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## Working Paper

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

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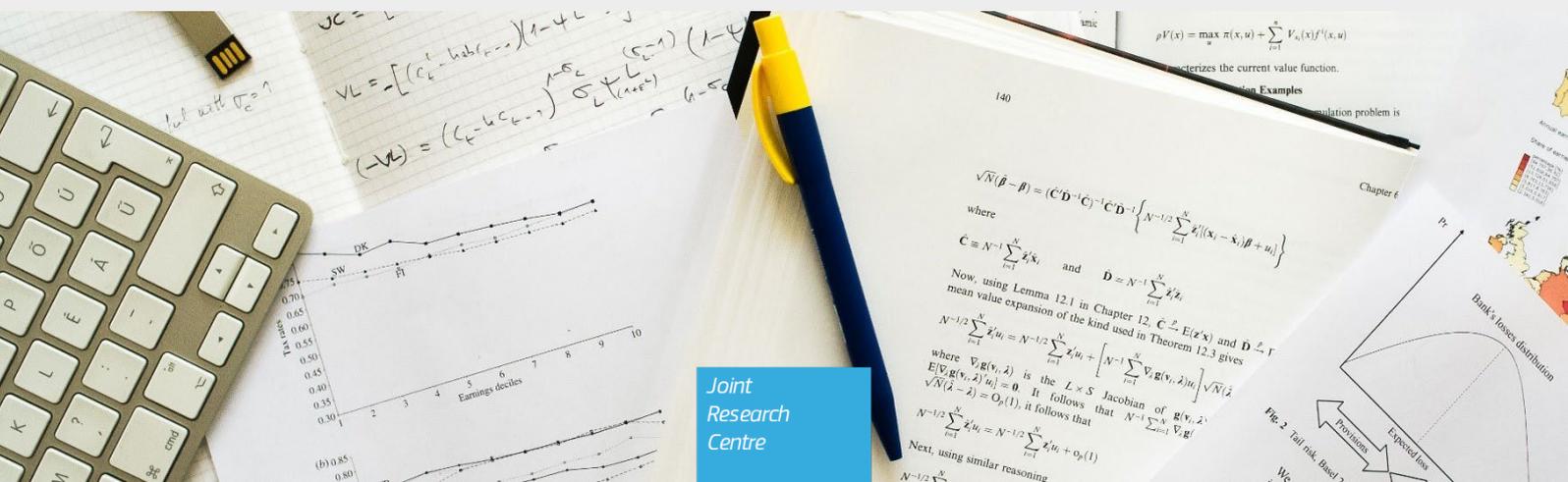


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# A climate stress testing exercise on loans to European small and medium enterprises

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## *Abstract:*

This paper assesses the impact of floods on credit to European small and medium-sized enterprises (SMEs) using a discrete-time survival model. We find a statistically significant relationship between the default probability of loans to SMEs and floods occurring in the region where the firm is located. We propose a micro-level stress testing exercise to assess the performance of small business loans under different climate scenarios. This approach enables the identification of European regions that exhibit heightened vulnerability under adverse climate scenarios. It also allows financial institutions and regulators to quantify the increase in default probability for each loan.

*Keywords:* climate change, loan default, natural disasters, risk modelling, stress testing

*JEL codes:* C55, G21, Q51, Q54

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.

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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 (Basel Committee on Banking Supervision, 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).

Climate stress testing is a widely used approach for measuring the effects of climate change on financial stability (Battiston et al., 2017; Acharya et al., 2023; Battiston et al., 2023). Most of the literature on climate stress testing is primarily focused on financial institutions or the corporate sector (ECB/ESRB, 2023; de Bandt et al., 2023; Alogoskoufis et al., 2021). However, small firms are significantly more vulnerable to the negative impacts of climate change, such as extreme weather events and climate-related natural hazards, than larger corporations (Benincasa et al., 2024; Skouloudis et al., 2020), given the localised nature of their operations (Fatica et al., 2024) and the limited possibility of sharing risks through capital market access. In particular, flooding has been found especially disruptive to the performance of European firms (Fatica et al., 2022). This paper aims to fill the gap in the literature by presenting a stress testing exercise for physical climate risk, specifically flood risk, on loans to European small and medium-sized enterprises (SMEs).

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. We build these models on a comprehensive dataset provided by the European DataWarehouse, which contains 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 15 basis points in Spain and 24 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.

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., 2021). Research on physical risks posed by natural disasters, such as floods and hurricanes, has mainly focused on their impacts on the mortgage market (Kousky et al., 2020; Rossi, 2021; Calabrese et al., 2024; Zanin et al., 2024). This focus stems from the significant damage that natural disasters can cause to residential real estate, which directly lowers property values, weakens lenders' capital adequacy, and often leads to borrowers' financial distress (Brei et al., 2019; Wong and Ho, 2023). For example, using a portfolio of mortgages in Florida, Calabrese et al. (2024) found that the impact of tropical cyclones on default more than doubles in magnitude when moving from a category two hurricane to a category three or more hurricane. Ho et al. (2023) conducted an empirical case study on a Canadian wildfire disaster, and found that it significantly increased mortgage arrears in the areas most severely affected, with both economic and statistical significance.

In contrast to the extensive research on mortgages, relatively little attention has been given to the impact of physical climate risks on credit risks for firms. 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. The impact is amplified by high credit risk or low confidence among firm managers, highlighting credit risk and expectations as key channels of influence. Lu et al. (2024) analysed the impact of climate change on credit spreads among listed companies issuing corporate bonds. Findings reveal that higher climate risk leads to wider credit spreads, reflecting market awareness of potential harm. Mechanism tests indicate this effect is driven by increased bankruptcy risk, profit volatility, and negative investor sentiment. Aguilar-Gomez et al. (2024) used loans extended by commercial banks to private firms in Mexico and found that the extreme heat increases credit delinquency rates for SMEs. 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.

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., 2023). 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; Federal Reserve Board, 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., 2023; Zanin et al., 2024; 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 European Central Bank (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., 2023; 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,

**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	3,1881	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

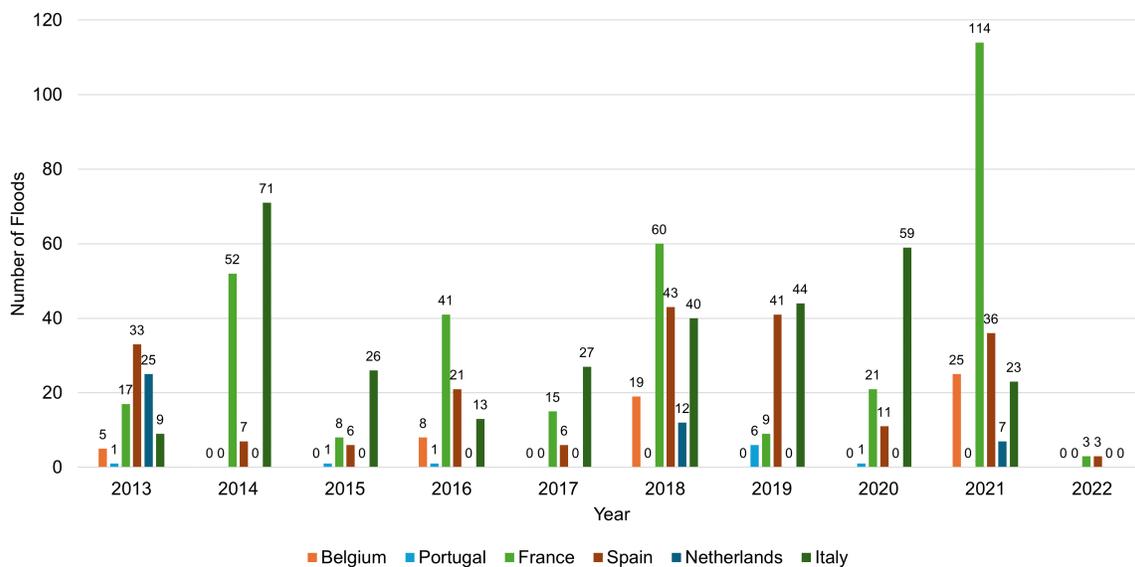
we have information on borrowers' location at the NUTS3 level, that is, local units corresponding approximately to US counties. Loan characteristics encompass both static elements (origination date, maturity date, original loan balance, and amortisation type) and dynamic elements (current loan balance 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 Basel Committee on Banking Supervision (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 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)<sup>1</sup>. 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 (European Central Bank and European Systemic Risk Board, 2021). The data aim is to inform further European financial supervisors’ analysis of climate risks and the development of relevant stress testing methodologies.



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

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. 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 at the NUTS3 level during a specified observation period (Yes = 1, No = 0). We define the observation period as five quarters, encompassing the current

<sup>1</sup>More details are available at <https://drmkc.jrc.ec.europa.eu/risk-data-hub/#/>.

quarter and the four preceding quarters. For example, for the observation date 2020Q1, *Flood.Indicator* is set to 1 if a flood occurred at any time during the current quarter (2020Q1) or any of the previous four quarters (2019Q4, 2019Q3, 2019Q2, and 2019Q1). We then merge the *Flood.Indicator* with the loan-level dataset described in the previous section, aligning by dates and NUTS3 levels 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 aligns with the intrinsic nature of credit risk analysis, where account records are typically observed in a fixed frequency, thereby rendering events fundamentally discrete. In this study, we have records of SME loans updated quarterly. Formally, let the random variable  $T$  be the number of quarters since a loan originated (duration time), and  $T$  takes values  $t_j$  ( $j = 1, \dots, J_i$ ) at distinct  $t_1 < t_2 < \dots < t_{J_i}$  for each loan  $i$  ( $i = 1, \dots, N$ ). The term  $Y_{ij}$  indicates whether loan  $i$  defaults at time  $t_j$  (0 = non-default or censored; 1 = default). In line with the Basel Accords, a loan is classified as default if it remains overdue for over 90 consecutive days. 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 been observed in the current quarter and the past four quarters in the NUTS3 region of the borrower.  $\mathbf{b}$  represents a vector of time-varying variables collected across the lifetime of the loan (e.g., current interest rate),  $\mathbf{c}$  represents a vector of time-invariant variables obtained at the time of loan origination (e.g., original loan balance), and  $\mathbf{w}$  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, we use  $h_{ij} = Pr(Y_{ij} = 1 \mid Y_{is} = 0 \text{ for all } s < j)$  to represent the conditional probability of loan  $i$  defaulting at time  $t_j$ . Assuming a logit link function, we can add all variables as follows:

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

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  $\alpha$  is an intercept, and  $\boldsymbol{\beta}_0$ ,  $\beta_1$ ,  $\boldsymbol{\beta}_2$ ,  $\boldsymbol{\beta}_3$ , 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:

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

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

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

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:

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

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<sup>th</sup>, 80<sup>th</sup>, 70<sup>th</sup>, 60<sup>th</sup>, 50<sup>th</sup>, 40<sup>th</sup>, and 30<sup>th</sup> 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<sup>th</sup> percentile, represents the least stressed scenario, where only the NUTS3 regions with flood risk scores above the 90<sup>th</sup> percentile of the pooled score distribution are associated with flood events. In contrast, Scenario 7, set at the 30<sup>th</sup> percentile, represents the most stressed scenario, where the NUTS3 regions are considered flooded when their scores are above the 30<sup>th</sup> percentile of the pooled score distribution.

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<sup>th</sup> to 30<sup>th</sup> 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.

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

**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

projected to occur in a specific quarter<sup>2</sup> and NUTS3 region, and then transfer it to the *Flood\_Indicator* by considering the observation period, as explained in Section 3.2.

Finally, we obtain seven *Flood\_Indicator* for seven stress scenarios for each country. To construct datasets under different stress scenarios, we use the information from the last quarter of each loan, excluding defaulted ones, and merge them with the *Flood\_Indicator* for each scenario based on the quarter and NUTS3 region.

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

## 5 Empirical results

### 5.1 Flood risk 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.3.

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 the one year window before the observation date. Specifically, the odds of default after experiencing at least one flood event are 1.18 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. Specifically, by pooling observations across Europe, the authors find that loans to borrowers affected by floods show a 1.2 times higher hazard ratio within the first year following the disaster, compared to those unaffected by flood damage.

**Table 3:** *Coefficient estimates for Flood\_Indicator in the survival model*

Country	Estimates	Std. Error	Flood_Indicator (=1, %)	Loan-quarter observation (Nr.)
Belgium	0.0146	0.0337	8.15	4,852,035
France	0.1666 **	0.0533	37.39	1,079,110
Italy	-0.1537 ***	0.0155	47.60	2,655,423
Netherlands	-0.1431	0.1243	19.57	104,648
Portugal	0.1546	0.1125	6.02	474,366
Spain	0.1136 ***	0.0131	14.46	4,569,405

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 Belgium, Portugal, or the Netherlands. From column 4 in Table 3, we find that Belgium and Portugal actually have the least percentages where the flood indicator is equal to 1. The rare flood events in Belgium and Portugal in our data may hint at insignificant findings. We find that Italian SMEs 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 extended 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 EUSF, making it 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. 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.

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 4, 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 significant 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 4:** *Coefficient estimates for Flood\_Indicator in the survival model with spatial random effects (NUTS2)*

Country	Estimates	Std. Error	Significance
Belgium	0.011	0.035	
France	0.186	0.056	***
Italy	-0.122	0.016	***
Netherlands	-0.143	0.124	
Portugal	0.156	0.112	
Spain	0.158	0.013	***

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

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.4 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 (0.064) and H-measure (0.547), 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, while LLS are consistent with good probabilistic forecasts, particularly in France (0.095) and Spain (0.059).

## 5.2 A 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 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 5 and 6 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. The increase is particularly dramatic for French SMEs, with an average default probability of 2% in one year, rising to 71% over the next 25 years, representing more than a thirty-five-fold increase. Spain shows a smaller default risk profile than France, with nearly half of the loans expected to default over the next 25 years.

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. The differences in mean default probability between the most and least stressed scenarios for France and Spain in the next year are 24.1 basis points and 14.9 basis points, respectively. This 10 basis points gap is directly linked to the magnitude of the coefficient estimates of the *Flood\_Indicator* variable from the survival model. For example, in Spain, the estimated coefficient from Table 3 is 0.11, while the estimated coefficient in France is 0.17, stressing that the associated variable in Spain implies a smaller increase in the predicted PD than in France.

**Table 5:** *Scenarios of mean default probability for various scenarios in France.*

		Projection year						
		1	2	5	10	15	20	25
Scenario	Base model	1.94	3.53	6.70	10.09	15.48	25.72	71.29
	1	0.00	0.00	1.79	3.63	1.58	2.06	1.46
	2	0.00	1.63	6.00	6.80	3.48	1.32	0.18
	3	0.97	3.51	10.93	9.06	4.62	2.52	4.81
	4	2.99	7.70	13.28	10.75	6.23	1.70	0.10
	5	6.50	14.41	17.03	13.75	6.54	1.14	0.18
	6	11.23	21.23	22.69	16.35	6.14	0.58	0.02
	7	14.88	28.29	26.62	17.30	7.26	1.38	0.06

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

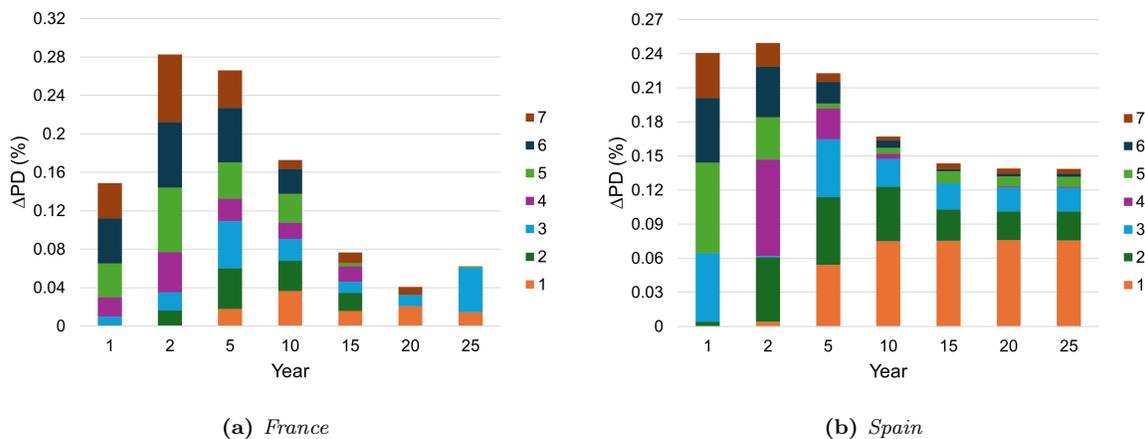
		Projection year						
		1	2	5	10	15	20	25
Scenario	Base model	4.01	7.88	19.76	37.61	45.58	46.91	46.97
	1	0.00	0.42	5.43	7.51	7.53	7.61	7.59
	2	0.42	6.20	11.39	12.29	10.30	10.13	10.11
	3	6.43	6.10	16.48	14.74	12.60	12.24	12.22
	4	6.43	14.69	19.20	15.20	12.60	12.32	12.30
	5	14.40	18.43	19.64	15.73	13.67	13.21	13.18
	6	20.12	22.87	21.54	16.38	13.85	13.46	13.44
	7	24.09	24.97	22.28	16.72	14.36	13.90	13.87

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

Figure 2 shows the percentage change in the mean default probability between every two adjacent scenarios. 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<sup>th</sup> percentile threshold; Legend 2 in the plot represents the percentage increase in the average default probability from Scenario 1 with a 90<sup>th</sup> percentile threshold to Scenario 2 with an 80<sup>th</sup> threshold. Initially, there are no significant differences in the mean default probability between the less stressed scenarios. However, differences begin to

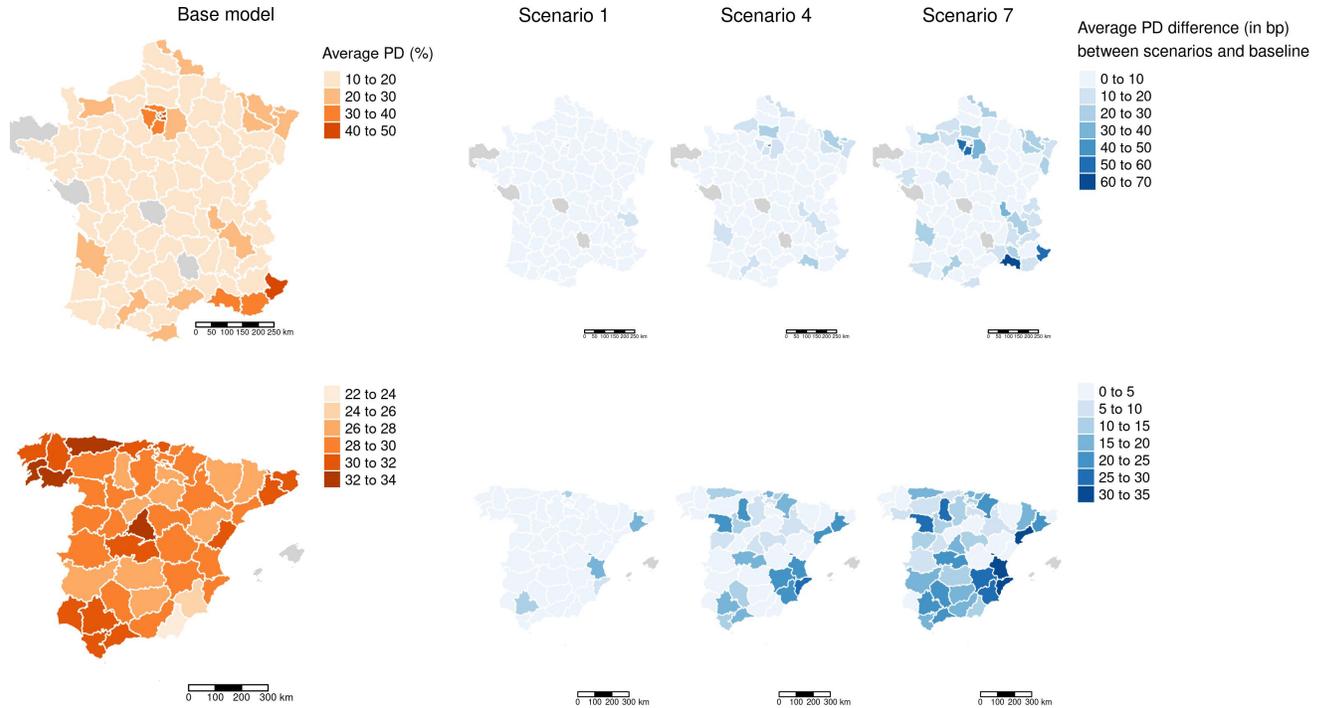
appear in the second year in Spain, and the fourth year in France. The total height of the stacked bar represents the change in the mean default probability between the most stressed scenario (Scenario 7) and the baseline model, highlighting the country-specific differences. In Spain, the difference tends to decrease, declining from 24 basis points to 14 basis points. In France, the trend is not monotonic, with the difference peaking at 28 basis points in the second year. Additional descriptive statistics of the default probability distribution for various scenarios are provided in the Appendix.



**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. In the first column, we plot the maps of the predicted probability of default of the base model averaged across the projection years. 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).

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 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



**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.*

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.

## 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 negative 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 15 and 24 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 SMEs. More broadly, our findings support the development of a climate-resilient financial system that can better absorb the growing risks posed by climate change.

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# 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)<sup>3</sup>. 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 cleansing 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.

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<sup>3</sup>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
	<b><i>Loan characteristics</i></b>					
Beigium	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
	Original Loan Balance (log)	8.52	14.29	11.20	11.12	1.26
	<b><i>Macroeconomic variables</i></b>					
	CPI (%)	-0.39	6.36	1.41	1.35	1.05
	GDP (%)	-12.73	15.50	1.24	1.59	3.79
	<b><i>Macroeconomic variables</i></b>					
	HUR (%)	5.10	8.87	7.15	7.23	1.34
	<b><i>Loan characteristics</i></b>					
Portugal	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
	Original Loan Balance (log)	8.52	14.68	10.87	10.46	1.22
	<b><i>Macroeconomic variables</i></b>					
	CPI (%)	-0.42	2.41	0.62	0.54	0.63
	GDP (%)	-17.78	17.20	1.18	1.88	3.25
	<b><i>Macroeconomic variables</i></b>					
	HUR (%)	6.13	18.10	11.75	12.30	3.26
	<b><i>Loan characteristics</i></b>					
France	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
	Original Loan Balance (log)	3.76	13.69	10.31	10.24	1.13
	<b><i>Macroeconomic variables</i></b>					
	CPI (%)	-0.24	3.33	1.49	1.30	0.71
	GDP (%)	-18.01	17.82	0.13	1.96	6.39
	<b><i>Macroeconomic variables</i></b>					
	HUR (%)	7.33	10.47	8.75	8.80	0.77
	<b><i>Loan characteristics</i></b>					
Spain	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
	Original Loan Balance (log)	7.67	13.92	10.60	10.55	1.31
	<b><i>Macroeconomic variables</i></b>					
	CPI (%)	-1.14	5.82	0.78	0.51	1.35
	GDP (%)	-21.67	19.44	0.94	2.21	5.48
	<b><i>Macroeconomic variables</i></b>					
	HUR (%)	13.40	26.33	19.24	18.20	4.47
	<b><i>Loan characteristics</i></b>					
Netherlands	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
	Original Loan Balance (log)	9.46	15.82	13.03	13.07	1.22
	<b><i>Macroeconomic variables</i></b>					
	CPI (%)	-0.47	5.35	1.17	0.44	1.54
	GDP (%)	0.96	11.65	4.30	2.30	3.71
	<b><i>Macroeconomic variables</i></b>					
	HUR (%)	3.80	8.67	6.55	7.43	1.80
	<b><i>Loan characteristics</i></b>					
Italy	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
	Original Loan Balance (log)	8.99	14.60	11.31	11.16	1.23
	<b><i>Macroeconomic variables</i></b>					
	CPI (%)	-0.39	3.74	0.72	0.40	0.87
	GDP (%)	-17.55	18.07	-0.58	0.34	6.57
	<b><i>Macroeconomic variables</i></b>					
	HUR (%)	8.57	12.93	10.64	10.37	1.35

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

Variable	Belgium		Portugal		France		Spain		Netherlands		Italy	
	Frequency	%	Frequency	%	Frequency	%	Frequency	%	Frequency	%	Frequency	%
<b>Maturity</b>												
<=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
<b>Business Type</b>												
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
<b>Amortisation Type</b>												
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
<b>NACE Industry</b>												
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		1	0.00

**Table B.3:** *Coefficient estimates for the discrete-time survival model except Flood\_Indicator*

	Belgium	Portugal	France	Spain	Netherlands	Italy
Duration	-0.137 *** (-0.019)	0.062 (-0.046)	-0.268 *** (-0.046)	0.381 *** (-0.018)	0.32 (-0.22)	-0.080 ** (-0.026)
Duration (square)	0.001 *** (0.0003)	-0.001 * (-0.0002)	0.002 *** (0.0003)	-0.002 *** (-0.001)	-0.002 (-0.001)	0.0001 * (0.0002)
Duration (log)	0.344 ** (-0.111)	0.595 *** (-0.142)	-0.406 * (-0.178)	1.878 *** (-0.126)	3.441 (-2.228)	-0.232 (-0.178)
Duration (log square)	0.102 (-0.062)	-0.212 (-0.109)	0.558 *** (-0.121)	-1.180 *** (-0.061)	-1.48 (-0.917)	0.259 ** (-0.088)
Original Loan Balance (log)	0.394 *** (-0.027)	-0.359 *** (-0.034)	-0.079 *** (-0.02)	-0.254 *** (-0.012)	0.178 (-0.164)	-0.228 *** (-0.013)
<i>Maturity (+10y)</i>						
<=3y	0.588 *** (-0.051)	-0.09 (-0.103)	-0.134 (-0.107)	0.275 *** (-0.029)	-13.401 (-498.81)	0.004 (-0.043)
3-5y	0.193 *** (-0.036)	-0.450 *** (-0.092)	0.069 (-0.089)	0.075 ** (-0.025)	-0.043 (-0.244)	-0.210 *** (-0.026)
5-10y	0.141 *** (-0.029)	-0.279 *** (-0.082)	0.162 * (-0.073)	0.026 (-0.023)	-0.175 (-0.14)	-0.181 *** (-0.022)
<i>Business Type (Individual)</i>						
Limited	0.211 *** (-0.03)	-0.045 (-0.06)	0.037 (-0.096)	0.468 *** (-0.011)	-0.002 (-0.198)	0.372 *** (-0.02)
Other	0.209 *** (-0.04)	-0.384 *** (-0.104)	0.331 ** (-0.103)	0.087 (-0.045)	-0.599 (-0.306)	0.195 *** (-0.034)
Partnership	-0.061 (-0.123)	0.634 (-0.456)	-0.733 *** (-0.204)	0.197 * (-0.1)	-12.735 (-651.292)	-0.027 (-0.025)
Public Company	-2.494 * (-1.001)	0.739 *** (-0.106)	0.975 ** (-0.37)	0.137 ** (-0.047)	-11.446 (-1377.576)	0.477 *** (-0.033)
<i>Amortization Type (Bullet or Partial Bullet)</i>						
French	0.085 (-0.21)	0.366 *** (-0.068)	1.477 * (-0.716)	-0.159 (-0.148)	0.28 (-0.415)	-1.092 *** (-0.165)
Linear	-0.014 (-0.211)	-0.072 (-0.097)	-2.870 *** (-0.731)	-0.29 (-0.148)	-0.045 (-0.2)	-0.927 *** (-0.166)
Other	0.345 (-0.34)	-0.610 *** (-0.08)	-0.315 (-0.72)	0.431 ** (-0.157)	0.473 (-0.346)	-1.055 *** (-0.173)
Revolving		-0.038 (-0.088)	2.455 *** (-0.714)	1.345 *** (-0.2)		-0.512 (-0.413)
<i>NACE Industry (A)</i>						
B	-1.422 * (-0.579)	0.646 * (-0.328)	2.378 ** (-0.825)	0.13 (-0.119)	-13.935 (-793.539)	0.204 (-0.199)
C	-0.407 *** (-0.047)	-0.121 (-0.101)	2.976 *** (-0.432)	0.174 *** (-0.024)	-0.494 * (-0.206)	0.076 (-0.04)

D	-0.637 *	-11.895	-8.274	0.067	-13.444	-0.372 *
	(-0.304)	(-105.213)	(-106.473)	(-0.07)	(-659.263)	(-0.158)
E	-0.643 ***	-2.001 **	2.925 ***	0.166	-13.395	-0.539 **
	(-0.178)	(-0.713)	(-0.512)	(-0.088)	(-320.007)	(-0.166)
F	-0.292 ***	0.026	3.093 ***	0.273 ***	-0.136	0.555 ***
	(-0.041)	(-0.109)	(-0.432)	(-0.026)	(-0.229)	(-0.038)
G	-0.492 ***	-0.112	3.071 ***	0.270 ***	-0.821 ***	0.312 ***
	(-0.04)	(-0.096)	(-0.431)	(-0.022)	(-0.178)	(-0.037)
H	-0.214 ***	0.192	2.825 ***	0.094 ***	-0.756 ***	-0.017
	(-0.055)	(-0.119)	(-0.436)	(-0.027)	(-0.225)	(-0.057)
I	-0.092 *	-0.044	3.382 ***	0.590 ***	-1.048 ***	0.445 ***
	(-0.047)	(-0.109)	(-0.432)	(-0.023)	(-0.281)	(-0.04)
J	-0.768 ***	-0.098	3.054 ***	0.334 ***	-2.650 **	0.203 **
	(-0.072)	(-0.157)	(-0.445)	(-0.035)	(-1.012)	(-0.066)
K	-0.777 ***	-0.288	2.210 ***	0.205 ***	-1.088 ***	0.068
	(-0.072)	(-0.194)	(-0.44)	(-0.062)	(-0.297)	(-0.093)
L	-0.557 ***	-0.362 *	2.408 ***	0.195 ***	-1.217 ***	0.167 ***
	(-0.05)	(-0.147)	(-0.436)	(-0.032)	(-0.249)	(-0.043)
M	-0.807 ***	-0.403 ***	3.048 ***	0.105 ***	-0.737 **	0.074
	(-0.046)	(-0.117)	(-0.434)	(-0.026)	(-0.236)	(-0.053)
N	-0.434 ***	0.187	2.708 ***	0.234 ***	-1.122 **	0.301 ***
	(-0.05)	(-0.129)	(-0.437)	(-0.035)	(-0.404)	(-0.058)
O	-8.579	-11.078	3.509 **	-0.846	-13.021	-8.473
	(-42.766)	(-92.157)	(-1.088)	(-0.5)	(-709.957)	(-48.423)
P	-0.608 ***	-0.067	3.027 ***	0.053	-1.389	0.094
	(-0.173)	(-0.177)	(-0.463)	(-0.045)	(-1.009)	(-0.136)
Q	-1.543 ***	-0.913 ***	2.065 ***	-0.254 ***	-1.182 ***	-0.302 ***
	(-0.063)	(-0.162)	(-0.444)	(-0.039)	(-0.295)	(-0.086)
R	-0.252 ***	-0.085	2.991 ***	0.246 ***	-0.469	0.319 ***
	(-0.074)	(-0.192)	(-0.462)	(-0.039)	(-0.344)	(-0.076)
S	-0.541 ***	-0.393 **	2.977 ***	0.291 ***	-1.928 **	-0.017
	(-0.064)	(-0.151)	(-0.44)	(-0.025)	(-0.595)	(-0.055)
T	-0.133	6.77	-5.676	0.302		0.025
	(-0.578)	(-416.819)	(-887.21)	(-0.163)		(-0.27)
U		-12.193	-9.633	-0.257 *		-7.982
		(-1332.133)	(-620.604)	(-0.111)		(-74.58)
Current Loan Balance (log)	-0.228 ***	0.304 ***	-0.046 *	0.152 ***	-0.107	0.168 ***
	(-0.023)	(-0.03)	(-0.019)	(-0.011)	(-0.145)	(-0.01)
Current Interest Rate	0.499 ***	0.182 ***	0.301 ***	0.140 ***	0.272 ***	0.203 ***
	(-0.009)	(-0.007)	(-0.018)	(-0.002)	(-0.05)	(-0.005)
CPI	-0.083 ***	0.120 **	0.168 ***	-0.029 ***	0.473 ***	0.214 ***
	(-0.011)	(-0.044)	(-0.043)	(-0.004)	(-0.091)	(-0.01)
GDP	0.019 ***	-0.034 ***	-0.005	0.007 ***	0.142 **	0.009 ***

	(-0.003)	(-0.007)	(-0.005)	(-0.001)	(-0.054)	(-0.002)
HUR	-0.216 ***	0.032 ***	0.09	-0.019 ***	0.814 ***	0.373 ***
	(-0.009)	(-0.009)	(-0.047)	(-0.001)	(-0.126)	(-0.007)
Intercept	-7.459 ***	-5.913 ***	-8.806 ***	-5.763 ***	-16.131 ***	-8.497 ***
	(-0.275)	(-0.346)	(-0.985)	(-0.201)	(-2.631)	(-0.272)
<i>Number of Obs.</i>	4852035	474366	1079110	4569405	104648	2655423
<i>logLik</i>	-89015.287	-17711.441	-14085.083	-261006.326	-2420.108	-102760.64
<i>AIC</i>	178112.575	35510.882	28258.166	522100.652	4920.216	205609.281

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.4:** *In-sample and out-of-time evaluation metrics across countries*

Country	In-sample				Out-of-time			
	AUPRC	H-measure	BS	LLS	AUPRC	H-measure	BS	LLS
Belgium	0.006	0.018	0.003	-17711	0.005	0.014	0.002	0.015
France	0.054	0.435	0.003	-2420	0.016	0.048	0.010	0.095
Italy	0.015	0.076	0.007	0.039	0.008	0.020	0.005	0.030
Netherlands	0.011	0.062	0.004	0.023	0.002	0.002	0.002	0.017
Portugal	0.022	0.147	0.007	0.037	0.010	0.124	0.002	0.016
Spain	0.020	0.068	0.010	0.057	0.015	0.034	0.011	0.059

**Table B.5:** *Some descriptive statistics of the default probability distribution for various scenarios: Belgium*

Year	Scenario	Predicted PD (%)				
		Mean	Median	90th percentile	95th percentile	99th percentile
1	Baseline	1.0421	0.8634	1.8634	2.3513	3.9335
	1	1.0421	0.8634	1.8634	2.3513	3.9335
	2	1.0421	0.8634	1.8634	2.3513	3.9335
	3	1.0421	0.8634	1.8634	2.3513	3.9335
	4	1.0426	0.8638	1.8638	2.3526	3.9345
	5	1.0467	0.8673	1.8715	2.3622	3.9532
	6	1.0478	0.8682	1.8733	2.3645	3.9557
	7	1.0482	0.8686	1.8742	2.3651	3.9560
5	Baseline	3.6175	3.0173	6.4716	8.1165	13.2619
	1	3.6178	3.0176	6.4722	8.1170	13.2624
	2	3.6183	3.0180	6.4729	8.1180	13.2624
	3	3.6201	3.0197	6.4763	8.1223	13.2705
	4	3.6214	3.0207	6.4790	8.1257	13.2751
	5	3.6228	3.0218	6.4812	8.1284	13.2760
	6	3.6233	3.0221	6.4820	8.1292	13.2777
	7	3.6244	3.0232	6.4846	8.1335	13.2857
20	Baseline	8.3420	6.5210	15.7034	21.1087	33.5907
	1	8.3435	6.5220	15.7075	21.1130	33.6001
	2	8.3439	6.5224	15.7073	21.1133	33.5957
	3	8.3448	6.5232	15.7087	21.1157	33.5971
	4	8.3459	6.5243	15.7122	21.1188	33.5984
	5	8.3470	6.5257	15.7147	21.1209	33.6013
	6	8.3478	6.5264	15.7153	21.1226	33.6054
	7	8.3485	6.5271	15.7168	21.1245	33.6054
25	Baseline	14.4646	9.6466	30.2076	47.2460	77.2051
	1	14.4658	9.6476	30.2111	47.2485	77.2051
	2	14.4662	9.6483	30.2112	47.2485	77.2063
	3	14.4671	9.6498	30.2113	47.2490	77.2057
	4	14.4681	9.6510	30.2128	47.2499	77.2056
	5	14.4691	9.6523	30.2138	47.2507	77.2058
	6	14.4699	9.6527	30.2147	47.2525	77.2076
	7	14.4706	9.6531	30.2147	47.2523	77.2082

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

Year	Scenario	Predicted PD (%)				
		Mean	Median	90th percentile	95th percentile	99th percentile
1	Baseline	4.0063	3.5027	6.6581	8.2237	12.9366
	1	4.0063	3.5027	6.6581	8.2237	12.9366
	2	4.0105	3.5065	6.6650	8.2336	12.9498
	3	4.0706	3.5562	6.7833	8.3737	13.1294
	4	4.0706	3.5562	6.7833	8.3737	13.1294
	5	4.1503	3.626	6.9171	8.5358	13.3660
	6	4.2075	3.6785	7.0170	8.6559	13.5672
	7	4.2472	3.7151	7.0755	8.7253	13.6756
5	Baseline	19.7600	18.1904	31.9083	37.9618	53.5769
	1	19.8143	18.2436	31.9973	38.0493	53.6597
	2	19.8739	18.3022	32.0924	38.1623	53.7651
	3	19.9248	18.3533	32.1807	38.2648	53.9078
	4	19.9520	18.3784	32.2162	38.2954	53.9438
	5	19.9564	18.3819	32.2222	38.3034	53.9544
	6	19.9754	18.3961	32.2463	38.3319	54.0117
	7	19.9828	18.4027	32.2528	38.3472	54.0251
20	Baseline	46.9062	47.4519	73.6215	80.7804	93.2290
	1	46.9823	47.5377	73.7073	80.8708	93.2747
	2	47.0075	47.5684	73.7365	80.8880	93.2943
	3	47.0286	47.5861	73.7563	80.8982	93.2971
	4	47.0294	47.5839	73.7531	80.8961	93.2925
	5	47.0383	47.5906	73.7586	80.8992	93.3005
	6	47.0408	47.5924	73.7572	80.9016	93.2982
	7	47.0452	47.5976	73.7636	80.9050	93.3005
25	Baseline	46.9712	47.5202	73.7367	80.8964	93.3017
	1	47.0471	47.6086	73.8248	80.9785	93.3386
	2	47.0723	47.6365	73.8528	80.9954	93.3557
	3	47.0934	47.6553	73.8659	81.0129	93.3615
	4	47.0942	47.6515	73.8611	81.0079	93.3586
	5	47.103	47.6598	73.8669	81.0175	93.3644
	6	47.1056	47.6586	73.8675	81.0157	93.3664
	7	47.1099	47.6643	73.8725	81.0210	93.3664

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

Year	Scenario	Predicted PD (%)				
		Mean	Median	90th percentile	95th percentile	99th percentile
1	Baseline	1.9368	0.0043	6.9928	14.9055	22.6848
	1	1.9368	0.0043	6.9928	14.9055	22.6848
	2	1.9368	0.0043	6.9928	14.9055	22.6848
	3	1.9465	0.0043	7.0489	14.9663	22.8074
	4	1.9667	0.0043	7.1278	15.1335	23.0664
	5	2.0018	0.0044	7.2696	15.3639	23.4533
	6	2.0491	0.0045	7.4657	15.7425	24.0471
	7	2.0855	0.0046	7.6092	15.9897	24.4626
5	Baseline	6.7005	0.0188	27.0634	51.3802	68.4448
	1	6.7184	0.0188	27.1775	51.5102	68.5652
	2	6.7605	0.0190	27.3978	51.8071	68.9058
	3	6.8098	0.0191	27.6652	52.1877	69.3282
	4	6.8332	0.0192	27.7971	52.3299	69.5098
	5	6.8708	0.0193	27.9499	52.5996	69.8408
	6	6.9274	0.0196	28.1881	53.0497	70.2244
	7	6.9667	0.0198	28.3615	53.3237	70.4959
20	Baseline	25.7185	2.7639	100	100	100
	1	25.7391	2.7734	100	100	100
	2	25.7317	2.7710	100	100	100
	3	25.7437	2.7737	100	100	100
	4	25.7355	2.7729	100	100	100
	5	25.7299	2.7725	100	100	100
	6	25.7243	2.7670	100	100	100
	7	25.7323	2.7712	100	100	100
25	Baseline	71.2932	94.0218	100	100	100
	1	71.3079	94.0433	100	100	100
	2	71.2951	94.0225	100	100	100
	3	71.3414	94.0897	100	100	100
	4	71.2943	94.0223	100	100	100
	5	71.2951	94.0264	100	100	100
	6	71.2935	94.0225	100	100	100
	7	71.2938	94.0222	100	100	100

**Table B.8:** *Some descriptive statistics of the default probability distribution for various scenarios: Portugal*

Year	Scenario	Predicted PD (%)				
		Mean	Median	90th percentile	95th percentile	99th percentile
1	Baseline	2.9749	1.9431	6.0932	9.2891	17.3424
	1	2.9749	1.9431	6.0932	9.2891	17.3424
	2	2.9749	1.9431	6.0932	9.2891	17.3424
	3	3.0271	1.9795	6.1972	9.4546	17.6225
	4	3.0271	1.9795	6.1972	9.4546	17.6225
	5	3.0271	1.9795	6.1972	9.4546	17.6225
	6	3.0317	1.9822	6.2081	9.4697	17.6652
	7	3.0629	1.9983	6.2907	9.5581	17.8968
5	Baseline	13.2988	9.6396	27.4080	37.5864	61.8292
	1	13.4702	9.7744	27.7642	38.0228	62.3510
	2	13.5059	9.8048	27.8164	38.1340	62.4419
	3	13.5125	9.8078	27.8274	38.1407	62.4492
	4	13.5612	9.8455	27.9282	38.2828	62.6394
	5	13.6075	9.8876	28.0128	38.3702	62.7569
	6	13.6383	9.9153	28.0843	38.4349	62.7791
	7	13.6928	9.9635	28.1697	38.6162	62.9319
20	Baseline	25.5925	20.8591	52.0197	64.3715	89.5302
	1	25.7403	21.0072	52.3005	64.6724	89.6686
	2	25.7673	21.0316	52.3505	64.7188	89.7368
	3	25.8006	21.0573	52.4188	64.7502	89.7406
	4	25.8336	21.0911	52.4640	64.7921	89.7620
	5	25.8777	21.1308	52.5372	64.8773	89.8281
	6	25.9291	21.1842	52.6365	64.9354	89.8906
	7	25.9773	21.2334	52.7196	65.0753	89.9962
25	Baseline	25.7469	21.0217	52.3278	64.6195	89.7151
	1	25.8942	21.1703	52.5925	64.9589	89.9026
	2	25.9210	21.1903	52.6582	65.0070	89.9451
	3	25.9543	21.2230	52.7229	65.0540	89.9473
	4	25.9872	21.2524	52.7772	65.0871	89.9662
	5	26.0310	21.2948	52.8466	65.1444	90.0211
	6	26.0822	21.3509	52.9274	65.2390	90.0984
	7	26.1302	21.400	53.0265	65.3426	90.2306

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