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Exploring the exposure of Slovak banks' corporate loan portfolio to flood risk

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Abstract

Climate change is expected to lead to more frequent and intense extreme weather events, such as floods and droughts, which in turn increase physical risks. In this paper, we assess the direct exposure of Slovak banks' corporate loan portfolios to riverine flood risk. We propose several monitoring metrics and estimate exposures at risk due to riverine flooding. Our analysis leverages a comprehensive dataset that integrates flood risk maps from the European Commission's Joint Research Centre, cadastral data on firm properties, credit register data, and firms' financial statements. While a significant share of firms are located in flood-prone areas, only a subset are likely to face flood levels that exceed critical thresholds. Consequently, the direct impact of riverine flooding on corporate credit risk appears to be relatively moderate — with the estimated increase of exposure at default ranging from 2 to 10 basis points of the corporate loan portfolio under standard scenarios, and up to 50–60 basis points in conservative stress cases accounting for asset value declines. Under counterfactual scenarios assuming a fivefold increase in the frequency of floods, the estimated increase exceeds 1 percentage point of the loan portfolio.

JEL codes: G21, Q54, R30.
Keywords: Riverine flood risk, credit risk, non-financial corporations, Slovakia.

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Non-technical summary

Floods are becoming more frequent and severe due to climate change, creating new risks not just for individuals and communities but also for the financial system. In this paper, we examine how exposed Slovak banks are to such risks through the corporate loans they provide. Specifically, we look at whether the companies borrowing from Slovak banks operate in areas that could be affected by riverine floods—and if so, how that might impact their ability to repay their loans.

To do this, we combined several types of data: detailed flood maps, land registry data showing where firms are located, financial information about these firms, and data on the loans they have from banks. Using this information, we calculated how likely different areas are to be exposed to floods and how severe the flooding might be. We then estimated how these floods could hurt the financial health of companies by reducing their revenues or damaging their assets, and how this might increase the chance that they default on their loans.

Our findings suggest that while many firms are located in areas at some risk of flooding, only a small share face levels of floodwater likely to cause serious damage. Even in more severe flood scenarios, the overall impact on banks' loan portfolios appears to be limited. In our baseline analysis, the increase in the expected exposure at default due to flooding is small—typically between 2 and 10 basis points of total corporate lending, and up to 50–60 basis points in the most extreme scenario where asset values also fall. Assuming a fivefold increase in the frequency of floods, this estimated increase may reach more than 1 percentage point of the corporate loan portfolio.

These results highlight the value of using detailed data to monitor environmental risks. Even though the immediate financial threat appears moderate, targeted attention to vulnerable sectors and locations can help banks and regulators prepare for the growing challenges posed by climate change.

1. Introduction

In recent years, the escalating impacts of climate change have captured global attention, highlighting the urgent need for comprehensive risk assessments across various sectors. Among the most pronounced consequences of climate change is the increased frequency and severity of extreme weather events, such as floods, which pose significant risks to economic stability and financial systems worldwide. Financial institutions, particularly banks, are increasingly recognizing the necessity to incorporate environmental risks into their risk management frameworks to safeguard their portfolios and ensure long-term resilience, while regulators scramble to better understand the underlying risks and consequently devise an appropriate policy response.

Floods represent a challenge for banks due to their potential to disrupt economic activities, damage infrastructure, and impair the financial health of businesses. This paper seeks to explore the extent of Slovak banks' exposure to flood-related risks within their corporate loan portfolios, offering insights into the potential financial repercussions for the banking system.

We leverage an extensive dataset integrating flood risk maps from the European Commission's Joint Research Centre with detailed cadastral data, corporate credit information, and financial statements of firms. By doing so, we aim to provide a comprehensive assessment of flood risk exposure and its implications for credit risk within the Slovak banking sector. Our analysis not only identifies firms situated in flood-prone areas but also quantifies the potential impact of extreme flood events on these firms' financial health and, consequently, on the credit risk of bank loan portfolios.

This study contributes to the growing body of literature on climate-related financial risks, emphasizing the importance of incorporating environmental factors into financial risk assessments. Through this research, we aim to inform academics, policymakers, as well as banking professionals, about the significance of proactive flood risk management and insurance, thus fostering a more resilient financial system in the face of climate change.

The methodological approach adopted in this study comprises three main steps, detailed in sections 4 and 5. First, we compute expected flood levels using, in parallel, a discrete (Section 4.1) and a continuous (Section 4.2) probability distribution, both interpreted from the same flood map data. Second, we map flood exposure to economic losses at the firm level by estimating revenue reductions based on flood depth and affected area (Section 5.1), which helps us estimate firms' baseline probabilities of default (PDs). In the same section, we simulate the impact of flood-induced PD shifts on loan portfolios using Monte Carlo methods, assessing changes in expected exposure at default (EAD) over one-year and maturity-adjusted horizons. We also perform robustness checks across alternative model and damage function specifications (Section 5.2). Finally, we provide counterfactual analysis of the impact of floods assuming an increasing frequency of floods in Section 5.3.

Results show that while a relatively large share of firms is exposed to flood, only a fraction of these firms is expected to be heavily affected by riverine flood. Assuming a negative impact of the flood only on the firms' sales, the estimated average probability of default of the firms would remain contained, not exceeding 30 basis points based on different assumptions and return periods. This would lead to an increase of the expected exposure at default of the loan portfolio by up to 11 basis points, as a share of the overall corporate loan portfolio. The results are more serious when we assume a negative impact of the flood on the firms' assets as well. In such a case, the average estimated PD may almost double under the once in a 500 years scenario, leading to an increase of the expected exposure at default by 50 basis points as a share of the overall corporate loan portfolio. Assuming five times higher frequency of floods, this share may reach 1 percentage point.

2. Literature review

In the European Union (EU), riverine floods are expected to be the most widespread, economically relevant climate risk driver over the next two decades (ECB, 2021). In the case of no climate mitigation and adaptation, direct damage from flooding could increase six-fold from present losses by the end of the century (Feyen et al., 2020), as global warming will impact and likely cause more frequent extreme events, including floods (Diffenbaugh, 2020). Furthermore, the European Central Bank (ECB) identifies Slovakia as one of the Euro area countries most exposed to flood risk (ECB, 2021).

There is growing empirical evidence of climate risks and extreme weather events having negative economic consequences. Huang et al. (2017) show, using the Global Climate Risk Index, that losses from extreme weather events, like major storms, flooding, heat waves, etc., are associated with lower and more volatile earnings and cash flows. Using the Risk Data Hub compiled by the Joint Research Centre, Fatica et al. (2022) find that water damages significantly and persistently worsen firms' performance. Based on their analysis, an average flood deteriorates total assets by about 2% in the year after the event and their sales by about 3%. Within-country case studies, Pan and Qiu (2022) show a significant negative impact of flooding on firm performance as well as local economic and employment growth using comprehensive flood data from China, and Yamamoto and Naka (2021) document a negative impact on the ratio of profit to sales, especially in the manufacturing sector in Japan. Interestingly, they find that the negative impact tends to be higher for firms located in municipalities that experience floods less frequently. Loberto and Russo (2024) use a large flood in Romagna, Italy, in May 2023 to show that, for assessing the impact of floods, it is important to account for branch offices.

Despite this increasing evidence, empirical literature also points to gaps in risk awareness when it comes to the potential impact of physical risks on firms and households. Kruttli et al. (2025) show that investors underestimate extreme weather impact on the eventual realized return volatility of the affected firms, even though this statistic has slightly improved since Hurricane Sandy in 2012. Mathews et al. (2021) use data from England and Wales to show that firms may lock in to flood-exposed locations due to gaps in risk awareness and exposure.

Beyond economic consequences, floods and other extreme weather events may directly and indirectly affect the financial system by increasing the probability of default and loss given default for firms and households. Turnbull (2023) incorporate the effects of physical and transition risks using a multiperiod scenario analysis. These risks can significantly increase the probability of default (PD), as well as the value-at-risk and the expected shortfall. For modeling PDs, they use the Merton model earlier adopted in Turnbull and Habahbeh (2020). The magnitude of the effect depends on the risk parameters and the initial creditworthiness of the firms. Cathcart et al. (2023) show the negative impact of temperature increase and heavy rainfall on the probability of default of small and micro enterprises in six different European countries. Using granular data on European small and medium enterprises (SMEs), Barbaglia et al. (2023) also show that firms in flooded counties are more likely to default on their loans than non-disaster firms. Furthermore, they provide evidence that European banks charge higher interest rates on loans granted to SMEs located in areas of high risk of flooding.

The increased recognition of flood risk as a potential future risk driver underscores the need for a forward-looking assessment that goes beyond case studies and evaluations of past impacts.

Dhima et al. (2025) employ theoretical modeling to integrate the impact of physical climate risk into their credit risk assessment and capital buffer calibration, with an extension of the Merton model for the PD assessment. Bikakis (2020) uses three different climate scenarios to evaluate the exposure of UK banks to flood-related mortgage defaults, finding an increasing share of common equity tier 1 (CET1) capital at risk with rising temperatures. Caloia and Jansen (2021) use a stress testing framework and a geo-coded dataset on Dutch banks' real estate exposures to study the potential impact of floods on financial stability. They find that the banking sector is sufficiently capitalized to withstand floods in unprotected areas, where there is relatively little real estate. However, capital depletion would increase quickly if more severe floods hit the densely populated western part of the Netherlands. Meucci and Rinaldi (2022) quantify, based on granular data on loans and the likelihood of climate-related events, to what extent physical risk can impair the loan portfolios of Italian banks. They point to the necessity of using granular data to accurately identify firms exposed to physical risks.

We contribute to the literature in several ways. Firstly, we enrich the debate about the potential impact of riverine floods on firms' credit risk by focusing on Slovakia, a country that is both heavily reliant on the manufacturing industry and considered by the ECB to be heavily exposed to flood risk in the near future. Secondly, we contribute to the literature by conducting a fine-grained analysis with granular micro data on the firms' production locations[1]. This enables us to have a detailed identification of firms' exposure to riverine flood at the production plant level. In combination with data from the credit register and firms' individual financial data, we obtain a rich and unique granular dataset. Third, using the flood maps[2], which provide information about flood hazards based on different return time periods, enables us to create forward-looking metrics utilizing the full distribution of expected floods instead of relying on artificially created scenarios. Last but not least, the data enable us to translate expected floods into changes in firms' PD even for smaller, unlisted firms, which is usually not possible with Merton-type models.

3. Data

To explore the impact of flood risk on the Slovak banking sector, we utilize four different datasets:

[1] From the Geodesy, Cartography and Cadastre Authority of the Slovak Republic
[2] From the Joint Research Centre of the European Commission

1. A flood map to quantify the probabilistic distribution of floods at a given set of geographical coordinates,
2. A credit registry database (AnaCredit) for the magnitude of exposure of Slovak banks to the borrowing firms,
3. A database of Slovak firm-level financial data (FinStat) to use for the simulation of losses, and
4. A Slovak cadaster dataset to obtain the geographical location of firms' production locations.

For the flood map, we use the Global River Flood Hazard Maps obtained from the European Commission's Joint Research Centre (JRC), which provide a comprehensive assessment of flood risks associated with river systems worldwide. The map was created using the LISFLOOD model, and a comprehensive description of its capabilities can be found in Dottori et al. (2022).[3] The map's original function is to support disaster risk management, urban planning, and climate change adaptation by providing critical information for policymakers, researchers, and communities. The JRC maps utilize various data sources, including satellite imagery, historical flood records, and hydrological models, to identify areas at risk of flooding. They categorize flood hazards based on different return periods, specifically over periods of 10, 20, 30, 40, 50, 75, 100, 200, and 500 years, helping to visualize expected flood depths at these intervals. For each period, the map contains the extreme value for the geographical locations within the map. In other words, if a value at a given location for the 100-year map is 2.1 meters, it means that—on average—once every 100 years, the height of flood water at this specific location reaches its maximum at 2.1 meters. For Slovakia, the spatial granularity of a single observation in terms of latitude/longitude is approximately 90 meters. For better illustration, Figure 1 shows the JRC flood map corresponding to the 20- and 500-year periods.[4]

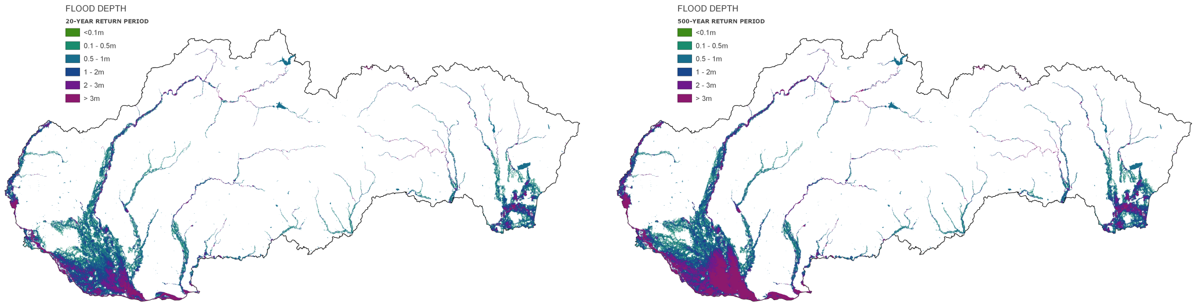
The direct exposure of banks to flood via loans to non-financial corporations (NFCs) is explored using data from AnaCredit, a dataset containing detailed information on individual bank loans in the euro area, harmonized across all Member States. In Slovakia, the database contains infor-

[3]The data itself can be found at https://jeodpp.jrc.ec.europa.eu/ftp/jrc-opendata/CEMS-EFAS/flood_hazard/.

[4]As a caveat, one should keep in mind that the flood maps are based on hydrological models and past meteorological data. As climate change has been causing extreme weather phenomena to occur more frequently in recent years, the quantitative predictions based on these models should be viewed as likely lower bounds rather than precise estimates.

Figure 1: Flood map of Slovakia

((a)) Once in a 20 years flood ((b)) Once in a 500 years flood



Notes: The chart shows the level of the once in a 20 years flood (left side) and the level of the once in a 500 years flood (right side) in meters in Slovakia.
Source: JRC.

mation about all loans granted to NFCs by Slovak banks, subsidiaries, or branches irrespective of the size of the loan. For each loan, there is a rich set of information available about the loan (e.g., the type of the loan, original amount, outstanding amount, interest rate-related information, maturity), the protection related to the loan (e.g., collateral or third-party guarantee), or the firms themselves (e.g., credit-risk related information or economic sector of the firm)[5]. For this project, we use data as of end-2023 about the outstanding volume of loans and their outstanding maturity. For the analysis, we selected more than 7,000 firms representing 90% of Slovak banks' corporate loan portfolio. For over 5,500 of these firms, there is data available in the cadaster about parcels they are exposed to[6]. Altogether, this constitutes over 2 million parcels and represents over three quarters of the relevant banks' loan portfolio, with more than 40,000 loans having a total outstanding amount of more than 21 billion EUR. The average outstanding amount of loans (with non-zero outstanding amount) is almost 700,000 EUR and the (volume-weighted) maturity is slightly more than 3.5 years.

For estimating the credit risk of non-financial corporations, we use financial data from the FinStat database and data about the default of firms on their loans from AnaCredit. FinStat is a database containing detailed firm-level information about the financial statements and balance sheets of Slovak firms. The most granular data are available with annual frequency since 2013. For estimating the probability of default of the firms, we selected the most relevant financial indices of the firms, including e.g., return on assets, gross margin, or interest coverage ratio.

[5]More information about AnaCredit is available on the website of the ECB: https://www.ecb.europa.eu/stats/ecb_statistics/anacredit/html/index.en.html

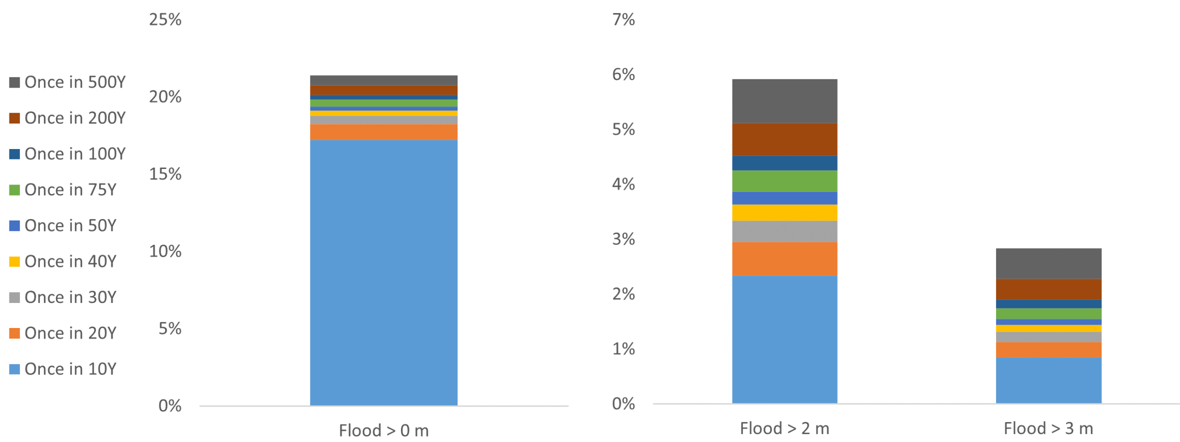
[6]Firms can own, rent, or be an administrator of a given parcel.

The indices are described in more detail in Appendix C. Total assets of the firms involved in the analysis ranged in the covered years between 14 and 28 billion EUR, with the total number of firms in the years changing between 18,000 and 44,000.

In the Slovak cadastre, an ownership document links one or more parcels with participants in a legal relationship, which can include individuals or firms. For each participant, the cadastre specifies the role (e.g., owner, administrator, tenant), type of legal right, ownership share in the property, and, if applicable, company identification number (IČO). Parcels are described by attributes such as area, land category, method of land use, and may also include information about any buildings located on them. This detailed information on parcels, their associated documents, and ownership structures was obtained from a third-party data provider. In addition, geographical coordinates for each parcel were sourced from the publicly available parcel dataset, updated for December 2023 and published by the Geodesy, Cartography and Cadastre Authority of the Slovak Republic[7]. Each parcel is defined by a polygon geometry, which was used to calculate zonal mean flood depth: when a parcel overlaps multiple flood zones with varying depths, it is assigned the average value based on its area coverage.

Figure 2: Share of parcels with non-zero flood levels

((a)) Exceeding 0 meter ((b)) Exceeding 2 or 3 meters



Notes: The chart on the left shows the share of parcels with a non-zero flood level based on the respective return periods (once in a 10-year, once in a 20-year, etc.). The chart on the right shows the share of parcels with flood level exceeding 2 or 3 meters. Parcels related to water (e.g. lakes or rivers) are excluded.
Source: JRC, CRIF, AnaCredit, own calculations.

Slightly more than 17% of the parcels are exposed to flood (i.e., the level of the smallest, once in a 10-year flood period, exceeds 0 meters). This share increases up to 21.4% in the case of a once in a 500-year flood (see Figure 2a). In the case of buildings, the damage is expected to be serious

[7]The data can be found at https://data.slovensko.sk/datasety/d7dd797f-7e55-4207-9e54-875beac0ffe7

once the flood level exceeds 2 meters and can cause critical damage to the building's foundation once it exceeds 3 meters. The share of parcels with such levels of flood is significantly lower, representing 2.3% - 5.9% in the case of floods that are at least 2 meters high and 0.9% - 2.8% in the case of floods that are at least 3 meters high (Figure 2b).

4. Expected flood level

In this methodological section, we introduce some terminology used in catastrophe modeling related to floods and construct several metrics that can be used to track the exposure of the corporate loan portfolio to the direct impact of floods. By direct impact, we mean the potential losses banks can face due to floods affecting NFCs that have loans from Slovak banks.[8]

4.1. Expected flood level - discrete case

Based on the data from the JRC Flood map and the Slovak Cadaster, we have information on the potential flood level for each parcel belonging to NFCs with loans from Slovak banks. This potential flood level is expressed in terms of once in a 10-year, 20-year, 30-year, 40-year, 50-year, 75-year, 100-year, 200-year, and 500-year flood. The periods of 10, 20, ..., 500 years correspond practically to the Return Period, which is the inverse of the Exceedance Probability (EP), as described by, e.g., Humphreys (2021).

In line with the literature in general (Volpi, 2019), we assume the events arise from a stationary distribution and are independent of one another. Let D_1, D_2, ... be a set of floods with decreasing return periods (once in 500 years, once in 200 years, etc.). Let p_i and X_i be the annual probability of occurrence and the corresponding level of the flood associated with the event D_i. Thus, D_i is a random variable with P(D_i occurs) = p_i and P(D_i does not occur) = 1 - p_i. The Exceedance Probability in this case is the probability that the flood level exceeds a certain height. Let X be a random variable of the flood level. Then

$$EP(x) = P(X > x) = 1 - P(X \leq x) \quad (1)$$

If $x = X_i$, which is a level associated with a flood event D_i, then

[8] We do not take into account potential contagion effects due to supply chain disruptions or the negative implications of decreased demand caused by the impact of floods on households.

$$EP(X_i) = P(X > X_i) = 1 - P(X \leq X_i) = 1 - \prod_{j=1}^{i}(1 - p_{\mathrm{j}}) \tag{2}$$

where $D_1, D_2, ..., D_i$ are events with higher level of flood such that $X_1 \geq X_2 \geq ... \geq X_i$.

Based on the relationship between the probability of occurrence and the exceedance probability described in equation 2, we can recursively calculate the probability of occurrence from the exceedance probability of floods, starting from the most severe, once in a 500-year scenario:

$$\begin{gathered} P(D_1\, occurs) = p_1 = EP(X_1) \\ P(D_i\, occurs) = p_i = 1 - \frac{1 - EP(X_i)}{\prod_{j=1}^{i-1}(1 - p_{\mathrm{j}})},\ i > 1 \end{gathered} \tag{3}$$

After obtaining the annual probability of occurrence for each flood event, we can calculate the average, or expected flood level (EFL):

$$EFL = \sum_i (p_i X_i) \tag{4}$$

This expected annual flood level can be obtained for each parcel in our sample, i.e., for each parcel owned by NFCs having loans from Slovak banks. The distribution of this expected flood level is depicted in Figure 3a). The flood level is shown only for parcels with a non-zero expected level that are not constantly under water (e.g., lakes are excluded). As is evident from the chart, the expected level is mostly up to 0.5 meters.

From the AnaCredit database, we have information about the remaining maturities of the NFCs' loans. Having the annual probability of occurrence for the respective flood events for each parcel, for each firm-parcel pair we can calculate the firm-parcel-specific occurrence probability for the average remaining period during which the firm has loans granted. If the annual probability of occurrence of a specific flood event, D_i, equals p_i, then the probability that such an event occurs in the next n years is given by

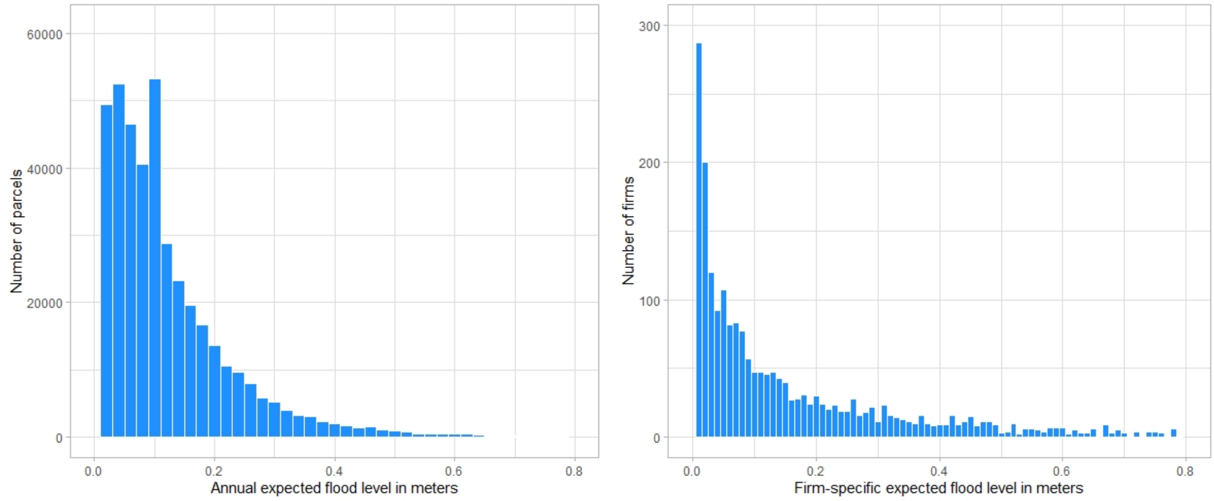
$$P(D_i\, occurs\, in\, next\, n\, years) = 1 - (1 - p_{\mathrm{i}})^n \tag{5}$$

By averaging the estimated flood level for each firm-parcel across parcels (weighted by parcel

Figure 3: Distribution of the expected flood level across parcels and firms

((a)) Distribution of the expected flood level across parcels

((b)) Distribution of the firm-specific expected flood levels



Notes: The chart on the left shows the distribution of annual expected flood level among parcels owned by or dedicated to NFCs in the sample having a loan from a Slovak bank. The chart on the right shows the distribution of firm-specific expected flood levels among firms in the sample having a loan from a Slovak bank.
Source: JRC, CRIF, AnaCredit, own calculations.

area), we can estimate the firm-specific average expected flood level for the period of the average maturities of the firm's loans. The distribution of this estimated flood level is depicted in Figure 3b).

4.2. Expected flood level - continuous case

Naturally, considering only a few cases of the possible flood level (once in 10 years, once in 20 years, etc.) and estimating the expected flood level based on these measures can undershoot the expected flood level, as the potential flood is a continuous random variable. The original data of the expected flood level as a function of the return period, i.e., the expected flood level once in 10 years, once in 20 years, etc., can be easily transformed into exceedance probability as a function of the flood level (as described in the previous section; for an example see Figure 4).

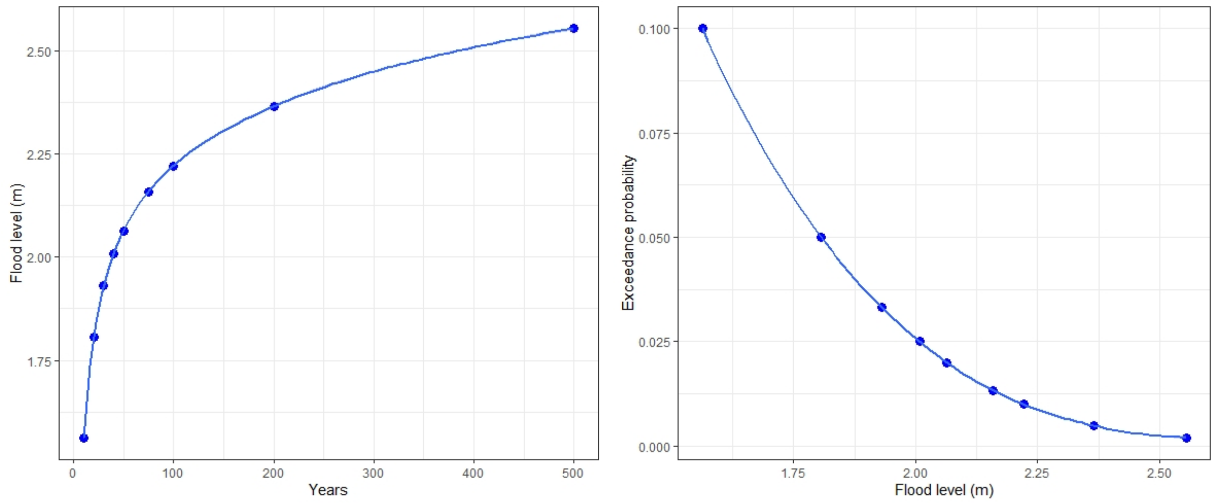
The probability that the flood level remains under a certain value, or the non-exceedance probability can be easily calculated as

$$NEP(X_i) = P(X \leq X_i) = 1 - EP(X_i) \tag{6}$$

In the continuous case, this is the cumulative distribution function (CDF) for the flood level. An

Figure 4: Flood level data - example

((a)) Flood level data based on the return period ((b)) Exceedance probability



Notes: The chart on the left shows the level of flood expected once in a given number of years depicted on the x-axes. The chart on the right shows the exceedance probability of a selected parcel.
Source: JRC, CRIF, own calculations.

example is depicted in Figure 5a). By estimating the CDF for each parcel, we can consequently estimate the probability density function and estimate the expected flood level by numerically integrating this density function (see Figure 5b) for an example of the estimation of the density function). However, the expected estimated value in this case can overshoot because the estimated density is skewed towards the right. This is due to the fact that 90% of the floods are up to the level of the once in a 10-years flood, but we have observations only for this 10-years or above flood levels.

Another possibility is to approximate the expected value of the flood level by using the *Riemann-Stieltjes* integral. Let *F(X)* and *f(X)* be the cumulative distribution function and the probability density function of a non-negative continuous random variable X. In this case, the expected value of this variable is calculated as

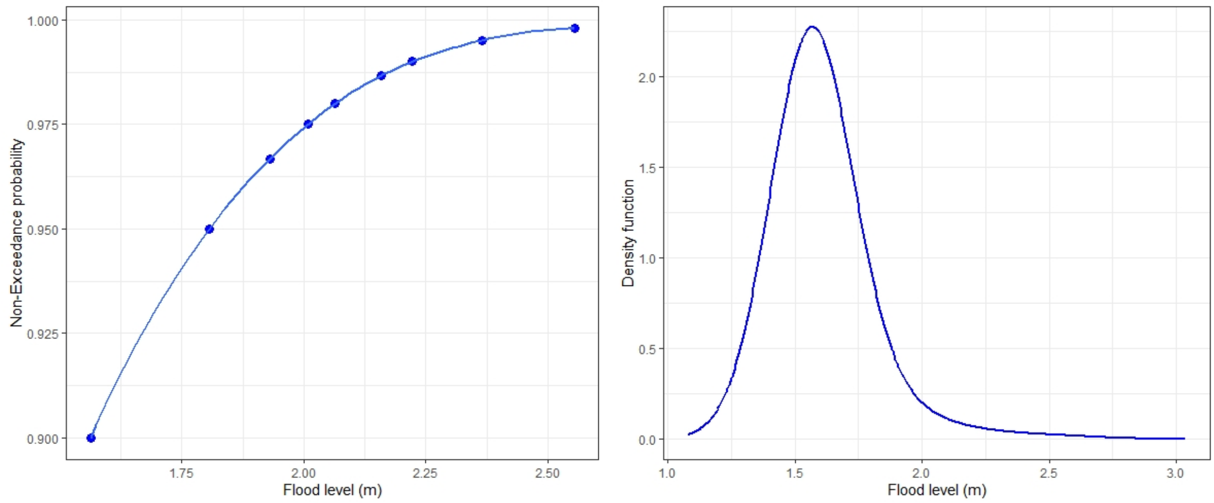
$$\mathbb{E}[X] = \int_0^\infty x f(x) dx = \int_0^\infty x dF(x) \tag{7}$$

The last expression in equation 7 can be approximated numerically (see, e.g., Dragomir (2011)) as

$$\int_0^\infty x dF(x) \approx \sum_{i=1}^{n-1} [F(x_{\mathrm{i+1}}) - F(x_{\mathrm{i}})] \frac{x_{\mathrm{i+1}} + x_{\mathrm{i}}}{2} \tag{8}$$

Figure 5: Flood related statistical distributions - example

((a)) Non-exceedance probability (CDF) ((b)) Density function - estimate

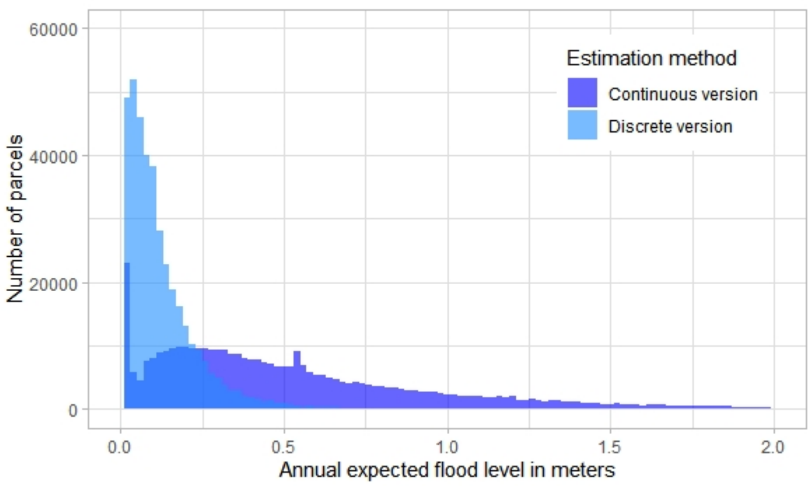


Notes: The chart on the left side shows the non-exceedance probability of a selected parcel. This non-exceedance probability is calculated as 1 - exceedance probability and can be interpreted as the Cumulative Distribution Function. The chart on the right shows the estimated density based on the cumulative distribution function.
Source: JRC, CRIF, own calculations.

In this approximation, we make use of the fact that

$$F(x_{i+1}) - F(x_i) = P(X \leq x_{i+1}) - P(X \leq x_i) = NEP(x_{i+1}) - NEP(x_i) = \\ [1 - EP(x_{i+1})] - [1 - EP(x_i)] = EP(x_i) - EP(x_{i+1}) \tag{9}$$

Figure 6: Annual flood level - comparison



Notes: The chart shows the distribution of annual expected flood level among parcels owned by or dedicated to NFCs in the sample having a loan from a Slovak bank, both based on the discrete or continuous approach.
Source: JRC, CRIF, AnaCredit, own calculations.

It means that we can calculate the expected flood level as the weighted average of the flood levels from the flood map, while the weights will be the difference between the consecutive pairs of the exceedance probabilities. In our example from Figure 4a), the once in 10-years flood level is 1.563 meters and the once in 20-years flood level is 1.806 meters. The first element of the sum in the approximation will thus be (1 - 1/10)(1.563 + 0)/2, and the second (1/10 - 1/20)(1.806 + 1.563)/2. From Figure 6, it is evident that the expected level of flood is significantly larger using this approach.

5. Direct impact of flood risk on the corporate loan portfolio

5.1. Baseline estimations

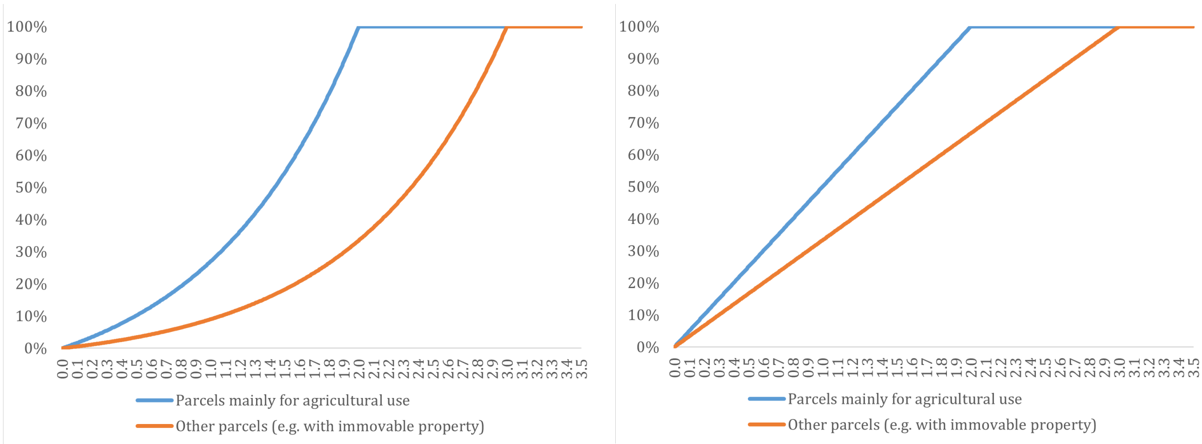
The direct impact of flood risk on the corporate loan portfolio is estimated via the potential impact of flood on firms' sales. Furthermore, we assume the sales will be affected proportionally to the share of affected parcels of a firm and the potential flood level of the parcels. I.e., the higher the flood level of a given parcel, and the larger the share of parcels affected on the total parcels owned by a firm[9], the larger the loss of sales will be. Based on information from the Slovak Water Management Company, we assume a non-zero loss in case the flood level exceeds 0.1 meter and a 100% loss if the flood level exceeds 2 meters for parcels mainly used for agricultural purposes and 3 meters for other parcels, e.g., with immovable property. While there are remarkable differences in the literature in terms of the damage functions used, these thresholds are to a large extent in line with the thresholds where serious damage is already expected (Huizinga et al., 2017). To capture potential different impacts of the increasing flood, we estimated the impact based on both linear and exponential increase (see Figure 7).

We also distinguish between parcels where the sales of a firm are affected in case of a flood (e.g., parcels with immovable properties or parcels used for agricultural purposes) and parcels where the sales are not affected (e.g., swamp or rivers and lakes). This distinction is based on two attributes of the parcels available from the cadaster. The first is the method of land use, details of which are provided in Appendix A, and the second is the nature of land use, details of which are provided in Appendix B. In case at least one of these attributes indicates a loss in case of flood, we assume the loss occurs. If the two tables indicate different loss rates, we opt

[9]The estimation is based on the weighted share of parcels, weighted by the size in square meters.

Figure 7: Loss of sales based on the flood level

((a)) Exponential loss curve ((b)) Linear loss curve



Notes: The chart on the left shows the share of sales lost based on an exponentially increasing loss curve. The chart on the right shows the share of sales lost based on linearly increasing loss curve. Horizontal axes display the flood level in meters.
Source: Own calculations.

for the higher.

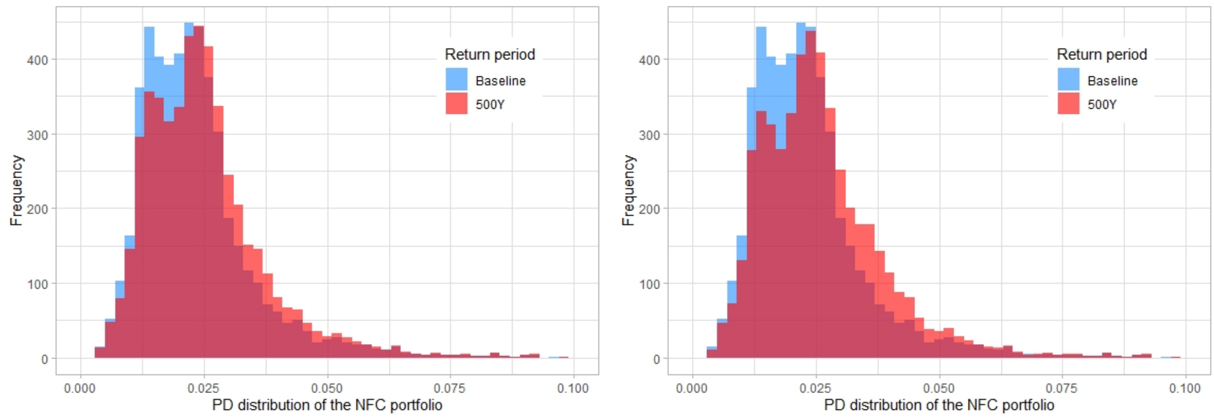
The partial loss of sales caused by the flood will consequently translate into an increased annual probability of default of the firms. The probability of default of each firm is estimated using a logit model including variables based on the financial statements of the firms. Further details of the model are provided in Appendix C. The probability of default is estimated using the latest available financial statements of the firms from 2023. Then, these financial statements are adjusted according to the expected loss of sales caused by the flood. Figure 8 displays the shift of the PD distribution of the NFC loan portfolio caused by the one in a 500 years flood. As expected, the shift is more pronounced using the linear loss curve, as there is a larger loss of sales even under lower flood levels.

The shift of the PD distribution of only those firms that are exposed to flood using linear loss curve is displayed in Figure 9. This is a subgroup of firms having at least one parcel with non-zero expected flood level.

Figure 10 (a) shows the average estimated probability of default of the NFC loan portfolio for the respective return periods. As is evident from the figure, the largest increase of the PD is between the baseline with no flood and the once in a 10 years flood level scenario. This is largely because, although the flood level increases with increasing return period, firms affected the most will be seriously hit even under this 10 years scenario. The share of firms affected will increase with increasing return period, but there is not a significant share of parcels with very

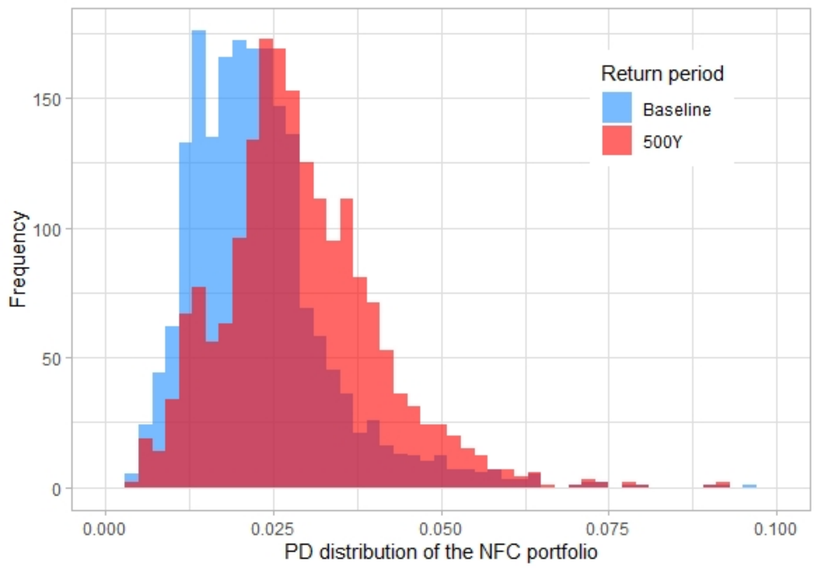
Figure 8: PD distribution change of the NFC loan portfolio

((a)) Exponential loss curve ((b)) Linear loss curve



Notes: The chart on the left shows the distribution of the probabilities of default under the baseline scenario and under the 500 years return period using the exponential loss curve. The chart on the right shows the same using the linear loss curve.
Source: JRC, CRIF, AnaCredit, FinStat, own calculations.

Figure 9: PD distribution change of the NFC portfolio affected by flood



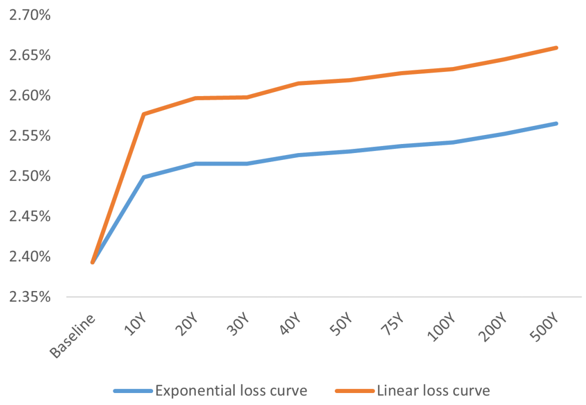
Notes: The chart shows the distribution of the probabilities of default under the baseline scenario and under the 500 years return period using the linear loss curve of the firms having at least one parcel exposed to non-zero flood level.
Source: JRC, CRIF, AnaCredit, own calculations.

low 10 years and very high 500 years flood levels. Another result visible from this figure is that the overall increase of the probability of default remains contained. Using the exponential loss curve, the PD under the 500 years return period increases compared to the baseline scenario by 17 basis points. The increase is 27 basis points when using the linear loss curve.

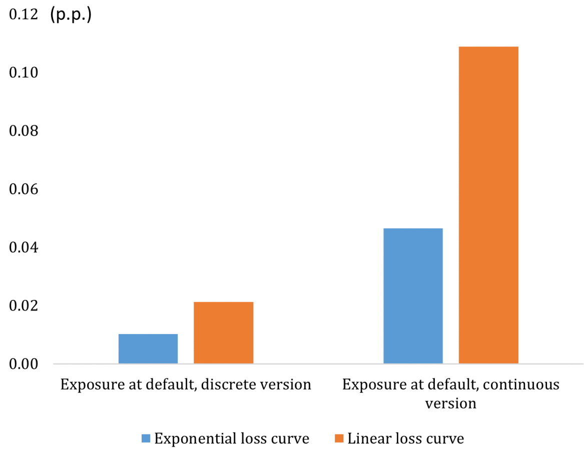
Having estimated the annual PD of firms, we use Monte Carlo simulations to estimate the

Figure 10: Estimated PD and expected exposure at default of the NFC loan portflio

((a)) Average estimated PD



((b)) Expected exposure at default



Notes: The chart on the left shows the (simple) average probability of default of the NFC loan portfolio under the respective return periods. The chart on the right shows the expected exposure at default attributable to flood risk using linear and exponential loss curve and based both on discrete and continuous case. The exposure at default is shown as a share on the total volume of loans, in percentage points.
Source: JRC, CRIF, AnaCredit, FinStat, own calculations.

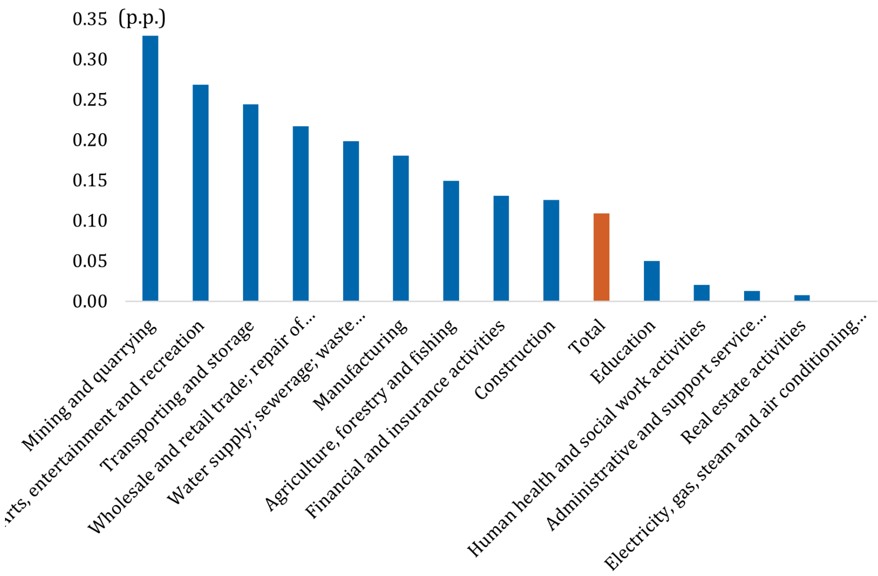
expected exposure at default attributable to flood risk[10]. We run 5,000 simulations, and in each simulation, we decide whether a particular firm defaults[11]. We run the simulations using both the exponential and linear loss curves. As can be seen in Figure 10 (b), the expected exposure at default is very small, up to 2 basis points as a share of the total volume of loans in the case of the discrete version. In the case of the continuous version, which takes into account the whole potential distribution of the return periods, the expected exposure at default is 5 basis points of the total volume of loans using the exponential and 11 basis points using the linear loss curve.

While the overall expected exposure at default remains relatively low compared to the total outstanding loan amount, there are notable differences across sectors. Figure 11 highlights the sectors most impacted by flood risk, with Mining and Quarrying being the hardest hit—showing an expected exposure at default approximately three times higher than the portfolio average. Other significantly affected sectors include Recreation, Transportation and Storage, as well as Wholesale and Retail Trade.

[10]The estimated yearly PD of firms does not take into account the size of the exposures of the banks to these firms. We use Monte Carlo simulations to obtain estimated losses and standard deviations taking into account the volume of loans granted to these firms.

[11]It should be noted that this setting implicitly treats firm defaults as independent events. Further extensions that would take into account correlated shocks due to riverine flooding would be an interesting extension of this approach.

Figure 11: Expected exposure at default, sectoral breakdown



Notes: The chart shows sectoral breakdown of the exposure at default for the continuous version using linear loss curve. The exposure at default is shown as a share on the total volume of loans, in percentage points.
Source: JRC, CRIF, AnaCredit, own calculations.

5.2. Robustness tests and alternative estimations

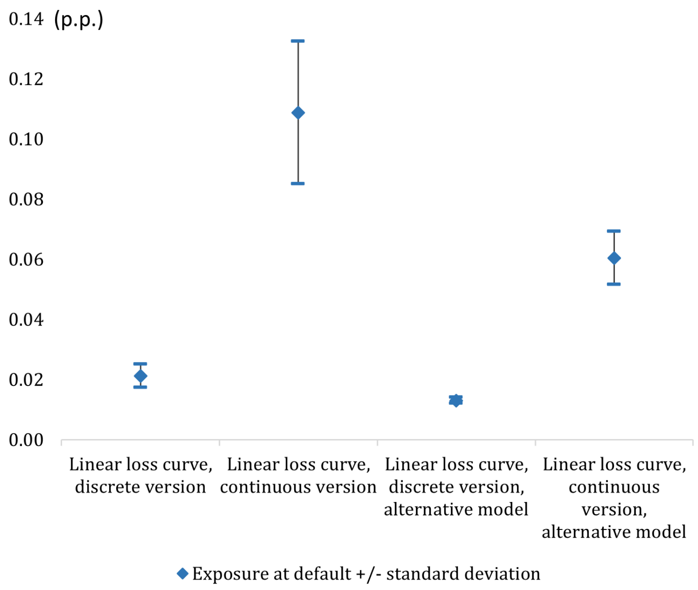
As a robustness check, we estimated the expected exposure at default using an alternative probability of default (PD) model. The baseline model applies bounded definitions for financial variables—for instance, setting a lower limit of zero for the interest coverage ratio, meaning that any negative reported values are truncated to zero. These bounds align with those used in PD estimations for NFC credit risk analysis, as in NBS (2024).

In contrast, the alternative model relaxes these bounds, allowing for a wider range of financial variable values and thus enabling a more gradual, nuanced impact of flood-related sales losses on firms' PDs. As illustrated in Figure 12, the expected exposure at default calculated with this alternative model is lower than under the baseline. This occurs because the broader variable bounds reduce the severity of the PD increase induced by flood impacts.

Additional technical details on both the baseline and alternative PD models can be found in Appendix C.

The estimated results presented so far reflect the expected 1-year ahead exposure at default (EAD) related to flood risk. This short-term perspective is particularly relevant for banks' internal capital planning processes. Extending the analysis, we also compute the expected

Figure 12: Expected exposure at default, baseline vs alternative PD model



Notes: The chart shows the expected exposure at default attributable to flood risk using linear loss curve based both on discrete and continuous case using the baseline and alternative PD model. The exposure at default is shown as a share on the total volume of loans, in percentage points.
Source: JRC, CRIF, AnaCredit, own calculations.

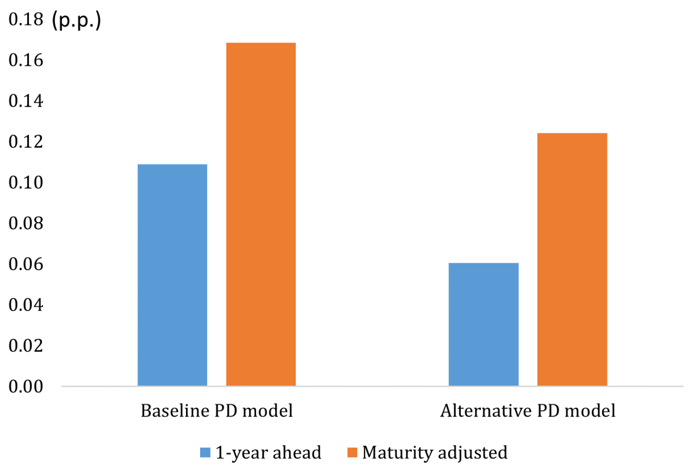
maturity-adjusted exposure at default for the corporate loan portfolio. This metric captures the cumulative flood risk that banks face over the remaining duration of loans granted to the firms, thereby providing a more comprehensive view of potential flood-induced credit losses over the full loan lifetime.

Using the linear loss curve and the continuous flood level distribution, the results—depicted in Figure 13—show that the maturity-adjusted exposure at default is roughly double the 1-year ahead estimate, for both the baseline and alternative PD models. This substantial increase mainly reflects the aggregation of default risk over the loans' remaining maturities. At the same time, the magnitude of this increase also indicates that the overall average remaining maturity of the non-financial corporation loans is relatively short, at just under 4.5 years.

In the next alternative specification, we extend the analysis by assuming that flood events affect not only the firms' sales but also the value of their assets. We apply the same functional assumptions for the asset value decrease as for the sales decline described in Subsection 5.1, meaning that both the flood height and the proportion of affected parcels jointly determine the magnitude of the asset value reduction.[12]

[12]While this assumption might overestimate the real impact of floods on firms' asset values, it provides a useful upper bound for our estimates.

Figure 13: Expected maturity-adjusted exposure at default



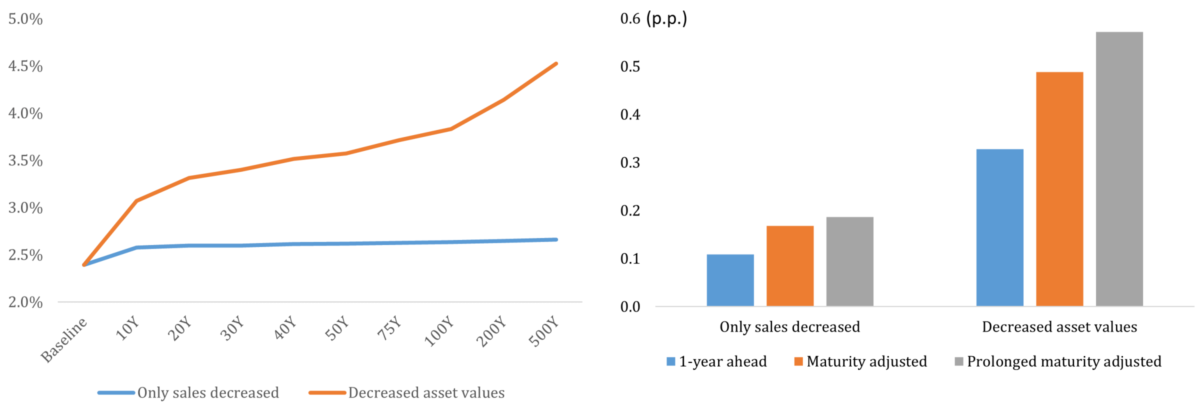
Notes: The chart shows the expected 1-year ahead and maturity adjusted exposure at default attributable to flood risk using linear loss curve based on continuous case using the baseline and alternative PD model. The exposure at default is shown as a share on the total volume of loans, in percentage points.
Source: JRC, CRIF, AnaCredit, own calculations.

Figure 14 illustrates the resulting average probability of default (PD) for the respective return periods, as well as the expected exposure at default (EAD), based on the baseline PD model and the linear loss curve. Incorporating asset value decreases leads to a notable increase in the average PD compared to previous results: the PD nearly doubles, rising from 2.4% under the baseline no-flood scenario to over 4.5% in the once in 500 years flood scenario. This amplification is also reflected in the overall credit risk impact, with both the 1-year ahead and maturity-adjusted expected exposures at default increasing substantially relative to the sales-only impact estimations. Specifically, compared to the baseline, the 1-year ahead expected EAD rises by more than 30 basis points (relative to the total NFC loan volume), and the maturity-adjusted expected EAD approaches a 50 basis points increase.

The final robustness test concerns the maturity of the loans. While some loans—particularly operating loans such as credit cards and revolving credit—may have relatively short reported maturities, firms often periodically extend these loans, resulting in an effective maturity longer than initially reported. To account for this, we adjusted the reported outstanding maturities of credit cards and revolving loans to a minimum of 5 years. That is, any loan with a reported maturity shorter than 5 years was reset to exactly 5 years, while maturities of other loan types remained unchanged. This adjustment increased the average maturity of the corporate loan portfolio from just over 3.5 years to nearly 6 years.

Figure 14: Estimated PD and exposure at default assuming decreased asset value

((a)) Average estimated PD ((b)) Expected exposure at default



Notes: The chart on the left shows the (simple) average probability of default of the NFC loan portfolio for the respective return periods. The chart on the right shows the expected exposure at default attributable to flood risk as a share of the total volume of loans. Estimations used linear loss function and the baseline PD model. Results are displayed for the baseline specification with only the firms' sales affected and for the alternative specification assuming also the decrease of asset value.
Source: JRC, CRIF, AnaCredit, FinStat, own calculations.

The results of this adjustment are shown in Figure 14 (b). Extending the average maturity further increases the expected exposure at default under the decreased asset value assumption, pushing it close to 60 basis points of the total corporate loan volume. This highlights the sensitivity of flood-related credit risk estimates to assumptions regarding loan maturities.

5.3. Counterfactual forward looking scenarios

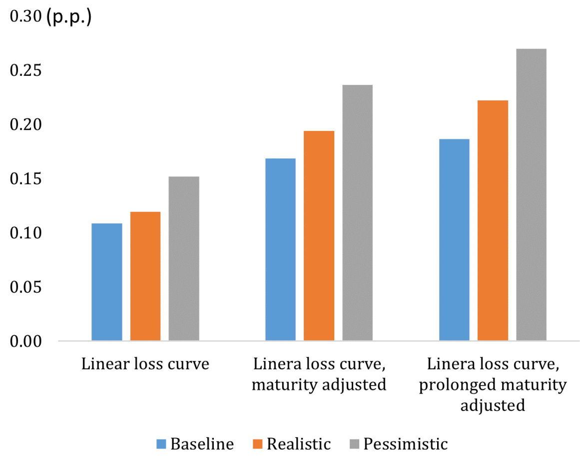
It is expected that global warming will increase both the magnitude and frequency of extreme precipitation events. According to the literature, floods that currently have a return period of once in 100 years on some European rivers may become more frequent, occurring once in 50 years or even once in 20 years (Dankers and Feyen, 2008; Kundzewicz et al., 2018).

To illustrate the potential impact of such increased flood frequencies using the current flood maps, we introduce two counterfactual flood scenarios. The first, referred to as the Realistic scenario, assumes that flood frequencies double; that is, a flood currently classified as once in 10 years becomes a once in 5 years event, a once in 20 years flood becomes once in 10 years, and so forth. The second, the Pessimistic scenario, assumes a fivefold increase in flood frequency. Practically, this means adjusting the event weights from Section 4 to reflect these increased frequencies.

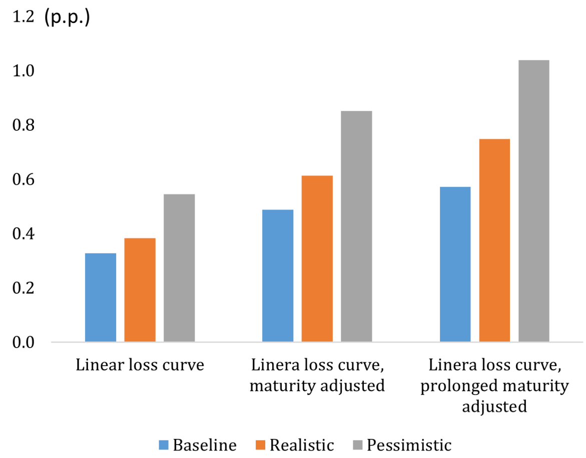
The results for the continuous case are presented in Figure 15. When considering only a de-

Figure 15: Estimated exposure at default under counterfactual scenarios

((a)) Only sales affected



((b)) Both sales and assets affected



Notes: The charts show the expected exposure at default as a share on the total volume of loans. Estimations used linear loss function and the baseline PD model.
Source: JRC, CRIF, AnaCredit, FinStat, own calculations.

crease in sales due to flooding (Figure 15a), the estimated exposure at default rises by up to 20% under the Realistic scenario and by nearly 50% under the Pessimistic scenario, reaching almost 30 basis points of the NFC loan portfolio. When accounting also for the negative impact of flooding on asset values (Figure 15b), the expected exposure at default increases by up to 30% under the Realistic scenario and up to 80% under the Pessimistic scenario. This amplification is due both to the higher relative weight of extreme flood events and to the stronger increase in firms' PDs when asset values are adversely affected. Thus, in the worst-case Pessimistic scenario, the increase in expected exposure at default attributable to flood risk exceeds 1 percentage point of the total NFC loan portfolio.

6. Conclusions

Riverine floods are expected to be the most widespread and economically significant climate risk driver in the European Union over the next two decades. Without adequate climate mitigation and adaptation measures, direct damages from flooding could increase six-fold by the end of the century, as global warming is likely to cause more frequent extreme events, including floods. Notably, the European Central Bank (ECB) identifies Slovakia as one of the Euro area countries most exposed to flood risk.

In this paper, we estimate how riverine flooding may affect the credit risk of the corporate loan portfolio of Slovak banks. Our analysis leverages granular data sources, including flood maps from the European Commission's Joint Research Centre, detailed parcel-level data attributed to firms from the Geodesy, Cartography and Cadastre Authority of the Slovak Republic, loan-level data from the credit register maintained by the National Bank of Slovakia, and financial and balance sheet data of Slovak firms provided by FinStat, an external data provider.

These granular datasets enable us to estimate expected flood levels at both the parcel and firm level, utilizing flood expectations for various return periods as provided by the flood maps. We implement both a discrete approximation of the expected flood—based on available return period data—and a continuous approximation, estimating the average expected flood over the entire distribution of return periods. Subsequently, we estimate the flood impact on credit risk using a straightforward probability of default (PD) model for the indebted firms, which is based on their financial and balance sheet data. The model assumes that flooding negatively affects the revenues and asset values of impacted firms.

Our results suggest that while a substantial share of firms is currently exposed to flood risk, only a limited subset is expected to be significantly affected by riverine flooding under present conditions. In the baseline scenario—assuming floods reduce only firms' revenues—the average estimated PD increases by up to 30 basis points, depending on assumptions and return periods considered. This increase corresponds to a rise in the expected exposure at default (EAD) of the loan portfolio by as much as 11 basis points as a share of the total corporate loan portfolio. These findings are robust across a range of alternative assumptions and sensitivity analyses. The effects become more pronounced when assuming the flood also reduces firms' asset values: in this scenario, the average PD nearly doubles under the once-in-500-year flood event, leading to an increase in EAD of approximately 50 basis points relative to the corporate loan portfolio. Under a scenario assuming a fivefold increase in flood frequency, the increase in expected exposure at default may reach as high as 1 percentage point.

As this study represents the first analysis focusing on flood impacts on firms from a credit risk perspective, several opportunities exist to expand the research. Currently, potential mitigating factors—such as insurance coverage by firms—are not incorporated. Similarly, estimating loss given default (LGD) is not possible due to limited information on flood impacts on collateral or other protective mechanisms. Lastly, it is important to note that while our estimates are based on expected riverine floods for respective return periods across Slovakia, such floods are unlikely to occur simultaneously nationwide. At the same time, individual flood shocks are not independent, and incorporating correlation structures based on river basin topology could be a valuable direction for future work.

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Appendix

A. Method of land use

Table 1: Method of land use

Method of Land Use	Loss in Case of Flood	Immediate Loss in Case of Flood
There is purpose-built protective agricultural and ecological greenery on the land against erosive measures and measures to ensure the ecological stability of the area	YES	YES
On the land there is a nursery for hop seedlings, a vine nursery, a nursery for fruit or ornamental trees, a forest nursery or a seed orchard and others	YES	YES
Land continuously planted with fruit trees, fruit bushes and fruit seedlings in one place, one or more species	YES	YES
Land planted with hops or land suitable for growing hops from which hops have been temporarily removed	YES	YES
Land used for plant production, on which cereals, root crops, fodder, technical crops, vegetables and other agricultural crops are grown, or land temporarily not used for plant production	YES	YES
A plot of land within the garden center on which ornamental low and tall greenery is grown or a plot of land temporarily used for the production of lawn carpets, Christmas trees and other ornamental greenery	YES	YES
Land on which vines are grown or land suitable for growing vines on which vines have been temporarily removed	YES	YES
Other	YES	YES
A greenhouse, Japanese garden, steam room and others are built on the land	YES	NO
Land mainly in the built-up area of the municipality or in the gardening settlement, on which vegetables, fruits, ornamental low and high greens and other agricultural crops are grown	YES	NO

Method of Land Use	Loss in Case of Flood	Immediate Loss in Case of Flood
Land with forest cover, temporarily without forest cover for the purpose of reforestation or after accidental logging	YES	NO
Land used according to the type of land	YES	NO
Land that is not used in any of the above ways	YES	NO
Land that is used for the extraction of minerals and raw materials	YES	NO
Land on which there is a botanical and zoological garden, an open-air museum, an amphitheater, a monument and others	YES	NO
A plot of land on which there is a cemetery or urn grove	YES	NO
Land on which there is a yard	YES	NO
A plot of land on which there is a playground, stadium, swimming pool, sports track, car park, campsite and others	YES	NO
Land on which there is a handling and storage area, an object and a building serving forestry	YES	NO
Land on which there is an ornamental garden, street and neighborhood greenery, a park and other functional greenery and forest land for recreational and hunting use	YES	NO
The land on which the building is built without being marked with an inventory number	YES	NO
The land on which the apartment building is built, marked with an inventory number	YES	NO
The land on which the engineering structure is built - road, local and purpose-built roads, forest road, field road, footpath, uncovered parking lot and their components	YES	NO
The land on which the engineering structure is built - highway and expressway and its components	YES	NO
The land on which an engineering structure is built - port, navigation channel and chamber, dam and other protective barrier, irrigation and melioration system and its components	YES	NO
The land on which the engineering structure is built - the airport's take-off, landing and taxiway and its components	YES	NO

Method of Land Use	**Loss in Case of Flood**	**Immediate Loss in Case of Flood**
The land on which the engineering structure is built - railway, ropeway and other track and its components	YES	NO
The land on which a non-residential building marked with an inventory number is built	YES	NO
The land on which the other engineering structure and its components are built	YES	NO
The land on which the entrance portal to the underground structure or cellar is built	YES	NO
The land on which the building is under construction	YES	NO
Land on which there is a waste dump	YES	NO
Land on which there is a common yard	YES	NO
The land on which there is a ruin	YES	NO
Swamp	NO	NO
Land of meadow and pasture permanently covered with grass or land temporarily not used for permanent grass	NO	NO
Land on which there are rocks, slopes, gullies, potholes, high borders with bushes or stones and other areas that do not provide a permanent benefit	NO	NO
Pond - an artificial water reservoir intended for fish breeding, including constructions	NO	NO
Water surface (lake, artificial water reservoir, exposed groundwater - gravel pit, dredging site and others)	NO	NO
Water flow (natural - river, stream; artificial - canal, stream and others)	NO	NO

B. Nature of land use

Table 2: Nature of land use

Nature of Land Use	Loss in Case of Flood	Immediate Loss in Case of Flood
Hop plant	YES	YES
Other	YES	YES
Arable land	YES	YES
Orchard	YES	YES
Vineyard	YES	YES
Garden	YES	YES
Forest plot	YES	NO
Other area	YES	NO
Permanent grassland	YES	NO
Built-up area and courtyard	YES	NO
Water surface	NO	NO

C. Estimating NFCs probability of default

The probability of default of the non-financial corporations is estimated using a logit model of the form

$$P(Default) = \frac{1}{1 + e^{-\mathbf{X}\beta}}, \tag{10}$$

where **X** is a set of explanatory variables including an intercept. The model uses input data from AnaCredit, the credit register of corporate loans granted by Slovak banks, and FinStat, a database of financial statements and financial indices of Slovak firms. From AnaCredit, we observe firms having loans from Slovak banks and firms' defaults. We estimate the model based on annual data from 2013 until 2024.

Explanatory variables were chosen based on whether they enter the regression with a significant coefficient having the expected signs. The list of variables and the expected sign of their coefficient is included in Table 3. Variables are included with a 1-year lag. Thus, the probability of default in year T is estimated based on the financial indicators in year *T-1*. The annual change of the variables refers to the annual change between *T-1* and *T-2*. The model includes sectoral dummies as well.

For the analysis, we use two specifications of the model. The first specification uses the definition of the variables in the same way they enter the credit risk analysis of the NFC loan portfolio in the Financial Stability Reports of the National Bank of Slovakia. The second uses an alternative definition of the variables with wider boundaries, i.e., upper and lower limits, to allow a more gradual impact of the increasing level of flood. Only the limits of those variables that are negatively affected by the decrease of sales are adjusted for the alternative model. The baseline and alternative specification of the variables is displayed in Table 4.

Table 5 shows the estimated coefficients of both the baseline and the alternative PD model. The model is estimated on the full sample[13]. The estimated intercept is calibrated to match the actual level of the share of firms defaulting in the latest year, 2023 in our case. The application of the PD model for the estimation of the impact of flood risk is relatively straightforward using

[13] As the number of defaulted firms is relatively low compared to the total number of firms in the sample, the model is estimated 5,000 times by randomly choosing non-defaulted firms. The number of non-defaulted firms chosen is twice the number of defaulted firms. The statistics provided in Table 5 are based on the average of 5,000 estimations.

Table 3: Variables used in the logit regression

Variable name	Variable description	Expected sign
Gross margin	Value added divided by total sales	-
Turnover time	Current liabilities divided by the total costs	+
Turnover time, change	Annual change of the turnover time	+
Interest coverage ratio	Earnings before interest and tax divided by interest expenses	-
Return on total assets	Earnings before interest and tax divided by total assets	-
Return on total assets, change	Annual change of the return on total assets	-
Liabilities to assets	Liabilities divided by total assets	+
Liabilities to assets, change	Annual change of liabilities to assets	+
Negative equity change	Dummy equaling 1 if the total equity of a firm decreased annually below zero, 0 in case of no change and + 1 if the total equity of a firm increased above zero	+

Table 4: Baseline and alternative boundaries of variables

Variable name	Minimum and maximum, baseline model	Minimum and maximum, alternative model
Gross margin	[-1, 2]	[-1, 2]
Turnover time	[0, 5]	[0, 5]
Interest coverage ratio	[0, 5]	[-60, 10]
Return on total assets	[-0.4, 0.4]	[-5, 5]
Liabilities to assets	[0, 2]	[0, 2]

some simplifying assumptions. First, we assume that the flood has a negative impact on the sales of the firms. The extent to which sales are decreased depends on the share of parcels impacted by the flood and the level of the flood[14]. Earnings are decreased to fully reflect the decrease of sales. Consequently, all the variables entering the PD model negatively affected by the decrease of earnings are adjusted to reflect this decrease[15]. Finally, the difference between the expected exposure at default based on the logit model using the original and the adjusted indices is attributed to the flood. Within the robustness checks, we also assume a negative impact of the flood on the value of total assets and thus adjust the indicator Liabilities to assets in the same way as the indices impacted by the decrease of sales.

[14]If 50% of the parcels (in terms of square meters) are impacted by flood and the level of flood exceeds 3 meters, we assume based on the loss function that the firm loses 100% of its sales related to half of its parcels, so altogether 50% of its sales. If 50% of the parcels are impacted, but the level of flood is only 1.5 m, based on the linear loss curve the firm loses 50% of its sales related to half of its parcels, so altogether the firm will have sales lower by 25%.

[15]The gross margin is, e.g., calculated as the value added divided by total sales. This means the decrease of sales would increase gross margin, so the expected impact on the firms' PD would be positive. In this case, however, we assume that the value added decreases due to the flood as well and therefore keep the value of gross margin unchanged.

Table 5: Logit model - estimation results

Variable name	**Baseline model**	**Alternative model**
Intercept	-0.798	-1.139
	(0.070)	(0.067)
Gross margin	-0.412	-0.017
	(0.042)	(0.005)
Turnover time	0.119	0.111
	(0.011)	(0.010)
Turnover time, change	0.102	0.110
	(0.014)	(0.014)
Interest coverage ratio	-0.051	-0.006
	(0.003)	(0.001)
Return on total assets	-0.356	-0.107
	(0.116)	(0.034)
Return on total assets, change	-0.018	-0.018
	(0.081)	(0.027)
Liabilities to assets	0.423	0.581
	(0.036)	(0.034)
Liabilities to assets, change	0.014	0.014
	(0.013)	(0.014)
Negative equity change	0.243	0.327
	(0.044)	(0.043)
Sectoral dummies	Yes	Yes
No. of observations	34,374	34,374
AUROC	68.0%	66.5%

Notes: Table shows estimated coefficients of the logit model. Standard errors in parentheses.