(0.714)	(0.200)		(0.413)
NACE Industry (A)						
B	-1.421 **	0.643 *	2.405 ***	0.130	-13.962	0.210
	(0.579)	(0.328)	(0.824)	(0.119)	(792.661)	(0.199)
C	-0.409 ***	-0.122	2.973 ***	0.174 ***	-0.489 **	0.077 *

	(0.047)	(0.101)	(0.432)	(0.024)	(0.206)	(0.040)
D	-0.639 **	-11.897	-8.271	0.067	-13.476	-0.372 **
	(0.304)	(105.220)	(106.562)	(0.070)	(658.112)	(0.158)
E	-0.644 ***	-1.999 ***	2.934 ***	0.166 *	-13.393	-0.536 ***
	(0.178)	(0.713)	(0.512)	(0.088)	(319.848)	(0.166)
F	-0.295 ***	0.026	3.092 ***	0.273 ***	-0.133	0.557 ***
	(0.041)	(0.109)	(0.432)	(0.026)	(0.229)	(0.038)
G	-0.494 ***	-0.112	3.069 ***	0.270 ***	-0.821 ***	0.314 ***
	(0.040)	(0.095)	(0.431)	(0.022)	(0.178)	(0.037)
H	-0.217 ***	0.194	2.828 ***	0.094 ***	-0.747 ***	-0.017
	(0.055)	(0.119)	(0.436)	(0.027)	(0.225)	(0.057)
I	-0.094 **	-0.044	3.378 ***	0.590 ***	-1.059 ***	0.448 ***
	(0.047)	(0.109)	(0.432)	(0.023)	(0.281)	(0.040)
J	-0.772 ***	-0.095	3.057 ***	0.334 ***	-2.658 ***	0.203 ***
	(0.072)	(0.157)	(0.445)	(0.035)	(1.012)	(0.066)
K	-0.780 ***	-0.287	2.202 ***	0.205 ***	-1.087 ***	0.066
	(0.072)	(0.194)	(0.440)	(0.062)	(0.297)	(0.093)
L	-0.560 ***	-0.359 **	2.408 ***	0.195 ***	-1.218 ***	0.167 ***
	(0.050)	(0.147)	(0.436)	(0.032)	(0.249)	(0.043)
M	-0.811 ***	-0.401 ***	3.049 ***	0.105 ***	-0.738 ***	0.076
	(0.046)	(0.117)	(0.434)	(0.026)	(0.236)	(0.053)
N	-0.439 ***	0.189	2.708 ***	0.234 ***	-1.128 ***	0.303 ***
	(0.050)	(0.129)	(0.437)	(0.035)	(0.404)	(0.058)
O	-8.584	-11.082	3.516 ***	-0.846 *	-13.002	-8.480
	(42.767)	(92.116)	(1.088)	(0.500)	(710.189)	(48.460)
P	-0.611 ***	-0.066	3.028 ***	0.053	-1.387	0.095
	(0.173)	(0.177)	(0.463)	(0.045)	(1.009)	(0.136)
Q	-1.546 ***	-0.910 ***	2.062 ***	-0.254 ***	-1.180 ***	-0.299 ***
	(0.063)	(0.162)	(0.444)	(0.039)	(0.296)	(0.086)
R	-0.254 ***	-0.082	2.989 ***	0.246 ***	-0.473	0.320 ***
	(0.074)	(0.192)	(0.462)	(0.039)	(0.345)	(0.076)
S	-0.544 ***	-0.393 ***	2.976 ***	0.291 ***	-1.926 ***	-0.017
	(0.064)	(0.151)	(0.440)	(0.025)	(0.595)	(0.055)
T	-0.140	6.766	-5.636	0.302 *		0.049
	(0.578)	(416.819)	(887.497)	(0.163)		(0.270)
U		-12.079	-9.620	-0.257 **		-8.001
		(1327.284)	(621.521)	(0.111)		(74.653)
Other	0.209 ***	-0.380 ***	0.337 ***	0.087 *	-0.598 *	0.185 ***
	(0.040)	(0.104)	(0.103)	(0.045)	(0.307)	(0.034)
Current Loan Balance (log)	-0.227 ***	0.303 ***	-0.045 **	0.152 ***	-0.107	0.168 ***
	(0.023)	(0.030)	(0.019)	(0.011)	(0.144)	(0.010)
Current Interest Rate	0.498 ***	0.180 ***	0.302 ***	0.140 ***	0.271 ***	0.204 ***
	(0.009)	(0.007)	(0.018)	(0.002)	(0.050)	(0.005)

CPI	-0.078 ***	0.084 *	0.200 ***	-0.029 ***	0.443 ***	0.220 ***
	(0.011)	(0.043)	(0.044)	(0.004)	(0.089)	(0.010)
GDP	0.019 ***	-0.035 ***	-0.001	0.007 ***	0.140 ***	0.008 ***
	(0.003)	(0.007)	(0.005)	(0.001)	(0.054)	(0.002)
HUR	-0.216 ***	0.022 ***	0.081 *	-0.019 ***	0.767 ***	0.379 ***
	(0.009)	(0.008)	(0.046)	(0.001)	(0.120)	(0.007)
Intercept	-7.453 ***	-5.745 ***	-8.755 ***	-5.763 ***	-15.821 ***	-8.627 ***
	(0.275)	(0.341)	(0.980)	(0.201)	(2.621)	(0.272)
Number of Obs.	4852035	474366	1079110	4569405	104648	2655423
logLik	-89009.135	-17708.408	-14081.871	-261006.326	-2420.028	-102796.010
AIC	178100.271	35504.815	28251.743	522100.652	4920.055	205680.019

Note: the original loan balance is a time-invariant variable, while the current loan balance and current interest rate are time-varying variables. Time-varying variables as well as macroeconomic variables (CPI, GDP and HUR) are included with a year (4 quarters) lag. The reference category is given in parentheses after the variable name. Standard errors are reported in parentheses after the coefficient estimates. Significance: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table B.5: *In-sample and out-of-time evaluation metrics across countries.*

	In-sample				Out-of-time			
Country	AUPRC	H-measure	BS	LLS	AUPRC	H-measure	BS	LLS
Belgium	0.006	0.018	0.003	0.018	0.005	0.015	0.002	0.015
France	0.054	0.435	0.003	0.013	0.016	0.047	0.010	0.096
Italy	0.015	0.076	0.007	0.039	0.008	0.017	0.005	0.030
Netherlands	0.010	0.059	0.004	0.023	0.002	0.003	0.002	0.017
Portugal	0.022	0.147	0.007	0.037	0.011	0.131	0.002	0.016
Spain	0.020	0.068	0.010	0.057	0.015	0.034	0.011	0.059

Table B.6: *Some descriptive statistics of the default probability distribution for various scenarios: Spain.*

		Predicted PD (%)				
Year	Scenario	Mean	Median	90th percentile	95th percentile	99th percentile
1	Baseline	4.02	3.55	6.53	7.93	12.81
	1	4.02	3.55	6.53	7.93	12.81
	2	4.03	3.56	6.54	7.94	12.83
	3	4.09	3.61	6.65	8.08	12.96
	4	4.09	3.61	6.65	8.08	12.96
	5	4.16	3.67	6.79	8.23	13.18
	6	4.22	3.72	6.89	8.35	13.40
	7	4.26	3.76	6.95	8.42	13.49
5	Baseline	19.97	18.58	31.50	36.90	53.50
	1	20.03	18.63	31.62	37.00	53.58
	2	20.09	18.69	31.71	37.09	53.69
	3	20.14	18.74	31.79	37.18	53.83
	4	20.16	18.77	31.82	37.22	53.86
	5	20.17	18.77	31.82	37.22	53.88
	6	20.19	18.79	31.84	37.25	53.91
	7	20.19	18.79	31.85	37.25	53.94
15	Baseline	46.41	47.15	71.60	78.03	92.13
	1	46.49	47.23	71.71	78.11	92.18
	2	46.51	47.26	71.74	78.14	92.20
	3	46.54	47.28	71.75	78.17	92.21
	4	46.54	47.28	71.74	78.16	92.21
	5	46.55	47.29	71.75	78.17	92.22
	6	46.55	47.29	71.75	78.16	92.21
	7	46.55	47.29	71.76	78.17	92.22
25	Baseline	47.78	48.71	73.88	80.21	93.35
	1	47.86	48.79	73.98	80.28	93.40
	2	47.88	48.82	73.99	80.32	93.41
	3	47.90	48.84	74.01	80.33	93.41
	4	47.90	48.84	74.01	80.32	93.42
	5	47.91	48.84	74.02	80.33	93.42
	6	47.92	48.84	74.01	80.33	93.42
	7	47.92	48.85	74.02	80.33	93.42

Table B.7: *Some descriptive statistics of the default probability distribution for various scenarios: France.*

		Predicted PD (%)				
Year	Scenario	Mean	Median	90th percentile	95th percentile	99th percentile
1	Baseline	2.02	0.02	9.72	13.83	19.48
	1	2.02	0.02	9.72	13.83	19.48
	2	2.02	0.02	9.72	13.83	19.48
	3	2.03	0.02	9.76	13.88	19.58
	4	2.05	0.02	9.85	14.02	19.81
	5	2.10	0.02	10.00	14.30	20.26
	6	2.17	0.02	10.27	14.77	21.00
	7	2.20	0.02	10.45	15.01	21.32
5	Baseline	7.47	0.08	37.78	48.74	63.07
	1	7.48	0.08	37.85	48.83	63.17
	2	7.51	0.08	38.05	49.05	63.42
	3	7.55	0.08	38.25	49.29	63.68
	4	7.57	0.08	38.33	49.42	63.83
	5	7.60	0.08	38.45	49.62	64.08
	6	7.64	0.08	38.68	49.85	64.29
	7	7.66	0.09	38.82	50.01	64.46
15	Baseline	21.25	0.45	94.84	99.68	100.00
	1	21.26	0.45	94.86	99.68	100.00
	2	21.27	0.45	94.90	99.68	100.00
	3	21.28	0.45	94.92	99.69	100.00
	4	21.29	0.45	94.94	99.69	100.00
	5	21.29	0.45	94.97	99.69	100.00
	6	21.28	0.45	94.94	99.69	100.00
	7	21.29	0.45	94.97	99.69	100.00
25	Baseline	94.78	100.00	100.00	100.00	100.00
	1	94.78	100.00	100.00	100.00	100.00
	2	94.78	100.00	100.00	100.00	100.00
	3	94.80	100.00	100.00	100.00	100.00
	4	94.78	100.00	100.00	100.00	100.00
	5	94.78	100.00	100.00	100.00	100.00
	6	94.78	100.00	100.00	100.00	100.00
	7	94.78	100.00	100.00	100.00	100.00