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Firm Credit Conditions and Flood Risk: Evidence from Ireland

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Abstract: In this paper, we examine the impact of the risk of flooding on the credit conditions of non-financial corporations in Ireland. Using detailed maps of the likelihood of flood events and geolocated loan data from the AnaCredit dataset, we compare the interest rates and collateral requirements of borrowers with similar characteristics but different levels of flood risk. We find that loans to borrowers in flood risk areas (around 7 per cent of our sample) face an interest rate premium (of roughly 7 to 13 basis points) and are more likely to provide a collateral (between 3 and 7 percentage points). Furthermore, our estimates indicate that the increased flood risk caused by climate change is partially factored in. Although the results suggest that lenders price this important source of climate risk, they also highlight an additional difficulty in obtaining credit for borrowers located in areas susceptible to floods.

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I INTRODUCTION

Climate change is a key global challenge for countries, irrespective of geographic location or wealth (Intergovernmental Panel on Climate Change, 2023). The resulting climate risk (which affects households, non-financial corporations and financial institutions) encompasses both physical and transition risk. The former is the direct damage resulting from a climatic event (such as flooding, wildfires, and storms), while the latter is the cost associated with policy actions taken to decarbonise the economy (Central Bank of Ireland, 2023). This paper focuses on the intersection of physical risk and non-financial corporations' lending conditions in Ireland – specifically, the impact of flood risk on the interest rate and collateral conditions of bank loans to firms. This is a key emerging financial stability question – from the perspective of both the bank and the firm. The economic costs following a flood event all impact a firm's ability to operate, its profit and loss account, and balance sheet position.[1] These damages and their resulting impact could, if severe enough, increase the probability of default and loss given default. In light of this, banks may require tighter lending conditions from firms in flood prone areas reflecting a higher risk of insolvency.

The main objective of this paper is to empirically examine whether, and the extent to which, flood risk results in more stringent collateral requirements and/or higher interest rates, as well as quantifying the magnitude of the flood risk premium. This is achieved by combining loan-level information on the characteristics of each credit contract with accurate flood risk maps, allowing us to identify borrowers at risk. In addition, we rely on climate change projections to study whether the expected worsening of climate conditions (and the resulting expansion of flood risk areas) is being taken into account by lenders. To preview our main findings, the results indicate that borrowers in areas at risk face a premium that is both statistically and economically significant, and that the predicted worsening of climate conditions is partially taken into account by lenders. From a policy perspective, this is of the utmost importance in the Irish context in light of Murphy *et al.* (2018), Clarke and Murphy (2019), and Domonkos *et al*. (2020) who highlight worsening rain-related weather trends, an upward trajectory of long-run rainfall trends, and winter and spring witnessing heavier rainfalls. While finding that banks are accounting for this increasingly relevant source of risk in their lending decisions can be reassuring in terms of the stability of the financial system, this also represents an additional barrier to accessing credit for firms located in areas susceptible to floods, whose number is expected to increase due to the predicted patterns of climate change.

[1] These costs include stranded assets, repair or replacement costs, loss of stock, decrease in property value, and loss of business.

In assessing whether flood risk affects firms' lending conditions, the key academic contribution of this paper is the use of precise, granular data to capture the risk. In particular, we rely on the exact borrower location combined with accurate flood maps which generates variation in the flood risk in our sample even within administrative areas (counties). This allows us to disentangle flood risk from other local (unobserved) factors which might affect firms' credit access. Most of the existing literature relies instead on climate risk dimensions that are defined at broader administrative areas. A number of related papers focus on the stability of the banking system with specific reference to climate risk. For example, Meucci and Rinaldi (2022) use Italian AnaCredit data to study lenders' vulnerability to climate risk in the form of loans to firms, finding that only a few relatively small lenders were overly exposed in the period under analysis. However, the measure of climate risk they employ is based on a province-level index rather than the exact location of the borrowers. In a similar work, Faiella and Natoli (2018) provide some evidence that Italian banks are generally less likely to provide credit to small and medium-sized firms located in areas at higher risk of floods and natural catastrophes. In this instance, the underlying measure of risk is based on municipal-level data. Elnahas *et al*. (2018) find that American firms in areas which are historically more prone to natural disaster are less leveraged due to less favourable lending terms received from financial institutions. In this instance, the historical risk variables are only defined at the county level. Similarly, Do *et al*. (2023) employ a panel dataset of nearly 1,000 US banks between 2010 and 2019 to study whether the occurrence of climate shocks in the county where lenders are located affected their performance and stability. Their results indicate that climate related shocks have a negative impact on lenders' risk of insolvency (measured by the banks' Z-scores) but tends to disappear after a few quarters.

Our paper also contributes to the rapidly expanding literature which empirically quantifies the impact of climate risk on the cost and access to credit for firms, households and municipalities. Also in this instance, the main contribution of our work is the use of more granular risk measures employed. Correa *et al*. (2022) find that banks in the US imposed higher premiums (up to 18 basis points) when lending money to firms which are more exposed to natural disasters, and that the effect is stronger in the aftermath of climate-related disasters which update lenders' awareness and expectations on climate change. The risk measured employed is the same as in Do *et al*. (2023) and only defined at the county level. Javadi and Masum (2021) study the impact of droughts on the cost of credit for US firms from 1986 to 2017 and find a statistically significant effect on interest rate spreads driven mostly by long loans to poorly rated firms. In this case, the climate risk is based on a drought index aggregated at the state-year level. Goldsmith-Pinkham *et al*. (2023) examine the premium on US school districts bond yields exposed to sea level rise. They find that lenders were charging significantly higher interest rates to municipalities at risk since 2013. In this instance, the authors aggregate the exposure to sea level rise at the district level by examining the share of the properties subject to this risk. Nguyen *et al*. (2022) also focus on sea level rise but look instead at the cost of mortgage credit comparing properties with similar distance to the coast but different levels of exposure. They find that properties located in areas with larger risk are indeed charged larger interests, though the magnitude is relatively small (a 7.5 basic point difference between a zipcode with zero and maximum risk respectively). In this case, the risk is assessed at the zipcode-level and measured as the share of the zipcode area likely to be inundated following a six-foot increase in sea level. Finally, Barbaglia *et al*. (2023) is arguably the most similar work. In particular, the authors provide some evidence of an interest rate premium on loans to SME borrowers located in high-risk areas in Belgium, France, Spain and Italy. Their estimates indicate an interest rate premium of about 6 basis points which, based on the authors' estimates on the probability of default driven by flood event, is not sufficient to cover the additional risk taken on by lenders. In this instance, the risk variable is aggregated at the NUTS-3 level.

Another related stream is the classic terms of lending literature which has focused on empirically explaining the determinants of collateral requirements and the risk premium in loans extended to firms. This study leverages the results and insights from this stream in constructing the empirical specification in Section III.[2]

Besides adopting a more precise definition of risk based on the exact location of the borrower, our paper also contributes to the literature by looking at both the interest rates and the collateral requirements as indicators of the credit conditions offered to firms. Additionally, we are able to separate current risk from the additional exposure predicted by existing scenarios of climate change to examine to which extent the latter is already being priced in by lenders and gauge their level of sophistication. Our results indicate that borrowers in areas at flood risk face an interest rate premium (of roughly 7 to 13 basis points) and are more likely to provide a collateral (between 3 and 7 percentage points). While these cannot be interpreted as causal estimates, the findings are robust across different specifications and are not sensitive to the inclusion of county fixed effects (i.e. the premium is also observed when comparing firms operating in the same county). While this is reassuring as it indicates that lenders are reducing their exposure to climate risk, these findings also suggest an additional obstacle to obtaining credit for firms located in affected areas. The remainder of this paper is organised as follows: Section II discusses our data sources in more detail and provide some descriptive statistics and an overview of the fuzzy matching technique, Section III outlines the empirical model and corresponding results while Section IV concludes.

[2] For a recent review of this literature, please consult Berger *et al.* (2011).

II DATA

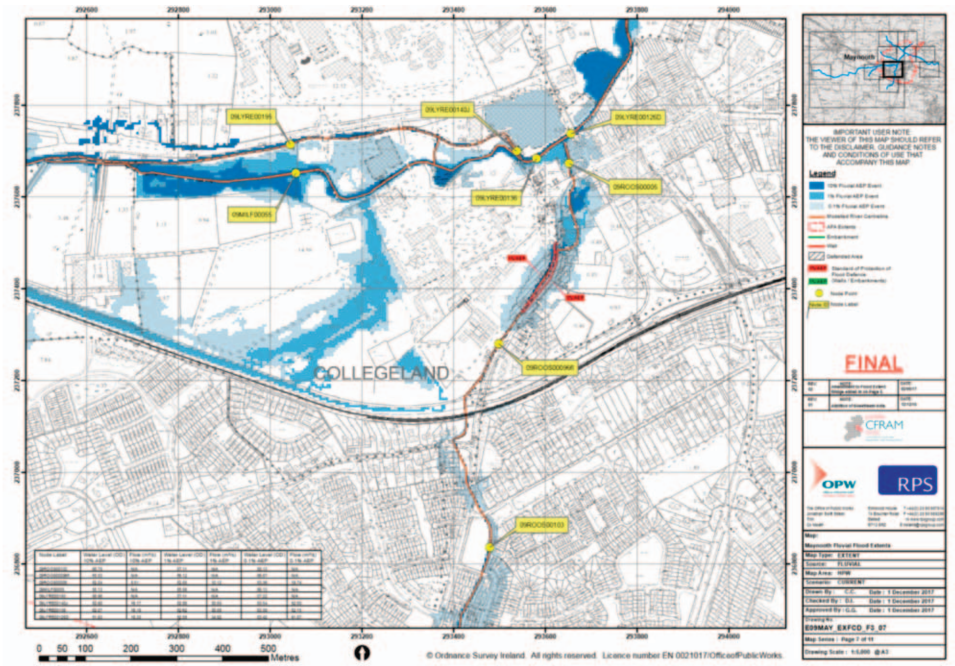
The main empirical contribution of this work is that we combine novel datasets that allow us to identify variation in flood risk within relatively small administrative areas. In this section, we provide a description of these datasets and of the procedure adopted to obtain the final sample used in the empirical analysis. We use three main data sources in this work, namely; the Office of Public Works flood maps (capturing flood risk), AnaCredit (which provides information on existing loans), and the Eircode Address Database (an alphanumeric code matching locations to exact coordinates). Their features are described separately in the next sections. We then provide an explanation of the matching procedure and some descriptive statistics for the resulting sample.

2.1 Flood Risk Datasets

The Office of Public Works (OPW) provides a series of different maps capturing the risk of flooding across Ireland. Formally, the data is presented in the form of polygons: georeferenced shapes/areas exactly identifying the locations which, according to the OPW model, are characterised by a certain level of flood risk. Importantly, the information refers to the predicted likelihood of a given area to be flooded during a theoretical event (with a certain estimated likelihood of occurrence) rather than being based on actual floods occurred in the past. For the purpose of this paper, we do not discriminate between different flooding events (coastal vs fluvial), which are modelled separately by the OPW and shown in different maps, but we focus on a comprehensive definition of flood risk which includes all types of events. In our baseline specification, flood risk is a binary variable taking value 1 where the exact location the borrower is located in is susceptible to either coastal or fluvial flooding.

To obtain this measure of flood risk, we combine the three OPW datasets: the Catchment Flood Risk Assessment Management (CFRAM, OPW, 2018), the National Coastal Flood Hazard Maps (NCFHM, OPW, 2021a) and the National Indicative Fluvial Mapping (NIFM, OPW, 2021b). While the three maps have the same objective of identifying areas at risk of flooding, they differ in terms of the geographical scope and the type of events considered. The CFRAM models both coastal and river flooding. However, the geographical scope is limited, covering 300 separate Areas for Further Assessment (AFAs) – based on 6,700 kilometres of watercourses and 90 coastal communities. These areas were identified by OPW through a Preliminary Flood Risk Assessment (PFRA) as required by the EU 'Floods' Directive [2007/60/EC]. This process was based on historic information of actual flood events, public consultation with Local Authorities, and engineering techniques aimed to measure the potential consequences of flooding. Overall, the areas cover about 3 million people. For example, Figure 1 shows the CFRAM map for Maynooth highlighting the areas at risk of fluvial flooding. The risk is not expressed merely as a binary outcome, rather it is based on the estimated likelihood of an event occurring in any given year. Technically, this likelihood is referred to as Annual Exceedance Probability (AEP) – which captures the annual probability that a given flood level is equalled or exceeded. For example, a polygon describing a 10 per cent AEP indicates areas which on average will be flooded once every ten years. This will be contained by bigger polygons (such as the 1 per cent AEP) which identify areas characterised by lower probabilities of flooding every given year.[3] For the CFRAM map, three different risk thresholds (AEP) are presented for fluvial and coastal events. In the former, the AEPs are 0.1 per cent, 1 per cent and 10 per cent, while the latter are 0.1 per cent, 0.5 per cent and 10 per cent. For the sake of tractability, we refer to these thresholds as minimum, intermediate and maximum (respectively) even if the intermediate thresholds are not directly comparable (since they are based on different AEP).

Figure 1: CFRAM Fluvial Risk Map (Maynooth)



Source: CFRAM, (OPW, 2018).

[3] These AEP are obtained using hydrodynamic modeling where river flows and sea levels are combined with digital terrain models to measure the extent of fluvial and coastal flooding. The procedure can be articulated in three key stages: (i) Hydrological analysis: The flood flows and tidal levels for the designed flood events are estimated; (ii) Hydraulic modeling: The flood levels at intervals along a river or for locations in a floodplain are estimated. (iii) Analysis of flooding: Estimation of the propagation from the river or tidal area over the land.

The other two datasets can be considered as a geographical extension of the CFRAM data as they provide information on coastal and fluvial flood risk beyond the 300 AFAs covered by the CFRAM. While based on simplified models, including these additional datasets allows us to extend the scope of our analysis to the entire Irish territory. More precisely, the NCFHM OPW (2021a) is only concerned with coastal flood events and unlike the CFRAM, it is available for all the Irish coastal areas. The AEP considered are directly comparable to the (coastal) events in the CFRAM map and the thresholds are categorised accordingly (maximum = 10 per cent, intermediate = 0.5 per cent and minimum = 0.1 per cent). Finally, the NIFM OPW (2021b), plays a similar role of the NCFHM in extending the coverage of the CFRAM beyond the 300 main AFAs, but is concerned with fluvial rather than coastal events. In particular it extends the geographical cover to 27,000 additional kilometres covering all the water bodies of at least 5 km^2. Notably, the AEP differs in the highest probability areas between the NIFM and the (fluvial) CFRAM.

Table 1: Flood Risk Datasets Comparison

Flood Map	*Coverage*	*Type*	*AEP range*		
			Minimum	*Intermediate*	*Maximum*
CFRAM (coastal)	300 AFAs	Coastal	0.1%	0.5%	10%
CFRAM (fluvial)	300 AFAs	Fluvial	0.1%	1%	10%
NCFHM	Whole Coastline	Coastal	0.1%	0.5%	10%
NIFM	Water bodies $\geq$ 5km^2	Fluvial	0.1%	1%	5%

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a) and NIFM (OPW, 2021b). AFAs refer to the 300 Areas for Further Assessment covered by the CFRAM, while AEP refer to the Annual Exceedance Probability considered by each flood map.

Table 1 provides a summary of the coverage and the type of information included in each of the OPW maps considered. It is clear that the minimum threshold of risk reported is common across the three datasets. For this reason, in combining the datasets, we use the polygons describing the extent of the (common) minimum flooding risk in order to maintain consistency across maps. This allows us to expand the geographical scope of the empirical analysis to the whole country without relying on different definitions of risk across datasets. Specifically, in our benchmark empirical analysis, a borrower is considered at risk where located within an area within the minimum risk threshold of any of the datasets considered.

While the benchmark findings are based on the current climate conditions, all the datasets are also available under two additional scenarios projecting the impact of climate change on the extent and severity of the flood risk. The two scenarios (mid-range future scenario and high-end future scenario) differ in the severity of the modelled changes in climate conditions and in turn on the related changes to flood risk. For example, an average sea level rise of 0.5 and 1 metre (respectively) are added to the flood risk model, as well as more or less severe deforestation and changes in rain and flood flows patterns. Table 2 outlines the exact differences between the mid-range and high-end climate change projections. Figure 2 illustrates the resulting extent of the flood risk area under current as well as medium and high-end climate change projections in Wexford town. It can be observed that areas which are currently at risk represent a subset of the territory predicted to be prone to flooding under the climate change scenarios. In a similar way, the polygons describing the high-end scenario are the largest as they are based on more extreme changes in climate patterns resulting in higher areas at risk of flooding events. In Section 3.3, we exploit this additional feature of the data to study the extent to which banks price in the expected climate change when setting their terms of lending.

2.2 AnaCredit

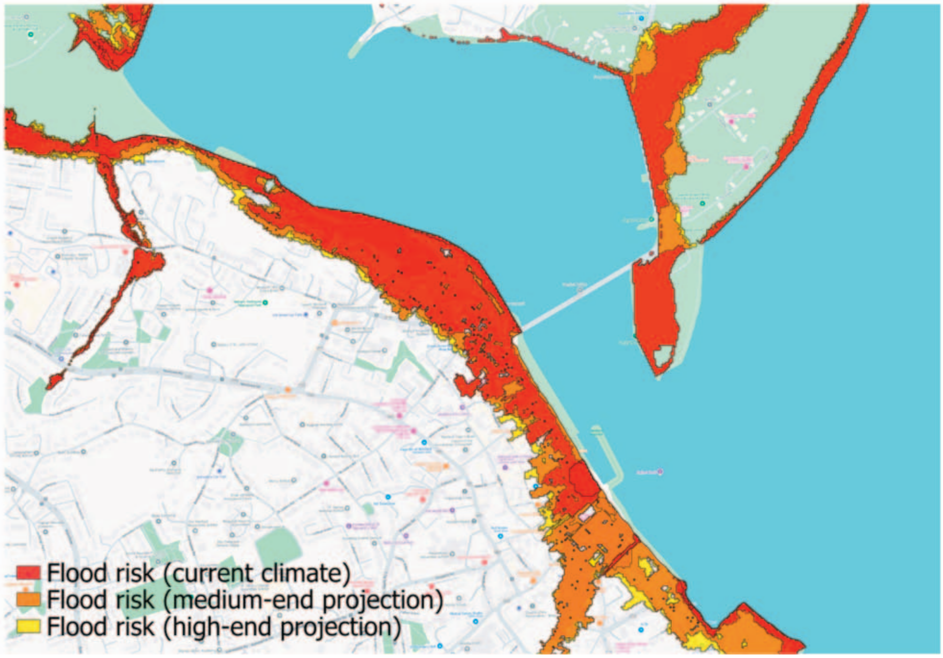
The Analytical Credit Dataset (AnaCredit, Central Bank of Ireland, 2022) is a granular credit dataset collected by EU members' central banks since September 2018 (following adoption by the ECB governing council of ECB Regulation ECB/2016/13). In this paper, we use the Irish data, which include information on all the existing loans and credit contracts from Irish resident credit institutions. The dataset is updated monthly to include new loans and input new information on the outstanding ones (while the ones fully paid back or defaulted exit the sample).

Table 2: CFRAM Climate Change Scenarios

Parameter	*Mid-Range Projection*	*High-End Projection*
Extreme Rainfall Depths	+20%	+30%
Peak Flood Flows	+20%	+30%
Mean Sea Level Rise	+500mm	+1000mm
Land Movement	–0.5mm/year	–0.5mm/year
Urbanisation	Reviewed case to case	Reviewed case to case
Forestation	–1/6 Tp sq	–1/3 Tp sq

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a) and NIFM (OPW, 2021b). Extreme rainfall depths represent the increase in the intensity of exceptional precipitation events which are expected to be more severe with climate change. Peak flood flows represent the maximum increase in volume of water bodies during a flood event. Sea level rise is linked to generally hotter conditions while land movement models the phenomenon of land subsidence where ground surface gradually sinks. Deforestation results in a reduction in the time to peak (Tp) which is more marked in the high-end scenario and increases the likelihood of floods for the same level of precipitation. The impact of urbanisation and change in surface area is modelled separately on a local basis.

Figure 2: Combined Flood Risk in Wexford Town



Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a) and NIFM (OPW, 2021b).

We use the June 2022 reference period, which includes all the outstanding loans and other credit contracts as of that date.[4]

For each credit contract, the issuers need to indicate some basic characteristics of the loan, such as the total original amount, the current amount outstanding, the interest rate applied, as well as the type of interest rate (fixed or variable), and the frequency of repayment. The starting as well as the legal maturity date can be used to determine the duration. Contracts are divided into eight different categories (credit card debts, non-revolving credit lines, deposits, finance leases, loans, overdrafts, revolving credit and trade receivables).[5] In addition, credit institutions are asked to report some basic features of the borrowers. In particular, we will use information on the firm size,[6] the industry they operate in, as well as the address.

[4] This implies that the sample we are working with includes mostly rather recent contracts. In theory, it would be possible to use previous iterations of AnaCredit to gather information on older loans. However, data have only been systematically compiled since 2018 and as such the sample size would only increase marginally by doing so.

[5] In some instances, the type of contract was not available in the data and flagged as "not required".

[6] Firm size follows the standard EU definition: micro firms have 0-9 employees and one of turnover less than €2 million or balance sheet less than €2 million; small firms have 10-49 employees and one of turnover less than €10 million or balance sheet less than €10 million; medium firms have 50-249 employees and one of turnover less than €50 million or balance sheet less than €43 million; large firms have 250+ employees.

The last is particularly relevant to our purposes as it allows us to determine the exact location of the borrower (see Section 2.3 for more details). Finally, for each loan, the issuer needs to provide information on all the collateral included in the contract as well as some information on their characteristics, type, and estimated value. In the final form of the dataset, each observation indicates a separate collateral for the ongoing loans.[7] Unfortunately, variables on the value and type of the collateral were only sparsely populated and as such in the empirical analysis we will only discriminate between contracts with and without a collateral asset.

2.3 Eircode Address Database

The Eircode Address Database (ECAD, DAC, 2022) includes the exact coordinates for over 2.2 million addresses in Ireland. Each address and coordinates pair is uniquely identified by an 7-digit alphanumeric code (Eircode), an innovative postcode system active since 2015 which allows for easy identification and location of each residential and commercial address. For our purposes, the main function of this database is to convert the addresses indicated in our loan-level data into coordinates, which in turn allows us to generate a borrower-level flood risk variable leveraging the flood risk maps described in Section 2.1. Specifically, the merging procedure was performed in three stages. First, the trivial case where the borrower's Eircode is present and indicated correctly in AnaCredit; this is a straightforward match as each code separately identifies a specific set of coordinates. Second, the case where the Eircode is absent from AnaCredit (either it is missing or not completed fully/properly), but the firm name is present in ECAD; since the firm name is in AnaCredit too, this is also a straightforward match. Here the merge is completed using firm names to find the corresponding Eircodes, address, and coordinates through the ECAD data. Third, the case where the Eircode is absent from AnaCredit and ECAD does not have the firm name, we employ a fuzzy matching methodology which allows us to match address strings in our loan-level data to similar addresses included in the ECAD.

Prior to implementing fuzzy-matching, in order to optimise its effectiveness some pre-processing parsing techniques were implemented. This involved removing potentially disruptive characters, as well as standardising and completing street addresses. For example, characters such as "@", "-", "&" are removed, while common street suffix abbreviations are expanded (for example like "RD" to "ROAD", "AVE" to "AVENUE", and "ST" to "STREET"). The "RapidFuzz" package in Python was employed to complete the fuzzy matching. In short, this combines additional parsing techniques with edit-distance[8] and token[9] matching by

[7] Where contracts do not include any collateral, the loan will enter as a single observation (row) with missing collateral code.

[8] Compares strings based on the number of operations needed to gain similarity – with matching based on the lowest number of operations needed to achieve similarity.

[9] A vectorial decomposition method which splits strings names into blocks (i.e. tokens) according to blank spaces.

integrating the "fuzz ratio", "fuzz partial ratio" and "fuzz token sort ratio" algorithms. To enhance the accuracy and robustness of the address matching process, this algorithmic combination addresses various types of discrepancies that commonly occur in large datasets – such as typographical errors, partial matches, and variations in word order. Specifically, the "fuzz ratio" algorithm serves as a baseline for evaluating the overall similarity between two strings by comparing their characters directly (using Levenshtein distance). It is particularly effective for identifying minor typographical errors or variations. For example, when comparing "123 Main St" and "123 Main Street", "fuzz ratio" detects the close similarity despite the abbreviation difference. Building on this, the "fuzz partial ratio" algorithm focuses on identifying the most similar substring within a larger string, which is useful when additional or missing information exists in one of the addresses. For instance, if an address in the dataset is simply "123 Main", "fuzz partial ratio" can match it effectively with "123 Main Street", capturing the essential similarity even when the input is incomplete. The "fuzz token sort ratio" algorithm further enhances our matching strategy by sorting the words within each address and comparing these sorted tokens. This approach is crucial for handling variations in word order, ensuring that "Main Street 123" matches correctly with "123 Main Street". By aligning the tokens, this algorithm ensures consistency even when addresses are entered in differing sequences.

An empirical threshold for similarity was established through preliminary analysis to optimally balance sensitivity and specificity effectively. Strings with similarity scores above this threshold (set at 90 per cent) were considered matches.[10] By integrating these three algorithms, a comprehensive matching approach that accommodates a wide range of discrepancies and variations in the address data was developed. Each potential match identified through this process was subsequently subjected to manual review or cross-validation with supplementary data sources to ensure the accuracy and reliability of the matching process. Following this procedure, we are able to attribute a specific location to 60 per cent of the loans in the sample.[11]

2.4 Final Sample and Descriptive Statistics

The original loan-level dataset contains information on 201,136 separate credit contracts representing loans not yet repaid as of June 2022. Out of these, we can obtain a precise set of coordinates for 120,111 – or 60 per cent of the original

[10] The results are robust to the use of more/less conservative thresholds; 90 was picked based on a qualitative assessment of the matches quality performed by the authors.

[11] In the appendix, we show that the matched and unmatched observations are comparable in terms of their observable characteristics and that the cross-county distribution of loans matches closely the distribution of companies operating in Ireland.

sample.[12] In order to work with a homogeneous sample of credit contracts, we focus on three categories: loans, non-revolving credit and financial leases. We choose these categories as they include the most straightforward forms of credit whose conditions can be easily observed and captured by interest rates and collateral requirements. This further reduces the sample size to 46,129 loans.[13] The final sample used in the empirical analysis is obtained by removing the outliers in terms of interest rates charged (where the values indicated are ≤ 0.01 or ≥ 20 per cent) and dropping the observations where variables of interest were missing. This leaves us with a final sample of 40,852 loans.[14]

Since borrowers are geolocated, it is possible to determine the share of loans at risk of flooding according to the standardised measures derived from the flood maps (OPW, 2018; 2021a; 2021b). Overall, in 6.8 per cent of the cases the borrowers are located in areas currently presenting some flood risk. When considering the mid-range and high-end climate change projections, the share increases to 8.9 per cent and 9.7 per cent (respectively). As shown in Figure 3, the flood risk is not homogeneous across counties. The figures are particularly high in the Southwest. In county Limerick, over 20 per cent of the existing loans are located in areas currently considered at risk, followed by Cork, Clare and Louth where the percentage exceeds 10 per cent. In contrast, in the Midlands the figures are very small (around 1 per cent in counties like Offaly, Westmeath and Tipperary). According to the OPW projection, climate change could lead to a drastic increase in these figures, especially in counties along the west coast as well as in counties Dublin and Louth.

The descriptive statistics for the variables used in the empirical analysis are shown in Table 3. As mentioned above, the vast majority of the loans in the sample are relatively recent, since only existing contracts (as of June 2022) are included in the AnaCredit sample. The distribution of the size of the loans appears to be strongly skewed to the right, with a prevalence of relatively small loans (median ≈ €40,000 and bottom quartile of ≈ €20,000) and a small number of bigger contracts resulting

[12] Specifically, 60 per cent of the coordinates were obtained directly by matching the Eircode, and 37 per cent through the fuzzy matching algorithm. Only about 4 per cent of the observations were matched using the company's name. Table A.1 in the appendix provides a comparison on the observable characteristics of the loans that could be geolocated and the others. Unfortunately, it is not possible to examine directly whether the quality of the matching depends on the location of the borrower (e.g. urban versus rural) since unmatched observations are not geolocated. However, Table A.2 shows that the distribution of matched loans across counties is largely comparable to the cross-county distribution of companies operating in Ireland in 2022.

[13] Specifically, the original dataset contained 76,663 of the contract types included in the analysis. We obtain the exact same matching rate of 60 per cent when considering these three types of contract only.

[14] Unfortunately, the quality of the entry of the AnaCredit data is uneven across banks and years and as such variables such as borrower size and loan amount are sometimes missing. Out of the 46,129 matched loans, more than 5,000 had missing values for either the firm size or the amount of the loan. Interest rates lower than 0.01 per cent or higher than 20 per cent are considered the result of misreporting and as such were dropped. The results are however not sensitive to the inclusion of these extreme observations.

in an average of ≈ €400,000. This is in line with the vast majority (about 80 per cent) of the loans being granted to micro- or small-sized borrowers. Contracts are relatively homogeneous in terms of the duration, whose average is just less than six years and the median just below five years. Most of the contracts in the sample have an expected duration of between three and six years. While the majority of the contracts are characterised by monthly payments, nearly 20 per cent of the loans in the sample present less frequent repayments. There is a nearly even split between contracts with fixed (55 per cent) and non-fixed (45 per cent) interest rates. Finally, we use the coordinates obtained to attach to each credit contract the relative Electoral Division's Deprivation Index computed by the Central Statistics Office (CSO) based on the 2022 Census (CSO, 2023). The index is expressed on a scale from 1 ((extremely/very disadvantaged) to 6 (extremely/very affluent) and is included to control for other location specific factors that might affect the credit score of the borrowers.[15]

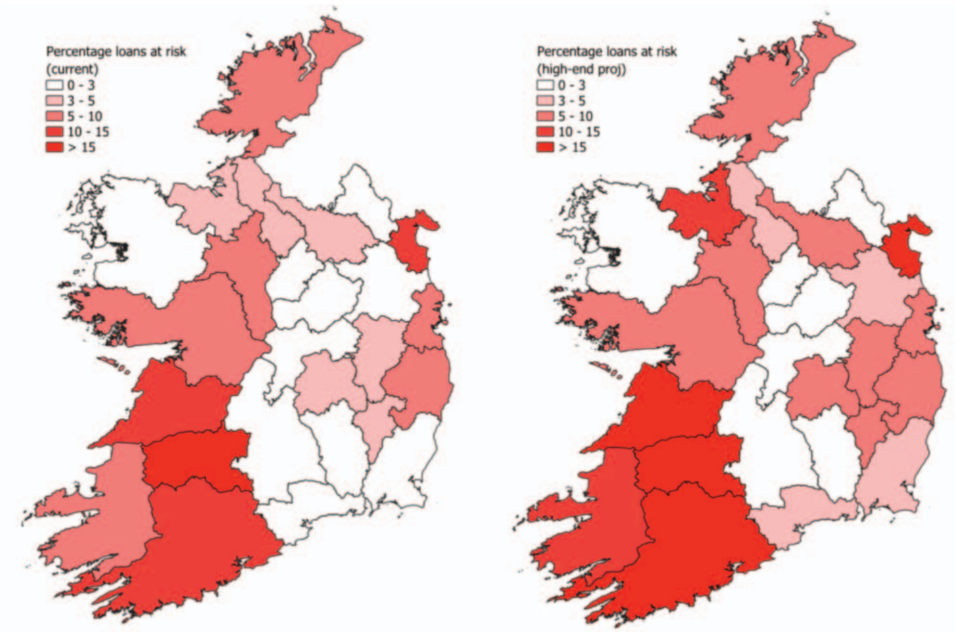
Table 3: Descriptive Statistics

Variables	*Mean*	*SD*	*Median*	*Bottom 25%*	*Top 25%*
Continuous					
Interest rate	4.58%	1.68%	4.25%	3.09%	5.89%
Starting Year	2019 M6	2.57	2020	2019	2021
Amount (€)	396,431	3,493,786	38,862	20,649	101,815
Duration (years)	5.37	3.77	4.95	3.01	5.50
Deprivation Index	4.59	0.72	5	4	5
			Percentage = 1		
Dummies					
Collateral			40.90%		
Micro			50.29%		
Small			29.47%		
Categorical					
Payment frequency					
Annual			8.35%		
Between annual and monthly			9.51%		
Monthly			82.14%		
Interest rate type					
Fixed			55.24%		
Others			44.66%		

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a), NIFM (OPW, 2021b) and AnaCredit (Central Bank of Ireland, 2022). The variables refer to the final sample of 40,852 observations employed in the empirical analysis.

[15] Ireland is divided in 3,440 Electoral Divisions. Borrowers in the sample are distributed across 2,549 of them.

Figure 3: Share of Loans at Risk by County (Current and High-end Climate Change Projection)



Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a), NIFM (OPW, 2021b) and AnaCredit (Central Bank of Ireland, 2022).

As captured by the variance in interest rates (the coefficient of variation is ≈ 0.36) and the mixed requirements in terms of collateral (with only 40 per cent of the loans in the final sample providing at least one), there appears to be some variation in the credit conditions faced by Irish firms. The aim of the empirical analysis is to examine the extent to which this can be linked with heterogeneity in flood risk of borrowers in our sample.

As discussed above, focusing on our credit contracts of interest there are 30,534 of them we are unable to precisely geolocate. Recall they are not geolocated either because the address data was insufficient (either partially completed or absent in AnaCredit) or because the match did not meet the 90 per cent similarity score threshold. Table A.1 in the appendix shows that there are only minimal differences in the distribution of the variables of interest between the 40,852 observations in the final sample and the 30,534 excluded credit contracts where we were unable to provide an accurate geolocation for the borrower. In a similar way, Table A.2 shows that the cross-county distribution of the loans in the matched sample is largely in line with the geographical location of businesses as reported by the Business in Ireland 2022 report (CSO, 2024). The following section is devoted to the explanation of the empirical specification adopted to study the empirical link between flood risk and credit condition using the geolocated sample discussed in this section, and to a discussion of the results obtained.

III EMPIRICAL SPECIFICATION AND RESULTS

3.1 Empirical Specification

The objective of the empirical analysis is to examine whether and the extent to which there is a link between the credit conditions faced by Irish firms and the risk of flooding they face. In particular, we consider two different dependent variables: the interest rate and whether a collateral is required. To begin we estimate Equation 1:

$$\text{Interest Rate}_{i,j,k,c,t} = \alpha + \beta \text{ Flood risk}_j + X'_{i,j,k,t}\gamma + Z'_{j,k,t} + \kappa_k + \xi_c + \tau_t + \varepsilon_{i,j,k,t} \tag{1}$$

where the dependent variable is the interest rate obtained in contract i by the firm j with contract type k in county c and year t.[16] The coefficient of interest is β which indicates the average premium paid by borrowers in flood risk areas. In the baseline specification, we capture the risk of flooding as a dummy variable taking value 1 where the firm is located in an area subject to flood risk under the current climate conditions.

In order to account for other factors which might affect the credit conditions faced by companies, we include two vectors X and Z of controls which are respectively contract and firm specific. The contract-specific variables considered are its (log) amount in euro and (the log of) its original duration in years as well as the type of interest rate, whether a collateral was included and the frequency of repayment.[17] The firm-specific variable considered is whether the firm was reported to be a micro- or small-size.[18] We also include a deprivation index (Pobal Deprivation Index) developed by the CSO (taking value from 1 to 6 and defined at the Electoral Division level) capturing the economic characteristics of the area the firm is located in. In addition, we add contract type (κ), county (ξ), and year (τ) fixed effects to control non-parametrically for systematic differences in borrowing costs across locations, years and different credit forms (non-revolving credit contracts, loans and financial leases). In different specifications, we include additional fixed effects to control for unobserved difference across banks and

[16] In Table A.3 in the Appendix, we show that the results are very similar where we consider the spread against quarterly short-term interest rates in Ireland from OECD (OECD 2024).

[17] See for example Berger *et al.* (2011). The results are left virtually unaffected when the levels of duration and amount are included instead of their logs.

[18] See for example Lehmann and Neuberger (2001); Voordeckers and Steijvers (2006); Godlewski and Weill (2011).

industries.[19] The inclusion of county fixed effects is particularly crucial for our identification strategy as it allows us to control for locally determined (unobserved) factors affecting credit conditions. Since we are able to observe the exact location of each borrower, we can exploit variation in flood risk within relatively small areas.

The other outcome we consider is whether or not a collateral was included in the contract. Now the dependent variable considered is a binary outcome taking value 1 where a collateral was provided in any given loan (and 0 otherwise). In this case, the regression estimated is defined in Equation 2:

$$\begin{aligned}\text{Collateral}_{i,j,k,c,t} &= \alpha + \beta \text{ Flood risk}_j \\ &+ X'_{i,j,k,t}\gamma + Z'_{j,k,t} + \kappa_k + \xi_c + \tau_t + \varepsilon_{i,j,k,t}\end{aligned} \tag{2}$$

where we include the same set of controls as for Equation 1 (excluding whether the collateral was included or not). In this instance, the increased likelihood of providing a collateral can be interpreted as an additional guarantee required from borrowers which are perceived to be more risky. When it comes to the loans included in the sample, the vast majority of collateral was physical. For this reason, we are unable to explore whether there is some heterogeneity in the type of collateral provided.

For the benchmark specification, we adopt a simple linear probability model and report the coefficients which can be directly interpreted as expected changes in probability. Table A.4 in the Appendix reports the marginal effects obtained when adopting probit models, which are largely comparable in terms of signs and magnitudes. It is important to point out that this specification presents a number of drawbacks. First of all, we are by definition only able to observe approved credit facilities. It is possible that in some instances the flood risk might prevent the borrower from obtaining credit to begin with (rather than obtaining it at worse conditions). We are unable to observe this dimension and as such we are providing only a partial analysis of the impact of such climate risk on credit access. Arguably, by looking at the "intensive margin", we are only capturing a lower bound of the actual impact of flood risk on credit availability. We believe it is important for future work to explore how flood risk affects the key credit condition approval.

Second, we are unable to observe whether the borrowers are insured from flood risk.[20] The lack of insurance data (coverage and price) is a limitation of our work as bank credit decisions may be informed by commercial insurance data rather than public data mapping flood risk. While we would expect overlap between these separate datasets (particularly in the current scenario), we acknowledge that our use of public data to understand bank lending decisions could introduce bias in our

[19] We consider industries at the NACE two-digit level as reported by AnaCredit.

[20] Granular insurance data, while commercially available (and in use by banks and insurers), is not available for this analysis at this time.

results. While county-level fixed effects might partially account for differences in insurance costs and availability, we are not able to fully address this concern. This, we believe, could be an important avenue for future research, in particular, in how public flood maps overlap with commercial risk data, and in quantifying the relationship between flood events, future risk and insurer decisions (coverage and premium).

Third, we are considering only the physical version of flood risk as captured by flood extent areas. It is very likely that additional factors related to the type of flood event and their gravity might affect their impact on credit conditions and we are ultimately just capturing one (although important) of the dimensions of flood risk. Indeed, physical climate risk within the Intergovernmental Panel On Climate Change framework is the combination of hazard, exposure and vulnerability. Within this framework, our work explores hazard (via flood maps) and exposure (via borrower location), but we are unable to use a continuous measure of vulnerability. This is a limitation of our work and a fruitful area of future improvements. Arguably, this can be treated as a source of measurement error as we are unable to discriminate between borrowers at high risk of flood damage from borrowers with more moderate exposure.

Finally, we are unable to exclude that the address reported by borrowers indicates the headquarters of the company versus the actual production location and as such we might be incorrectly labelling as at risk some borrowers whose actual business is not subject to physical flood risk and vice versa. Similar to the point raised before, this is realistically introducing some measurement error which might result in some attenuation bias in our results. Reassuringly, we find that the results are very similar where considering the subsample of small and micro-enterprises where multiple addresses are less likely to be an issue. With these caveats in mind, the following sections present the results of our empirical analysis.

3.2 Baseline Results

Table 4 displays the results of the benchmark specification where we consider the impact of flood risk on the cost of credit. Regardless of the fixed effects included, the point estimates for the coefficient β are always positive and statistically significant. This indicates that borrowers located in areas at risk face higher interest rates, even when controlling for differences in contract characteristics and the borrower's size. Crucially, the estimates are very similar where (from column 2 to column 5) county fixed effects are included, and the relationship is identified by variation in the exposure to flood risk across borrowers located in the same county. The magnitude of the coefficient varies from 7 to 13 basis points. Interestingly, these findings are very similar to the estimates from Barbaglia *et al*. (2023) for other EU countries, which argue that this premium is not fully reflective of the actual increased default risk following a flooding event. While the estimates are statistically significant, it is worth considering their magnitude in economic terms. The highest point estimate indicates a premium of 0.13 percentage points which is roughly a 3 per cent increase over the average interest rate charged in the sample.

When considering the estimated coefficients for the controls included, we find that micro and small firms face an additional premium. This is unsurprising as smaller companies are generally considered less safe and the higher interest rates obtained reflect this. We estimate the premium faced by small companies to range between 30 and 50 basis points, and the one for micro firms to be 60 to 95 basis points (compared to medium and large enterprises). Such 'size' premium represents a potentially useful benchmark to interpret the size of the flood risk effect. Across the five specifications considered, the point estimate for the flood risk premium ranges in size from 15 (column 1) to 34 per cent (column 4) of the 'size' premium faced by small firms. This points towards a substantial correlational link between flood risk and interest rate, especially considering that it might be downward biased due to the attenuation bias discussed above.

It is noticeable that both the duration and the amount of the loan are negatively correlated with the interest rates charged (a percentage point increase in either is associated with a reduction in interest rates of around one-fifth to one-half of a basis point). While everything else being fixed, one could expect a larger premium for longer time horizons and larger transfers; this probably indicates that borrowers able to obtain larger sums and longer loans were also those considered most safe by the lenders, resulting in lower interest rates charged. A similar argument can be made for the signs of payment frequency, where contracts with monthly repayments were also characterised by larger interest rates. Interestingly, location characteristics captured by the Deprivation Index only seem to have the expected sign (lower premium in more affluent area) where all fixed effects are included (column 4). In line with our expectations, providing some form of collateral (everything else being fixed) generally reduces the cost of borrowing, though the point estimates range from 15 to over 40 basis points and are particularly sensitive to the inclusion of bank fixed effects. This potentially signals that contracts issued by the same lenders are more homogeneous in terms of collateral requirements and conditions.

The second dimension we consider is the collateral requirements in the loan contract. As in the case of the interest rate, we only observe loans that were actually obtained by the borrower, and as such it is impossible to use these data to study the impact of collateral on the likelihood of obtaining a loan and the potential differential effect for areas at risk. However, as shown in Table 4, there seems to be some substitutability between providing a collateral and the interest rate premium, as the borrowers offering a collateral (41 per cent of the sample) obtain a significant reduction in borrowing costs. For this reason, we interpret the provision of a collateral in the loan as a potential signal of tighter credit conditions faced by the borrower. Table 5 shows the coefficients obtained when estimating Equation 2 for different combinations of fixed effects and considering our benchmark measure

Table 4: Impact of Flood Risk on Interest Rates

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Flood risk	7.635***	10.976***	13.201***	13.032***	11.222***
	(2.744)	(2.806)	(2.675)	(2.667)	(2.938)
Amount (log)	–33.502***	–33.996***	–38.304***	–38.254***	–34.412***
	(0.742)	(0.741)	(0.811)	(0.832)	(0.746)
Duration (log)	–21.129***	–22.353***	–53.647***	–50.401***	–25.557***
	(1.589)	(1.587)	(1.593)	(1.632)	(1.634)
Small	53.852***	58.791***	41.866***	30.697***	60.655***
	(1.957)	(2.003)	(2.032)	(2.088)	(2.100)
Micro	89.267***	94.064***	71.108***	63.307***	93.259***
	(1.989)	(2.040)	(2.224)	(2.306)	(2.111)
Collateral	–41.184***	–42.221***	–14.847***	–14.669***	–42.706***
	(1.501)	(1.499)	(1.580)	(1.577)	(1.516)
Deprivation Index	1.950**	–0.440	–1.159	–1.762*	0.904
	(0.950)	(1.011)	(0.955)	(0.946)	(1.041)
Non-fixed rate	–27.998***	–26.957***	–44.174***	–42.306***	–25.192***
	(2.072)	(2.112)	(1.989)	(1.974)	(2.164)
Annual to monthly payments	72.668***	70.384***	46.080***	39.090***	71.819***
	(3.663)	(3.662)	(3.644)	(3.623)	(3.705)
Monthly payments	70.350***	65.113***	49.797***	40.168***	65.084***
	(3.015)	(3.046)	(3.130)	(3.195)	(3.101)
FE					
Year	Yes	Yes	Yes	Yes	Yes
Contract type	Yes	Yes	Yes	Yes	Yes
County	No	Yes	Yes	Yes	Yes
Bank	No	No	Yes	Yes	No
Industry	No	No	No	Yes	No
Year × County	No	No	No	No	Yes
N	40,852	40,852	40,852	40,852	40,852
R-squared	0.347	0.358	0.423	0.445	0.371

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a), NIFM (OPW, 2021b) and AnaCredit (Central Bank of Ireland, 2022). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Flood risk is a dummy variable taking value 1 where the borrower's location is at risk of flooding given the current climate conditions. The dependent variable is the interest rate expressed in basis points.

Table 5: Impact of Flood Risk on Collateral

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Flood risk	0.0613***	0.0476***	0.0174**	0.0206**	0.0421***
	(0.0087)	(0.0091)	(0.0081)	(0.0082)	(0.0095)
Amount (log)	0.0014	0.0016	0.0320***	0.0278***	0.0024
	(0.0021)	(0.0021)	(0.0022)	(0.0021)	(0.0021)
Duration (log)	0.0627***	0.0577***	0.0958***	0.0932***	0.0567***
	(0.0046)	(0.0047)	(0.0046)	(0.0046)	(0.0049)
Small	–0.1125***	–0.1026***	–0.0764***	–0.0625***	–0.0881***
	(0.0071)	(0.0073)	(0.0063)	(0.0065)	(0.0075)
Micro	–0.1886***	–0.1818***	–0.1236***	–0.1213***	–0.1723***
	(0.0066)	(0.0069)	(0.0065)	(0.0067)	(0.0071)
Deprivation Index	–0.0151***	–0.0195***	–0.0231***	–0.0206***	–0.0170***
	(0.0031)	(0.0033)	(0.0029)	(0.0029)	(0.0034)
Non-fixed rate	0.0565***	0.0579***	–0.0857***	–0.0925***	0.0537***
	(0.0056)	(0.0057)	(0.0061)	(0.0060)	(0.0058)
Annual to monthly payments	0.0464***	0.0454***	0.1558***	0.1673***	0.0447***
	(0.0141)	(0.0141)	(0.0137)	(0.0138)	(0.0142)
Monthly payments	0.0423***	0.0376***	0.1729***	0.1983***	0.0391***
	(0.0121)	(0.0121)	(0.0121)	(0.0125)	(0.0122)
FE					
Year	Yes	Yes	Yes	Yes	Yes
Contract type	Yes	Yes	Yes	Yes	Yes
County	No	Yes	Yes	Yes	Yes
Bank	No	No	Yes	Yes	No
Industry	No	No	No	Yes	No
Year × County	No	No	No	No	Yes
N	40,852	40,852	40,852	40,852	40,852
R-squared	0.167	0.172	0.396	0.412	0.192

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a), NIFM (OPW, 2021b) and AnaCredit (Central Bank of Ireland, 2022). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Flood risk is a dummy variable taking value 1 where the borrower's location is at risk of flooding given the current climate conditions. The dependent variable is a dummy taking value 1 where there is at least one collateral asset in the credit contract.

of flood risk (i.e. any flood risk under current climate conditions). The results indicate that borrowers in areas at flood risk are between 2 and 6 percentage points (or 4 per cent to 15 per cent) more likely to provide a collateral. Since most of these collaterals are physical, this seems to indicate that lenders accept such collateral as a way to reduce their exposure to flood risk and that borrowers unable to provide them might be denied access to credit to a larger extent where they face some risk of flooding.

The coefficients of the control variables indicate that a collateral is more likely to be included in the contract for loans with longer duration and larger amount. This is in line with lenders requiring some form of insurance where the operation is riskier and/or a larger amount is involved. In a similar way, borrowers located in more affluent areas present a significantly lower likelihood to be including a collateral in their loans. In every specification, smaller firms are shown to be less likely to provide a collateral, which might reflect the lack of assets availability, or capturing the fact that they typically borrow lower amounts where lenders do not require any collateral.

It is important to point out that these findings are based on the comparison of loans originated in the same year and with similar characteristics where the borrowers are of the same size. Adding fixed effects allows us to capture the difference across companies operating in the same county, industry and bank. While the results are rather robust across specifications and both statistically and economically significant, we cannot exclude that the regressions are picking up the effect of other unobserved loan/firms characteristics determining the observed differences in terms of interest rate premia and collateral requirements. As such, the results should be interpreted as suggestive correlations rather than necessarily as evidence of a causal link.

3.3 Different Projections

In the benchmark specification, we capture flood risk as a simple dummy taking value 1 where the borrower is in a location experiencing any level of risk in the current climate. However, as discussed in Section 2.1, the datasets also allow us to identify locations that will become subject to flood risk due to the effect of climate change. As shown for example in Figure 3, existing projections indicate that a significantly larger share of companies can be considered at risk of experiencing a flood event when climate change is accounted for. In our final sample, the share of loans considered at risk would increase considerably from 6.8 per cent to 9.1 per cent and 10.4 per cent respectively where the mid-range and high-end climate change projections are taken into account (respectively).

Given the availability of these scenarios, it is possible to study the extent to which additional flood risk brought about by expected climate change is priced in in the lending decisions. Empirically, we do so by estimating Equation 3:

$$
\begin{aligned}
y_{i,j,k,t} = \alpha + \beta_1 \text{ Risk}_j^{HP} + \beta_2 \text{ Risk}_j^{MP} + \beta_3 \text{ Risk}_j^{C} \\
+ X'_{i,j,k,t}\gamma + Z'_{j,k,t} + \kappa_k + \xi_c + \tau_t + \varepsilon_{i,j,k,t}
\end{aligned}
\tag{3}
$$

where y represents either of our two outcome variables of interest (interest rate or collateral). The difference compared to the baseline regressions is that flood risk is captured by three mutually exclusive binary variables. Risk^C is the same risk measure considered in the benchmark specification, and takes value 1 for the 2,782 (6.8 per cent) observations which are at risk under the current conditions. Risk^{MP} takes value 1 only for the additional 939 observations (2.3 per cent) which are at risk in the mid-range climate change scenario. Risk^{HP} takes value 1 only for the 510 observations (1.31 per cent) which are only at risk in the high-end climate change projection. Since the three categories are mutually exclusive, each coefficient should be interpreted as the difference compared to the baseline (no risk) group.

Thus, rather than cumulative effects, β_2 and β_1 should be interpreted as the observed average differences (once the other observable factors are accounted for) between borrowers currently not at risk, but that will become subject to flood risk due to climate change (in the mid-range or high-end scenario respectively) compared to those who will not face any risk even when climate change is accounted for. Finding insignificant point estimates for β_1 and/or β_2 would thus indicate that we are unable to identify any significant difference between borrowers that will be at risk due to climate change and those who are never at risk (i.e. banks are not factoring in climate change). Overall, we would expect the coefficients to be higher for current risk and progressively lower for the mid- and high-projection climate change scenarios (i.e. $\beta_3 > \beta_2 > \beta_1$) as lenders might fail to price in the (more extreme) projections of climate change or impose lower premia to risk caused by climate change rather than existing in the current climate conditions.

The resulting estimates are shown in Tables 6 and 7 for the impact on interest rates and collateral requirements respectively. Overall, we find some evidence that banks account for the effects of climate change on flood risk – primarily in the mid-range projection. In general, a number of points are worth highlighting. First, in both tables only where the current flood risk is considered is the effect positive and statistically significant across all specifications. This is in line with our benchmark findings. Second, the coefficients for the borrowers at risk in the mid-projection climate change scenario provide some evidence that banks are pricing in the impact of climate change on flood risk in current loans, as in the case of interest rates the point estimates are consistently positive and statistically significant with the sole exception of the model including all fixed effects. In the case of collateral, β_2 is also always positive indicating higher likelihood of collateral requirements for borrowers that are at risk in the mid-end projection. However, the coefficients are not precisely estimated and are not statistically different from zero in most

Table 6: Impact of flood risk on interest rate – different projections

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Flood risk (high-end)	11.491*	8.451	–6.421	–9.534	5.830
	(6.701)	(6.798)	(6.337)	(6.122)	(6.771)
Flood risk (medium-range)	21.026***	16.851***	8.367**	3.621	16.403***
	(4.408)	(4.464)	(4.156)	(4.152)	(4.501)
Flood risk (current)	8.319***	11.591***	13.348***	12.981***	11.801***
	(2.747)	(2.810)	(2.678)	(2.671)	(2.942)
FE					
Year	Yes	Yes	Yes	Yes	Yes
Contract type	Yes	Yes	Yes	Yes	Yes
County	No	Yes	Yes	Yes	Yes
Bank	No	No	Yes	Yes	No
Industry	No	No	No	Yes	No
Year × County	No	No	No	No	Yes

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a), NIFM (OPW, 2021b) and AnaCredit (Central Bank of Ireland, 2022). *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. Flood risk is captured by a set of mutually exclusive dummy variables taking value 1 for the most conservative projection (including the current scenario) at which the borrower is at risk. The dependent variable is the interest rate expressed in basis points. Controls are included but not displayed.

specifications. Conversely, β_1 is not statistically significant in either case once bank, county and industry fixed effects are accounted for. This indicates that currently, borrowers that will be considered at risk only in the more extreme climate change scenario seem not to receive different credit conditions from the ones who are never at risk.

While these results cannot be interpreted as causal, they provide some suggestive evidence of an empirical link between credit conditions obtained and borrowers' current flood risk. A similar interest rate premium seems to be observed also when looking at borrowers who are considered not at risk under current climate conditions but will be according to a mid-range scenario modelling the impact of climate change on the likelihood of flood risks in Ireland, indicating that lenders seem to be at least partially pricing in the expected deterioration in the environmental conditions. The corresponding coefficients for the collateral specification are also positive yet not statistically significant. The following section concludes the empirical analysis presenting some robustness checks and sub-sample analysis.

3.4 Heterogeneous Effects and Robustness Checks

In this section, we discuss some additional robustness check and heterogeneity analysis based on regressions considering only a certain subsample of firms, whose point estimates are shown in Tables 8 and 9 for the interest rates and the collateral respectively.

First of all, the point estimates obtained when restricting the sample to small and micro enterprises are for the most part comparable. This addresses some concerns related to the potential issue of multiple addresses which is less likely to arise in the case of small borrowers. However, when examining collateral requirements, some specifications including many fixed effects (3 and 4) return an insignificant (if positive) point estimate. Also, separating the sample into loans and other contracts (non-revolving credit and financial leases) do not affect the coefficients in the case of the collateral requirement, while the effect on interest rates seems to be driven primarily by the latter group. It is however worth mentioning that the point estimates are less precise due to the lower number of observations, and that the confidence intervals are largely overlapping with the ones obtained for the full sample. Similarly, we are not able to detect any differential empirical link when looking separately at industries which we consider a priori more susceptible of physical flood damage, namely hospitality, retail and manufacture. The average interest rates and collateral requirements are very similar to the other industries (regardless of the flood risk), and the point estimates for the impact of the flood risk virtually indistinguishable from the ones obtained for the full sample.

Table 7: Impact of Flood Risk on Collateral – Different Projections

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Flood risk (high-end)	0.0576***	0.0596***	–0.0068	0.0023	–0.0055
	(0.0193)	(0.0193)	(0.0173)	(0.0171)	(0.0169)
Flood risk (medium-range)	0.0351**	0.0320**	0.0197	0.0170	0.0189
	(0.0153)	(0.0154)	(0.0143)	(0.0142)	(0.0142)
Flood risk (current)	0.0630***	0.0494***	0.0179**	0.0212***	0.0129**
	(0.0088)	(0.0091)	(0.0081)	(0.0082)	(0.0055)
FE					
Year	Yes	Yes	Yes	Yes	Yes
Contract type	Yes	Yes	Yes	Yes	Yes
County	No	Yes	Yes	Yes	Yes
Bank	No	No	Yes	Yes	No
Industry	No	No	No	Yes	No
Year × County	No	No	No	No	Yes
N	40,852	40,852	40,852	40,852	40,852
R-squared	0.167	0.173	0.396	0.412	0.179

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a), NIFM (OPW, 2021b) and AnaCredit (Central Bank of Ireland, 2022). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Flood risk is captured by a set of mutually exclusive dummy variables taking value 1 for the most conservative projection (including the current scenario) at which the borrower is at risk. The dependent variable is a dummy value taking value 1 where there is at least one collateral asset in the credit contract. Controls are included but not displayed.

Table 8: Impact of Flood Risk on Interest Rates by Subsample

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*N*	*Share at risk*	*Average dep var*
Benchmark	7.635***	10.976***	13.201***	13.032***	11.222***	40,852	6.81%	4.68%
	(2.744)	(2.806)	(2.675)	(2.667)	(2.938)			
Small	7.425**	7.834**	5.154*	1.627	8.184***	32,584	6.29%	4.77%
	(3.100)	(3.120)	(2.928)	(2.924)	(3.144)			
Susceptible	5.844*	10.429***	12.352***	11.941***	9.738***	27,943	6.55%	4.53%
	(3.291)	(3.435)	(3.242)	(3.257)	(3.684)			
No collateral	21.757***	19.984***	13.879***	8.340**	20.486***	24,145	5.83%	4.92%
	(4.113)	(4.138)	(3.992)	(3.909)	(4.151)			
Loans	3.186	8.917*	4.687	3.025	10.327**	16,021	5.77%	4.83%
	(5.138)	(5.063)	(4.990)	(4.803)	(5.048)			
Other contracts	7.205**	9.603***	11.161***	11.778***	9.736***	24,831	7.48%	4.44%
	(3.020)	(3.184)	(2.987)	(3.001)	(3.442)			

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a), NIFM (OPW, 2021b) and AnaCredit (Central Bank of Ireland, 2022). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. The coefficients indicate the point estimates for the flood risk variable dummy across different subsamples. The benchmark row displays the results obtained where all the observations are kept. "Small" only includes borrowers which are either small or microenterprises, "susceptible" includes firms in retail, hospitality and manufacturing which are considered potentially more susceptible to physical flood damage, "no collateral" considers only the contracts where no collateral was provided. "Loans" includes only contracts listed as simple loans, while "Other contracts" combines financial leases and non-revolving contracts. The dependent variable is the interest rate, expressed in basis points. Controls are included but not displayed. Different columns show the results for different combinations of fixed effects, following the benchmark specification. the full sample.

The only subsample for which we find some evidence of increased interest rate premium is for the credit contracts providing no collateral, where in some specification a significantly larger interest rate premium is displayed. This is in line with a scenario in which collateral provision can be used to mitigate the additional costs brought about by flood risk and where firms unable to provide such collateral must face an even steeper risk premium for flooding events. However, this difference is only marked where industry and bank fixed effects are not included and as such cannot be interpreted as conclusive.

IV CONCLUSION

We combine AnaCredit data from Ireland with detailed maps describing the risk of flooding under different assumptions and projections in order to examine empirically whether this source of risk affects borrowers' conditions where accessing credit. Since we are able to derive the exact location of the firms, unlike other existing studies, we are able to control for locally determined factors affecting credit conditions and exploit differences in flood risk within the same county.

We find that, among existing loans, around 7 per cent are undertaken by borrowers located in areas at risk of flooding, and that this figure is predicted to increase significantly due to the expected patterns of climate change. Although we are unable to make causal claims, our results suggest that firms located in areas considered currently at risk face steeper costs in accessing credit both in terms of interest rate premium (quantifiable in 7 to 13 basis points) and of collateral requirements (4 per cent to 16 per cent more likely to provide a collateral). Since we only observe existing credit contracts, we can only measure the differences across borrowers who obtained a loan, and we cannot exclude that the actual impact is more significant as some might be completely unable to access credit.

In addition, we provide some evidence that the additional risks brought about by climate change are to a certain extent already factored in by lenders, as borrowers located in areas predicted to become susceptible to flooding risk as a result of the worsening environmental conditions face (conditional on other observable characteristics) significantly larger interest rates. While this indicates that Irish lenders are effectively pricing in this source of risk, this might prove to be detrimental for borrowers located in such areas and the issue is expected to worsen in the coming years.

A significant drawback of our analysis is the lack of data on insurance availability and coverage (which represents an important source of mitigation of flood risk) and the use of a simple, physical measure of flood risk based on the maximum extent of potential flooding, which fails to factor in other features that realistically affect the potential damage brought about by flood events. Future studies taking these factors into account could provide a more precise analysis and exact quantification of the relationship between this increasingly widespread source of climate risk, credit access and financial stability.

Table 9: Impact of Flood Risk on Collateral by Subsample

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*N*	*Share at risk*	*Average dep var*
Benchmark	0.0613***	0.0476***	0.0174**	0.0206**	0.0421***	40,852	6.81%	40.90%
	(0.0087)	(0.0091)	(0.0081)	(0.0082)	(0.0095)			
Small	0.0365***	0.0301***	0.0028	0.0038	0.0311***	32,584	6.29%	36.76%
	(0.0104)	(0.0105)	(0.0093)	(0.0094)	(0.0105)			
Susceptible	0.0546***	0.0272**	0.0084	0.0166	0.0200*	27,943	6.55%	40.85%
	(0.0107)	(0.0113)	(0.0100)	(0.0102)	(0.0121)			
Loans	0.0672***	0.0695***	0.0314	0.0342	0.0692***	16,021	5.77%	50.75%
	(0.0158)	(0.0160)	(0.0319)	(0.0321)	(0.0164)			
Other contracts	0.0626***	0.0431***	0.0434***	0.0693***	0.0617***	24,831	7.48%	34.45%
	(0.0109)	(0.0113)	(0.0108)	(0.0112)	(0.0122)			

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a), NIFM (OPW, 2021b) and AnaCredit (Central Bank of Ireland, 2022). *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. The coefficients indicate the point estimates for the flood risk variable dummy across different subsamples. The benchmark row displays the results obtained where all the observations are kept. "Small" only includes borrowers which are either small or microenterprises, "susceptible" includes firms in retail, hospitality and manufacturing which are considered potentially more susceptible to physical flood damage. "Loans" includes only contracts listed as simple loans, while "Other contracts" combines financial leases and non-revolving contracts. The dependent variable is a binary outcome variable taking value 1 when a collateral is provided. Controls are included but not displayed. Different columns show the results for different combinations of fixed effects, following the benchmark specification.

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APPENDIX

A.1 Comparison with Contracts With No Available Geolocation

Table A.1 provides a comparison in the average and median of the main variables of interest between the (geolocated) sample used in the empirical analysis and the corresponding observations for which we were unable to derive precise coordinates due to the unavailability of the Eircode and/or the unsuccessful fuzzy matching procedure (with similarity scores lower than 90).

Specifically, we identify 30,534 loans from AnaCredit which are the same contract types as the ones considered in the analysis, and are obtained (similar to our final sample) after dropping observations with extreme interest rates and/or missing variables of interest.

Since these contracts are not geolocated, it would *a priori* not be possible to derive information on flood risk. However, for 13,940 of such (not included) contracts, a set of coordinates (and thus information on flood risk) is available, and they are only removed from the final sample due to the relatively low similarity score not guaranteeing that the ECAD address used is actually the same as the borrower's. We use this subset of observations to generate a flood risk variable for the unmatched sample.

For the most part, the distribution of the variables of interest seems to be similar between the two samples. In particular, average and median interest rates are virtually the same and there is a great overlap in the size distribution of the borrowers. The average amount is larger for the unmatched sample, though the median values are very close. A slightly larger percentage of the non-geolocated loans is covered by at least a collateral asset. Notably, the share of loans at risk of flooding (given the current climate conditions) seems to be larger (6.81 per cent) in the geolocated sample than in the other contracts (5.56 per cent). Arguably, this is due to the fact that urban addresses are typically more precise (easier to be merged and obtain higher similarity scores through the applied fuzzy matching procedure) and also generally more subject to flood risk.

However, as shown in Table A.2, the resulting geographical distribution of loans in our final sample is largely in line with the distribution of businesses operating in Ireland as reported by the 2022 business in Ireland report. The largest difference in absolute terms is observed in Dublin, which appears to be underrepresented in terms of the total share of loans. With a few exceptions, the absolute difference is always below the 1 per cent threshold which indicates that the cross-county distribution of loans in our sample mirrors the distribution of operating businesses.

Overall, the findings above suggest that while we cannot exclude that the matched sample represents a non-random subset of all the existing loans, the observations included in the empirical analysis do not differ systematically from the ones we were unable to match, and their resulting cross-county distribution is largely in line with the existing figures of active businesses operating in Ireland.

Table A.1: Comparison Between Matched and Unmatched Observations

	Average		*Median*	
	Matched	*Not matched*	*Matched*	*Not matched*
Interest rate	4.58%	4.57%	4.25%	4.25%
Collateral	40.90%	41.71%	0	0
Flood risk	6.81%	5.56%	0	0
Amount	396,431	850,180	38,862	40,069
Duration	5.37	5.34	4.95	4.96
Starting year	*2019 M6*	*2019 M10*	*2020*	*2021*
Micro	50.29%	54.03%	1	1
Small	29.47%	26.39%	0	0
Medium	13.90%	11.71%	0	0
Large	6.34%	7.87%	0	0

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a), NIFM (OPW, 2021b) and AnaCredit (Central Bank of Ireland, 2022).

Table A.2: Comparison in Loans and Business Distribution

County	*Share loans*	*Share businesses*	*Difference*
Carlow	1.06%	1.04%	0.02%
Cavan	1.40%	1.39%	0.02%
Clare	2.03%	2.47%	–0.43%
Cork	11.00%	10.69%	0.30%
Donegal	2.44%	3.07%	–0.63%
Dublin	27.53%	35.05%	–7.51%
Galway	4.80%	5.39%	–0.60%
Kerry	3.07%	3.15%	–0.08%
Kildare	4.80%	4.20%	0.60%
Kilkenny	2.56%	1.65%	0.91%
Laois	1.44%	1.19%	0.26%
Leitrim	0.39%	0.69%	–0.29%
Limerick	5.56%	3.44%	2.12%
Longford	0.46%	0.68%	–0.23%
Louth	2.94%	2.42%	0.52%
Mayo	2.18%	2.55%	–0.37%
Meath	3.93%	3.88%	0.05%
Monaghan	1.58%	1.17%	0.41%
Offaly	1.11%	1.22%	–0.10%
Roscommon	0.96%	1.12%	–0.16%
Sligo	0.73%	1.20%	–0.47%
Tipperary	4.18%	2.78%	1.39%
Waterford	3.66%	1.99%	1.67%
Westmeath	2.67%	1.73%	0.94%
Wexford	5.04%	2.86%	2.19%
Wicklow	2.45%	3.00%	–0.55%

Source: Authors' computation based on AnaCredit Central Bank of Ireland (2022) and Business in Ireland report CSO (2024). The share of loans refers to the percentage of contracts in the final (geolocated) sample located in each county. The share of businesses refers to the fraction of the total active businesses operating in each county in 2022.

A.2 Additional results

Table A.3 presents the results we obtain where we use the spread (instead of the raw interest rate) to measure the cost of credit. Specifically, the spread is obtained by subtracting from the raw interest rate the short-term interest rate for Ireland for the respective quarter as measured by the OECD.

There is a very high ($\rho \approx 0.9$) correlation between the two measures and, as a result, the point estimates are comparable. Similar to the benchmark scenario, the effect of flood risk ranges between 6 and 10 basis point and is always significant to at least the 95 per cent level. The only appreciable difference is a general increase in the R-squared, arguably driven by the fact that the dependent variable, now the interest rate less the short-term interest rate at the quarter level (i.e. quarter-specific differences in general credit conditions are netted out), and as such a larger share of the remaining variation is explained by the controls included in the specification.

Table A.3: Impact of Flood Risk on Spread

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Flood risk	7.840***	10.945***	13.132***	12.945***	11.268***
	(2.737)	(2.803)	(2.674)	(2.667)	(2.935)
FE					
Year	Yes	Yes	Yes	Yes	Yes
Contract type	Yes	Yes	Yes	Yes	Yes
County	No	Yes	Yes	Yes	Yes
Bank	No	No	Yes	Yes	No
Industry	No	No	No	Yes	No
Year × County	No	No	No	No	Yes
N	40,852	40,852	40,852	40,852	40,852
R-squared	0.346	0.357	0.423	0.445	0.372

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a), NIFM (OPW, 2021b), AnaCredit (Central Bank of Ireland, 2022) and OECD (2024). *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. Flood risk is a dummy variable taking value 1 where the borrower's location is at risk of flooding given the current climate conditions. The dependent variable is the spread (in basis points), obtained as the difference between the loan's interest rate and the Irish short-term interest rates in the corresponding quarter (OECD, 2024). Controls are included but not displayed.

Table A.4 shows the results we obtain to estimate the impact of flood risk on collateral using a probit rather than a simple linear probability model. The figures indicate the average marginal effects. The findings are entirely comparable when it comes to both the significance and the size of the effect, and point towards a significantly higher likelihood (between 2 to 6 percentage points) for borrowers which are located in areas at risk.

Table A.4: Impact of Flood Risk on Collateral – Probit Model

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Flood risk	0.0611***	0.0493***	0.0214**	0.0201**	0.0407***
	(0.0087)	(0.0088)	(0.0083)	(0.0076)	(0.0072)
FE					
Year	Yes	Yes	Yes	Yes	Yes
Contract type	Yes	Yes	Yes	Yes	Yes
County	No	Yes	Yes	Yes	Yes
Bank	No	No	Yes	Yes	No
Industry	No	No	No	Yes	No
Year × County	No	No	No	No	Yes
N	40,852	40,852	40,852	40,852	40,852
Pseudo R-squared	0.130	0.332	0.345	0.350	0.164

Source: Authors' computation based on CFRAM (OPW, 2018), NCFHM (OPW, 2021a), NIFM (OPW, 2021b) and AnaCredit (Central Bank of Ireland, 2022). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Flood risk is a dummy variable taking value 1 where the borrower's location is at risk of flooding given the current climate conditions. The dependent variable is a dummy taking value 1 where there is at least one collateral asset in the credit contract. The figures represent the estimated average marginal effect. Controls are included but not displayed.