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Impacts of extreme weather events on mortgage risks and their evolution under climate change: A case study on Florida

Raffaella Calabrese[1], Timothy Dombrowski[2], Antoine Mandel[3], R. Kelley Pace[4], Luca Zanin[5],

Abstract: We develop an additive Cox proportional hazard model with time-varying covariates, including spatio-temporal characteristics of weather events, to study the impact of weather extremes (heavy rains and tropical cyclones) on the probability of mortgage default and prepayment. We compare the survival model with a flexible logistic model and an extreme gradient boosting algorithm. We estimate the models on a portfolio of mortgages in Florida, consisting of 69,046 loans and 3,707,831 loan-month observations with localization data at the five-digit ZIP code level. We find a statistically significant and non-linear impact of tropical cyclone intensity on default as well as a significant impact of heavy rains in areas with large exposure to flood risks. These findings confirm existing results in the literature and also provide estimates of the impact of the extreme event characteristics on mortgage risk, e.g. the impact of tropical cyclones on default more than doubles in magnitude when moving from a hurricane of category two to a hurricane of category three or more. We build on the identified effect of exposure to flood risk (in interaction with heavy rainfall) on mortgage default to perform a scenario analysis of the future impacts of climate change using the First Street flood model, which provides projections of exposure to floods in 2050 under RCP 4.5. We find a systematic increase in risk under climate change that can vary based on the scenario of extreme events considered. Climate-adjusted credit risk allows risk managers to better evaluate the impact of climate-related risks on mortgage portfolios.

Keywords: OR in Banking, Credit Risk, Climate Change, Mortgage, Survival Analysis

[1]Business School, University of Edinburgh, Edinburgh EH8 9YL, United Kingdom

[2]University of Missouri–St. Louis, Department of Finance and Legal Studies, St. Louis, MO 63121, United States

[3]Climate Finance Alpha, 75009, Paris, France & Centre d'Economie de la Sorbonne, Paris School of Economics, University Paris 1

[4]Louisiana State University, Department of Finance, Baton Rouge, LA 70803

[5]Corresponding author, Prometeia, Piazza Trento e Trieste 3, 40127, Bologna, IT; luca.zanin@studio.unibo.it

1 Introduction

In his seminal 2015 speech on "breaking the tragedy of the horizon," Mark Carney, then Governor of the Bank of England and Chairman of the Financial Stability Board (FSB), emphasized that climate change could impact the soundness of financial institutions and pose a threat to global financial stability (Carney, 2015). Since then, concern among central banks and regulators about the implications of climate change for credit institutions has been growing steadily. In particular, the FSB set up the Task Force on Climate-related Financial Disclosures (TCFD) to establish a set of recommendations for *"disclosures that will help financial market participants understand their climate risks"* (FSB-TCFD, 2017). The Network of Central Banks and Supervisors for Greening the Financial System (NGFS), which gathers over 100 financial regulators representing almost all major economies, has put forward as one of its core objectives *"the development of environment and climate risk management in the financial sector"* (NGFS, 2017). The US Federal Reserve has stressed in a recent report how climate change can increase financial shocks and financial instability (Board of Governors of the Federal Reserve System, 2020). Finally, the Basel Committee on Banking Supervision has recently published 18 principles for the effective management and supervision of climate-related financial risks (Basel Committee on Banking Supervision, 2022), which emphasize in particular that *"Banks should take into account the unique characteristics of [climate-related] risks" (principle 8)* and that *"Banks should take material physical and transition risk drivers into consideration when developing and implementing their business strategies" (principle 12).*

Despite these major concerns among regulators and practitioners alike, the literature on the impacts of climate change on credit risk is still in its infancy. This paper aims to contribute to the development of the knowledge base on the topic by (a) providing two models of a mortgage default and prepayment that account for risks due to extreme weather events, (b) applying them to analyze the impact of tropical cyclones and heavy rainfall events on mortgage risk in Florida, and (c) projecting future changes in flood risk exposure induced by climate change. We demonstrate that the inclusion of weather-related variables leads to more accurate default and prepayment predictions and find that climate change can increase default risk, particularly in flood-prone areas.

Mortgages are of particular concern in the context of climate-related financial risks because their collateral, composed of immovable assets, is fully exposed to physical risks. Florida is a relevant case study as it has been visited by some of the most destructive and devastating hurricanes on record in the United States causing over $450 billion in damage since the early 20th century and because the value of property in Florida insured against windstorm damage is the highest in the country and on the rise (Malmstadt et al., 2009). Our analysis focuses on a portfolio constructed by extracting origination and performance data from Moody's Analytics mortgage dataset. This dataset offers an overview of the non-agency U.S. mortgage market, which corresponds to loans within private-label securitizations (PLS)[6]. New originations of these PLS largely vanished in 2008; however, in recent years, they have begun to regain a small share of new first-lien originations, growing to 4.8% in Q1 of 2022 (Urban Institute Housing Finance Policy Center, 2022). As for weather-related covariates, we focus on tropical cyclones and the associated flood risks because these are the most quantitatively relevant hazards for the United States. For example, they represent over 50% of damages for the period 1980–2020 in the 'billion-dollar events' database of the NOAA (Smith and Katz, 2013). Furthermore, the increasing exposure to flood risks due to climate change (Hinkel

[6]PLS are mortgage-backed securities that are not issued by one of multiple government agencies.

et al., 2014) flows through to financial risks via major natural disasters that can have devastating impacts on real estate values, and subsequently, mortgage markets.

From a methodological perspective, we use a spatial additive survival approach as a scoring model to incorporate the effects of extreme weather events in the analysis of credit risk. This choice is motivated first by results from the literature on scoring models that show the importance of including spatial effects to improve the performance of these models (Calabrese et al., 2019). Second, the survival approach is widely used in credit scoring to predict not only if but also when a loan might default (Thomas et al., 2017). Third, additive models have been used to capture non-linear underlying covariate-response relationships Berg (2007); Calabrese et al. (2015). Yet, to our knowledge, our paper is the first to merge these three approaches in a scoring model to capture the effect of extreme weather events on the default and prepayment probability.

Finally, to project the impacts of climate change on credit risks, we perform a scenario analysis that considers the evolution in the exposure to flooding risks given by the First Street (FS) Foundation Flood model (First Street Foundation, 2020; Bates et al., 2021). Specifically, we consider the exposure at the 2050 horizon (FS2050) according to the FS model under the RCP[7] 4.5 scenario, compared to the current conditions (FS2020). For the FS2050 scenario, global climate projections are applied to forecast how flood risk will change over the next 30 years through changing environmental factors including sea-level rise, increasing cyclonic intensity, higher probabilities of cyclone landfall locations at higher latitudes, shifting precipitation patterns, and shifts in river discharge.

Our results first highlight that there is an improvement in the predictive accuracy of default and prepayment when we include weather-related risks. Specifically, we find that a borrower exposed to a hurricane has a higher probability of default than when tropical cyclones do not occur, while no significant effect is observed on the prepayment behavior. Moreover, we see a positive, statistically significant impact of intense rain events on default probability when they occur in areas with a high percentage of properties that are at risk for flood damage. However, the event of intense rainfalls in areas at risk for flood damage tends to discourage prepayment. A homeowner without a loan has only insurance to protect their equity in the event of a disaster, and many borrowers have difficulty getting insurers to pay after a disaster. However, borrowers with a loan have the option to default if insurance fails to pay. Therefore, borrowers have incentives to keep a loan (not prepay) as this can limit their loss and shift it to the lender. Overall, our results confirm previous findings as far as the impact of tropical cyclones on default is concerned. Furthermore, our approach allows quantifying more precisely the specific impact of extreme weather events by accounting for spatio-temporal effects, for the physical characteristics of the events under consideration and for the interactions between hazard and exposure.

These features also enable us to provide a micro-founded assessment of the future impacts of climate change on mortgage risk. In this respect, we find an increase in credit risk, in the sense of first-order stochastic dominance, as one shift from FS2020 exposure to FS2050 exposure. The average probability of default exhibits a mild increase between the FS2020 scenario and FS2050 scenario when considering (i) 300mm precipitation without a tropical storm (single event) and (ii) 200mm precipitation with a category two hurricane (compound event), respectively.[8] The effect is

[7]Representative Concentration Pathways (RCP) are scenarios for pathways of greenhouse gas concentrations developed by the Intergovernmental Panel on Climate Change (IPCC) that are used in particular to standardize the projections of future climate impacts. RCP 4.5 corresponds to a likely range of global mean surface temperature increase between 1.1 and 2.6°C in 2100 (IPCC, 2013).

[8]Scenarios (i) and (ii) are defined based on extreme events of rainfalls observed in Figure 4 below.

more pronounced in the tail of the distribution of PDs at the 99th percentile with an increase of 9 and 10 basis points for scenarios (i) and (ii), respectively. We also find substantial geographical heterogeneity in the impacts of climate change, even at the very local scale. The largest increase in exposure and risk occurs in coastal areas and is likely due to sea-level rise.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data used in our analysis. Section 4 presents the modeling method considered for the empirical analysis. Section 5 reports the estimation results for mortgage defaults and prepayments and compares performance across various model specifications. Section 6 concludes.

2 Relation to the literature

From the methodological point of view, our paper contributes to the literature on credit scoring and more precisely to the survival approach to credit scoring (Stepanova and Lyn, 2002). It more specifically relates to recent contributions that add spatial features to this class of models (Zhu and Pace, 2014; Calabrese and Crook, 2020). Considering the spatial dimension allows us to capture in particular the geographical heterogeneity of the impacts of weather events.

From the empirical perspective, our paper contributes to the literature on the impacts of weather extremes on credit risk, particularly mortgage default and prepayment risk. A number of studies have found a significant impact of natural disasters on mortgage defaults. The literature has investigated the impact of different types of climate events, such as wildfires (Issler et al., 2020), hurricanes (Kousky et al., 2020; Vigdor, 2008), or natural disasters in general (Klomp, 2008). It also has focused on different geographical areas such as California (Issler et al., 2020), Louisiana and Mississippi (Vigdor, 2008) or the global scale (Klomp, 2008).

The contributions most closely related to ours are Rossi (2021), Kousky et al. (2020) and Ouazad and Kahn (2021), which investigate the impact of tropical cyclones on the mortgage market. Rossi (2021) finds a substantial impact of exposure to hurricanes on mortgage default. Kousky et al. (2020) investigates mortgage credit risk in the aftermath of Hurricane Harvey. They find that, in the short term, loans on moderately to severely damaged homes are more likely to become 90 days delinquent. They further emphasize the key role of insurance in the longer term: in areas where flood insurance is required, prepayment rates rise. In areas where flood insurance is not required, default rates rise. Ouazad and Kahn (2021) analyses the impact of tropical cyclones on lenders' behavior on the mortgage market. They find a significant effect of the disaster on lenders' risk perception as measured by securitization behavior: there is a substantial increase in securitization activity in years following a large disaster, and the increase is larger in neighborhoods that do not have a long history of hurricanes. They then simulate the impacts of climate change by considering a scenario with declining real-estate prices. In contrast with these studies, Breia et al. (2019) find that hurricanes in the Caribbean do not increase the risk of default.

A major difference between our approach and that of the preceding contributions is that we consider the physical characteristics of extreme events as explanatory variables rather than the ex-post assessment of damages. This approach allows us to link default probability to the physical characteristics of weather events, e.g. we show that the impact of tropical cyclones more than doubles in magnitude when moving from a hurricane of category two to a hurricane of category three or more (see Table 2 below). More fundamentally, such an approach is necessary to integrate changes in the distribution of extreme events induced by climate change and thus to develop projections of the impacts of future climate change on mortgage default, as we do in Section 5.5.

As a matter of fact, previous contributions (Breia et al., 2019; Klomp, 2008; Issler et al., 2020; Kousky et al., 2020; Rossi, 2021) do not account for future changes in risk induced by climate change.

Through this focus on the future impacts of climate change, the paper contributes to the emerging literature on climate finance (see e.g. Battiston et al., 2017; Mandel et al., 2021). In this setting, credit risks have been assessed at the sectoral or macro level on the basis of forward-looking projections of climate impacts, but the models used are not backed by empirical estimations on micro-level data.

3 Data

This section discusses the sources of data for our analysis and describes the process of cleaning and preparing the final dataset for our models. The starting point for this data work is from Moody's Analytics, which provides details about mortgage loan characteristics and performance over time. This mortgage data is combined with more data from the Federal Reserve Economic Data (FRED), First Street Foundation (FS), National Flood Insurance Program (NFIP), the National Hurricane Center, and Copernicus.

3.1 Moody's Analytics Mortgage Data

The Moody's mortgage dataset consists of several large tables providing an overview of the non-agency mortgage market in the U.S. The full dataset contains origination details for more than 35 million mortgages; however, this total is reduced to roughly 24 million loans when requiring that the loans have a recorded five-digit ZIP code. In addition to loan characteristics, the dataset also contains monthly updates to track performance at the loan level, as well as deal-level information regarding the mortgage-backed securities (MBS) that contain these loans.

We start with the set of mortgages that originated in 1990 or later and are labeled as active in January 2010. This avoids capturing the surge in defaults associated with the 2008 recession. We then examine the performance of those loans over the 2010–2019 period.[9] In the January 2010 update, there are over 8 million unique loans in total, with over 6 million classified as active. This set of active loans is further restricted to 30-year fixed-rate mortgages secured by single-family properties.

Beyond those data restrictions, we remove any loans that already met our default definition (90+ days delinquent) as of January 2010. We also remove any loans that appear to have errors in their loan-to-value (LTV) ratios.[10] Next, we narrow the focus to loans secured by properties in the state of Florida,[11] which is an intuitive case study for examining the impact of extreme weather events. This yields 109,603 loans.

After merging the loan characteristics with their monthly performances, we made a few more restrictions to ensure sufficient data for the analysis. First, any loans that are missing more than

[9]The monthly data is observed through August 2019.

[10]These are detected by identifying those where the original LTV ratio differs from the Moody's cleaned origination LTV ratio by more than 0.1%, which typically is just indicative of a misplaced decimal.

[11]In addition to Florida being the state that experiences the highest frequency of hurricane impacts, it is also a recourse state that allows for deficiency judgments within a court's discretion. Thus, this provides a conservative setting for examining the impacts on mortgage defaults and the expected impacts would larger for non-recourse states.

25% of monthly observations prior to termination are removed. Then we remove any loans that are missing more than 50% of the dynamic LTV ratios.[12] After removing any loans with insufficient data, any remaining missing values are imputed using the most recent non-missing value, which effectively assumes that LTV ratios remain constant until there is an update in the data. After all of these merges and restrictions, we are left with a final set of 69,044 loans and 3,707,779 loan-month observations.[13]

To further summarize the representative nature of this sample in regard to securitization, these loans span 3,688 unique MBS deals, which corresponds to an average of 18.7 loans per deal. Further, among those deals, there are 37 distinct lead managers, which are financial institutions that take on the primary responsibility for issuing the securities. The distribution of these deals among the largest financial institutions shows the largest share (Bank of America) at over 10%, and 17 institutions have a share $> 1\%$ (see Figure 10 in the online Appendix). However, nearly 30% of loans have missing values for that variable. Thus, our sample is fairly representative of the non-agency mortgage market. These private-label securitizations tend to be riskier than government-backed loans, which contributes to the large default rates observed in our sample.[14]

3.2 Mortgage Outcomes

The mortgage outcomes fall under one of three categories: loan performance, prepayment, or default. Since our sample period spans less than 10 years, many loans remain current throughout the entirety of the period. Possible early termination options include default and prepayment. As alluded to above, we define $default$ in this study as a loan that is observed as 90+ days delinquent or worse, which follows the guidelines set forth by the Basel Committee on Banking Supervision (2017). We construct a binary variable following the rule:

$$default_{i,t} = \begin{cases} 1 & \text{if borrower } i \text{ is 90+ days delinquent at time } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

This classification of 90+ days delinquent is derived from a variable named *mbadelinqstatus* in the Moody's dataset, which includes several categories for a distressed loan as it moves through various delinquency stages, and out to foreclosure, REO (real estate owned), and liquidation. These classifications follow from the methodology put forth by the Mortgage Bankers Association.

Prepayments are directly observed in the data with its own category in the *mbadelinqstatus* variable. We construct a binary variable following the rule:

$$prepayment_{i,t} = \begin{cases} 1 & \text{if borrower } i \text{ fully repays the mortgage in advance at time } t \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

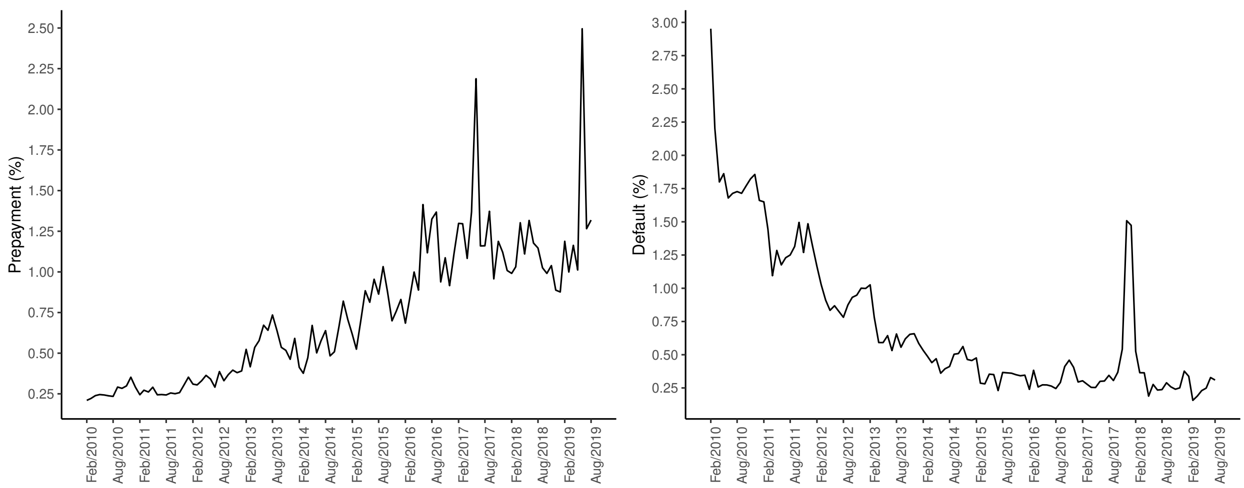
Once a loan is observed as terminated (either from default or prepayment), any subsequent observations are removed since the termination has been observed. We find that roughly 50% of

[12] These incorporate not just the amortizing loan balances, but also the adjusted property values based on a quarterly CBSA-level house price index from the Federal Housing Finance Agency.

[13] This filtering down from 109K loans to 69K loans does not substantially alter the observed default/prepayment rates. However, it does result in the omission of the Miami metro from our sample since the dynamic LTV estimates in the data are missing.

[14] We find that the observed default rates for our sample are similar to those observed in sub-prime mortgage markets in Amromin and Paulson (2009) using a similarly large number of observations.

loans in the sample terminate through default, 30% terminate via prepayment, and 20% remain active throughout the entire period. Figure 1 depicts the default and prepayment rates for the loans in our sample over the 2010–2019 period. Figure 9 in the online Appendix shows the distribution of loan ages at termination to summarize the lifetime of the loans in our sample.



((a)) ((b))

Figure 1: Monthly time series of the percentage of prepayments and defaults of Moody's mortgages in Florida observed in 2010–2019. The percentages of events are relative to the number of non-terminated loans as of the prior month.

Figure 1 provides a representation of the evolution of the prepayment (left-panel) and default (right-panel) rates of a cohort of mortgages over time. As for the default rate, one observes a downward trend which corresponds to the progressive sorting-out of higher quality mortgages and of the decreasing incentives to default due to decreasing LTV ratios. However, one observes a spike in default between late 2017 and early 2018. We posit that this spike can be explained by the exposure of corresponding borrowers, in the previous four months, to some extreme climate events including hurricanes (Irma and Nate) and intense rainfalls (maximum consecutive 5-day precipitation above 140mm). The actual quantitative impact of these extreme events on default is captured in our subsequent analysis. Furthermore, our scenario analysis, investigates how the increased frequency of such extreme events under climate change could increase the rate of mortgage defaults. As for prepayment rates, the upward trend can be explained by the amortizing loan balances lowering the cost of fully prepaying the mortgage. Regarding the two spikes in 2017 and 2019, these followed periods of decreasing mortgage rates, which may be a possible explanation.

3.3 Predictor Variables

From the Moody's dataset, we retain several predictor variables for our models. We use the included dynamic LTV ratios in the Moody's dataset to measure a borrower's home equity and capture strategic incentives to default which could arise when the value of the house is worth less than the mortgage. In addition to this, the data includes the borrower's FICO score at origination, as well as several characteristics about the loan/property. These include classifications for the property's occupancy type, number of units, loan purpose, loan product, whether there is an active prepayment penalty, and the lead manager for the MBS deal containing the loan. Tables 11 and 12 in the online Appendix provide some summary statistics for these explanatory variables.

This set of loan-month observations from Moody's data is then merged with macroeconomic variables to control for general economic factors impacting the mortgage outcomes, in line with the literature (Bellotti and Crook, 2009).

First, the variable "Mortgage30US" is the average 30-year fixed mortgage rate from Freddie Mac (FRED, 2021a). This is used in combination with the fixed interest rate of each loan (i) to construct a dynamic interest rate spread, denoted as Spread $\mathrm{IR}_{i,t}$, where t indexes time at a monthly frequency.

$$\text{Spread IR}_{i,t} = \text{Loan Rate}_i - \text{Mortgage30US}_t. \tag{3}$$

This rate spread captures much of a borrower's incentive to refinance a mortgage in order to attain a lower rate. When property values are rising, termination of a loan via prepayment (and refinancing to a new loan) can be an alternative for distressed borrowers who might otherwise default.

Second, we consider the state-level unemployment rate. The data is available at the monthly frequency from the Bureau of Labor Statistics (FRED, 2021b). The unemployment rate is often used in the literature as one of the main indicators to monitor the "health status" of the economy over business cycles, and its impact on mortgage default and prepayment (Bellotti and Crook, 2009; Zanin, 2014; Gerardi et al., 2017). Furthermore, there is substantial evidence of the impact of extreme weather events (Hsiang and Jina, 2014) and of hurricanes in particular (Ewing and Kruse, 2005; Groen et al., 2020) on unemployment and thus on income. Although the evidence on the long-term impact of extreme events is mixed (Deryugina et al., 2018), there is no ambiguity on the short-term impacts that are the most relevant to explain mortgage defaults. In the aftermath of extreme events, unemployment rises and income falls.

3.4 Weather Events

The key novelty of our approach is to integrate weather-related variables to account for the impact of extreme weather events and of their spatio-temporal characteristics on mortgage risk. In the Florida case, tropical cyclones are by far the most relevant hazards (Smith and Katz, 2013). They can impact properties directly through wind damage, indirectly through flooding caused by heavy rainfalls or storm surges, and through a combination of factors (Wahl et al., 2015). To account for these potential impacts, we take into consideration the spatio-temporal characteristics of tropical cyclones and heavy rainfall episodes at a high level of geographical granularity.

As regards tropical cyclones, the data source is the second-generation North Atlantic hurricane database (HURDAT2; Landsea and Franklin, 2013) of the National Hurricane Center. The database covers the period 1851 to 2019. It includes information on the name, date, hour (typically a record every six hours), and typology of the event, its geographical coordinates, and its maximum wind speed (in knots). However, it does not provide information on wind speed at the five-digit ZIP code level. We estimate this information by applying the wind speed model proposed by Willoughby et al. (2006) and implemented in the *stormwindmodel* R package.[15] The model allows estimating the

[15]`https://github.com/geanders/stormwindmodel`.

maximum sustained winds (in knots) for each five-digit ZIP code considering the tropical cyclone's track.

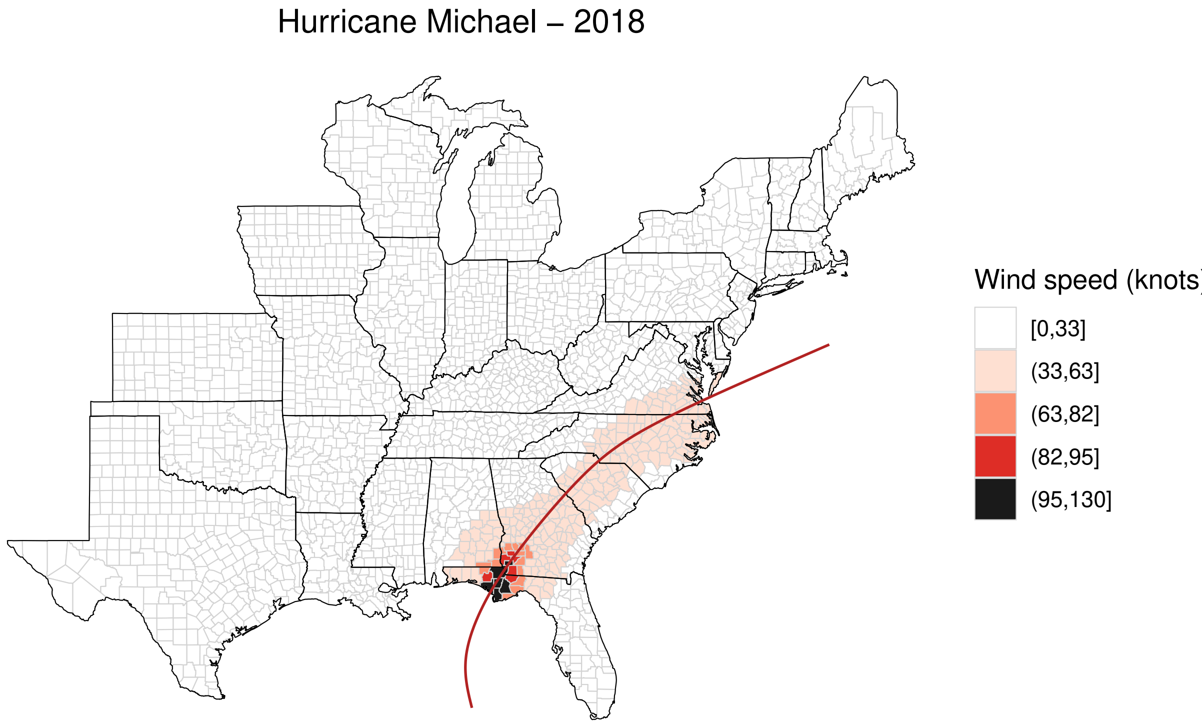


Figure 2: Hurricane Michael's track (October 2018) and the estimated maximum sustained wind speeds (knots) by applying the wind speed model of Willoughby et al. (2006).

Figure 2 shows a graphical representation of the estimation for Hurricane Michael's case in 2018. Hurricane Michael was one of the most recent major hurricanes (category three or greater) in Florida. The plot reports a spatial detail at the county's level instead of at the five-digit ZIP code for better graphical visualization. The red line represents the tropical cyclone's track, and around, the estimated maximum sustained winds (in knots) for each location. We can see maximum sustained winds greater than 95 knots (black areas) at Hurricane Michael's landfall in Florida. After estimating wind speed for each location, we have used the Saffir-Simpson hurricane wind scale to classify the tropical cyclone category. Specifically, we have defined a categorical variable as follows: no events (in the absence of tropical cyclones or wind speeds lower than 34 knots), tropical storm (34–63 knots), hurricane category 1 (64–82 knots), hurricane category 2 (83–95 knots), hurricane category 3+ (greater than 95 knots). In the 2010–2019 period, based on the National Hurricane Center classification, Florida was exposed to eight tropical storms and six hurricanes. In particular, Figure 3 displays how hurricanes of category 2+ have been rare events. However, they are important events for risk managers because they can potentially cause material damages when they occur (e.g., Pielke et al. (2008)).

Looking at precipitations, several indices of intensity of rainfall are proposed in the literature

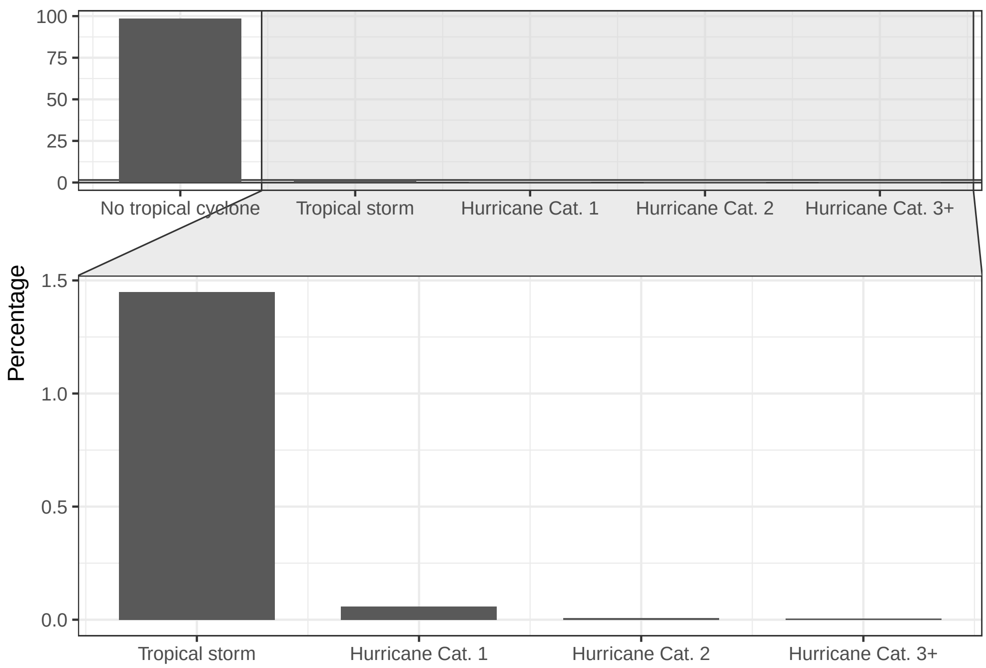


Figure 3: Histogram of the tropical cyclone events in Florida during the 2010–2019 period. Percentages calculated on 3,707,779 loan-month observations.

(e.g. Zhang et al., 2011). We consider using as a measure of rainfall intensity the monthly maximum accumulated consecutive 5-day precipitation (Rx5day) in millimeters (mm). The Rx5day is computed as the $max(PREC_{tmy})$, where $PREC_{tmy}$ is the precipitation amount $> 1mm$ for the 5-day interval ending t, in the month m of the year y. We compute the Rx5day using the information on total precipitations recorded in the ERA5 database of Copernicus (Hersbach et al., 2018). The data on precipitations (accumulated liquid and frozen water, comprising rain and snow, that falls to the Earth's surface) are in a regular latitude-longitude grid of $0.25° \times 0.25°$ (≈ 30 km) with an hourly temporal resolution.

For each five-digit ZIP code, we have associated the value of $Rx5day_{my}$ (computed for each grid point) with the loan-month observation that satisfies the minimum Haversine distance[16] between the centroid of the five-digit ZIP code and each grid point. After the merging process, we observe the median distance is 10.37 km between the two geographical points, while the maximum distance is 18.07 km. Some studies use Rx5day to describe flood risks (e.g. Wu and Huang, 2015). In areas that drain slowly, heavy rain increases the risk that water accumulates rapidly, causing flooding. In addition, heavy rain increases the risk that rivers can overflow their banks. Figure 4 shows that heavy rain mainly occurs jointly with a tropical cyclone. So that, we are in the presence of compound extreme weather events. The median values of Rx5day are typically highest as the tropical cyclone's category increases. However, we also observe some intense rainfall events that occur outside a tropical cyclone.

[16]The distance between two points on a sphere given the information on latitude and longitude.

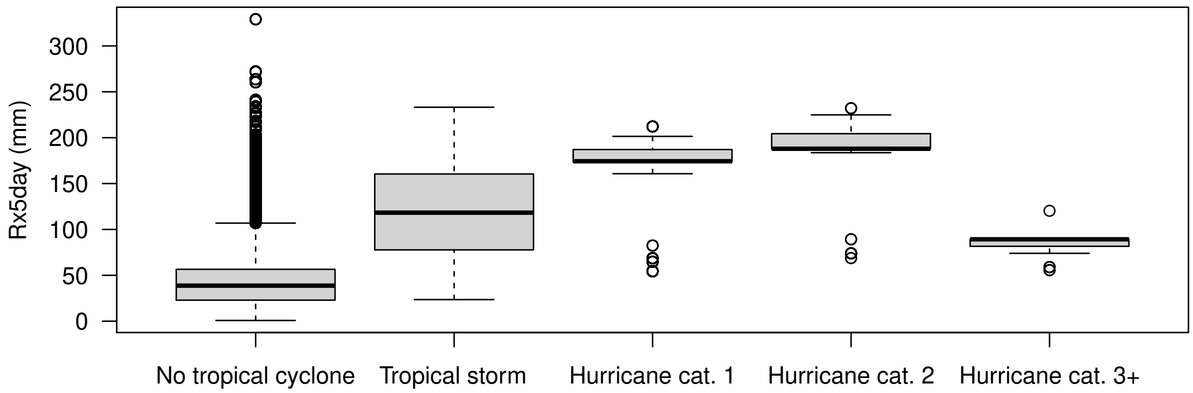


Figure 4: Boxplot of the monthly Rx5day indicator in the absence or during a tropical cyclone in the areas where there is a Moody's mortgage during the 2010–2019 period.

3.5 Flood Risk and Insurance

Lastly, we incorporate measures of exposure to flood risk and insurance take-up. For exposure to flood risk, we use data from the First Street Foundation (FS) Flood Model (First Street Foundation, 2020; Bates et al., 2021). The FS model is a high-resolution model of the risk of flooding in the contiguous United States due to rainfall (pluvial), riverine (fluvial), and coastal surge flooding (First Street Foundation, 2020; Bates et al., 2021). It provides in particular an estimate of the percentage of properties at risk in 2020 at the ZIP code level. We denote this variable as (FS2020) and use it as a benchmark measure of exposure to flood risk, corresponding to current climate conditions. In addition to the 2020 estimates, the FS dataset includes projections of the impact of climate change on the percentage of properties exposed to flood risk. Namely, the FS model considers the IPCC RCP 4.5 climate change scenario, which corresponds to radiative forcing being stabilized at $4.5 W.m^{-2}$ after 2100 and to a likely range of global mean surface temperature increase between 1.1 and 2.6°C in 2100 IPCC (2013). For this climate change scenario, it estimates the share of properties exposed to flood risk in 2050. We denote this variable as (FS2050) and use it as a measure of exposure to flood risk under future conditions induced by climate change.

When considering flood risk and the impacts of climate change, insurance is an important factor. The National Flood Insurance Program (NFIP) is the predominant flood insurance provider in the U.S. They also publish policy-level data that we use to compute monthly take-up rates at the ZIP code level (FEMA, 2022). These are computed by dividing the number of active policies in the ZIP code (*# NFIP Policies*) by the total number of properties provided by the FS data (*# Properties*). We denote this as $FItakeup_{j,t}$ where j is the j-th 5-digit ZIP code

$$\text{FItakeup}_{j,t} = \frac{\#\ \text{NFIP Policies}_{j,t}}{\#\ \text{Properties}_{j}}. \tag{4}$$

4 Methodology

We model the probability of mortgage default and prepayment using an additive Cox proportional hazard model with time-varying covariates. This time-to-event framework is appealing because it allows assessing the hazard of default or prepayment over the mortgage life-cycle when predictors are changing over time.

We consider a Generalized Additive Model (GAM) to flexibly capture non-linearities in the outcome-predictor relationships. GAM framework allows to relax assumptions on the functional form that represents the relationship between predictors and outcome. Instead of imposing a given parametric relationship, the function is estimated by the model. To avoid overfitting, we use a penalty to estimate the splines, therefore called penalized splines. Studies in different disciplines show that penalized splines increase the interpretability of the models (e.g. Zanin and Marra, 2012; Djeundje and Crook, 2019b), as well as the predictive accuracy (e.g. Berg, 2007; Zanin, 2020).

In line with the literature (Stepanova and Lyn, 2002; Bellotti and Crook, 2009; Calabrese and Crook, 2020), we use a survival approach not only to predict the probability that a borrower will default or prepay the mortgage loan but also to study the behavior of these probabilities over time. Let $\boldsymbol{z} = (z_1,z_2,...,z_k)'$ be a vector of k covariates and let T be a corresponding absolutely continuous time to default or prepayment. We consider a Cox model which is specified by the hazard relationship

$$\lambda(t;\boldsymbol{z}) = \lim_{h \to 0^+} P(t \leq T < t+h | T \geq t, \boldsymbol{z})/h = \lambda_0(t) r(t,\boldsymbol{z}) \quad t > 0 \tag{5}$$

In equation (5), $\lambda_0(t)$ is a baseline hazard function and the risk function $r(t,\boldsymbol{z})$ represents the relationship between the explanatory variables $\boldsymbol{z}$ and the hazard function. Cox (1972) proposes the exponential form for the relative risk function which yields the model

$$\lambda(t;\boldsymbol{z}) = \lambda_0(t) \exp\left[\boldsymbol{Z}(t)'\boldsymbol{\beta}\right] \tag{6}$$

where $\boldsymbol{Z}(t) = [Z_1(t),...,Z_k(t)]'$ is a vector of time-invariant and time-dependent covariates obtained as functions of t and the basic covariate vector $\boldsymbol{z}$. The baseline hazard function $\lambda_0(t)$ corresponds to $Z(t) = [0,0,...,0]'$ for all t and $\boldsymbol{\beta} = [\beta_1,...,\beta_k]'$ is a vector of unknown regression parameters. The additive Cox model generalises equation (6) with the following semiparametric form

$$\lambda(t;\boldsymbol{z}) = \lambda_0(t) \exp\left[\sum_{j=1}^{k} \eta_j[\boldsymbol{Z}(t)]\right] \tag{7}$$

where $\{\eta_j(\cdot), j = 1,2,...,k\}$ are univariate unknown smooth functions. Some empirical analyses show that they could reach higher predictive accuracy using survival additive models for credit risk (Djeundje and Crook, 2019a; Luo et al., 2016).

Use of maximum likelihood to estimate the additive Cox proportional model in equation (7) would result in over-fitting estimates of the splines η_j. For this reason, additive models are usually fit using penalized likelihood maximization, in which each smooth function in the likelihood has a penalty (Hastie and Tibshirani, 1990). To control the trade-off between penalizing and over-fitting, each penalty is multiplied by an associated smoothing parameter (Wood, 2017).

We define $\boldsymbol{\eta}_j = [\eta_j(z_{j1}),\eta_j(z_{j2}),...]^T$ so $\boldsymbol{\eta}_j = \Theta_j \boldsymbol{\beta}_j$ where Θ_j is an $n \times p_j$ model matrix for the smooth that contain its basis functions evaluated at the observed values, while $\boldsymbol{\beta}_j$ is the corresponding coefficient vector. We can write the smoothing penalty for η_j as $\boldsymbol{\beta}_j^T \mathcal{S}_j \boldsymbol{\beta}_j$, where $\mathcal{S}_j$ contains known coefficients. For identification, we apply the following constraint $\sum_i \eta_j(z_{ji}) = 0$.

If we consider the smoothing parameters $\boldsymbol{\lambda}$, we can write a combined smoothing penalty as

$$\sum_j \lambda_j \boldsymbol{\beta}_j^T \mathcal{S}_j \boldsymbol{\beta}_j = \sum_j \lambda_j \boldsymbol{\beta}^T S_j \boldsymbol{\beta} = \boldsymbol{\beta}^T S_\lambda \boldsymbol{\beta}$$

where S_j is a zero padded version of $\mathcal{S}_j$ and $S_\lambda = \sum_j \lambda_j S_j$. We now apply a penalised likelihood approach

$$\hat{\boldsymbol{\beta}} = \arg\max_{\boldsymbol{\beta}} \left[l(\boldsymbol{\beta}) - \frac{\boldsymbol{\beta}^T S_\lambda \boldsymbol{\beta}}{2} \right]. \tag{8}$$

For the maximization of (8), we use the penalized iteratively reweighted least squares (PIRLS) approach suggested by Wood et al. (2017) and suitable for large sample sizes.

Different typologies of reduced rank model terms are available in the literature for representing the unknown functions η_j (for example, cubic splines, P-splines, thin-plate splines) that are included in the model (7). Wood (2017) provides an overview of the smooth functions available. If the covariate described in Section 3.3 is a continuous variable, we consider η_j as a penalized cubic regression spline for a low setup cost (Wood, 2017, Sections 5.3.1 and 5.3.2).

To study the joint impact of intense rainfall (Rx5day) and the exposure of properties to flooding risks (FS2020) on mortgage default and prepayment, we include in the model a spline for the interaction between these two variables. To estimate this spline, we use a tensor product interaction approach based on the ANOVA decomposition of the smooths as it is well-suited to investigate smooth models with main effects and an interaction structure (Wood, 2017, Section 5.6.3). Particularly, the marginal smooths of Rx5day and FS2020 in the tensor product are summed to zero before constructing the tensor product basis to ensure identification.

Finally, we consider a smooth function η_j that captures the spatial effects in the model. We consider a low-rank Gaussian process smooth based on the Matérn correlation function as suggested by Kammann and Wand (2003) to ensure numerical stability (Wood, 2017, Section 5.8.2). Empirically, we use the latitude and longitude coordinates of the centroids of the 5-digit ZIP code where the property is located.

5 Empirical results

5.1 Model selection

Before estimating the models, we split the observations in a training sample and a control sample within a K-fold cross-validation framework (with k set to 5) using the $createfolds()$ function available in the R package *caret* (Kuhn et al., 2020). We construct the K-fold by sampling from the list of 69,046 loans. Afterward, we merge the training and control sample IDs with loan-month observations to estimate the model and assess the predictive accuracy. For simplicity, we describe the results of one of the five training samples defined within the cross-validation framework. As we found similar estimates on the different sets, we can infer that our empirical results are robust.

We estimate the additive Cox proportional hazard model with time-varying covariates using the *bam*() function implemented in the R package mgcv (Wood, 2021). To choose the sets of

Model	Variables	Default model *AIC*	Default model *BIC*	Prepayment model *AIC*	Prepayment model *BIC*
Additive	Base model	259,530.46	263,229.54	191,369.92	195,316.50
Survival	Cyclone	259,339.20	263,110.40	191,366.08	195,354.68
	Rx5day	259,356.52	263,175.24	**191,277.96**	**195,301.38**
	Cyclone+Rx5day	**259,235.84**	**263,081.46**	191,283.84	195,351.42

Table 1: Model selection measures. The models with the lowest AIC and BIC are reported in bold.

independent variables to include in the semiparametric models, we consider the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (BIC). According to these criteria, the best model shows the lowest AIC or BIC.

We report the results in Table 1 for the scoring and the prepayment models. The base model is without any weather-related variables. For the default model, the lowest AIC and BIC values are achieved when tropical cyclones (*Cyclone*) and intense rainfalls (*Rx5day*) are included. On the contrary, the prepayment model shows the lowest AIC and BIC when only intense rainfalls (*Rx5day*) are considered. The two semiparametric approaches show coherent results for the scoring and the prepayment models.

Sub-sections 5.2 and 5.3 below describe the estimates for the additive survival model (6) that minimize the AIC and the BIC for the probability of default and the probability of prepayment.

5.2 Estimation results for mortgage defaults

We compare the results obtained from the estimated survival model ignoring (*base model*) and including weather variables (*base model + weather*). Table 2 reports the parameter estimates, the standard deviation and the significance level for the parametric components. The semiparametric components are $s(\cdot)$ and $ti(\cdot)$, where $s(\cdot)$ indicates that the variable is estimated as an univariate smooth function, while $ti(\cdot)$ represents a tensor product interaction that is appropriate when the main effects are also included. Table 2 reports the estimated degrees of freedom (*edf*) and the approximate significance for the semiparametric components. Therefore, the values for the semiparametric components represent the strength of the relationships, and not the direction of the relationship as the parametric components show. Figure 5 shows the plots of the semiparametric components for the continuous variables.

We perform a sensitivity analysis for the variables of tropical cyclones and the best goodness-of-fit is achieved for a four-month lag between the mortgage default and the tropical cyclone variables. Some important results in Table 2 show that all the tropical cyclone variables are significant and have direct effects on the default probability, in line with the expectations. Of interest, we note that the parameter estimate of tropical cyclones more than doubles in magnitude when moving from a hurricane of category two (with a coefficient equal to 1.657) to a hurricane of category three or more (with a coefficient equal to 3.347). This is in line with damages associated with the description of Saffir-Simpson Hurricane Wind Scale,[17] which describes how a hurricane of category 3+ can produce devastating or catastrophic damages, such as loss of the roof structure and/or some

[17] https://www.nhc.noaa.gov/aboutsshws.php

exterior walls of homes. Similar results have been captured by Rossi (2021).

In Figure 5, we report among the estimated smooth components the main effects of Rx5day and the FS2020 and the structure of the interaction between Rx5day and FS2020. Coherently with expectations, we observe that Rx5day has a non-linear increasing pattern on the default probability. This means that the survival probability of the mortgage reduces as intense rainfalls and likely damages to properties occur (for example, intense rainfalls increase the probability of flooding events or flash flooding; see Section 3.3). FS2020 has a significant impact on the default probability at a 0.1 level of significance. When we consider the interaction between Rx5day and FS2020, the level of significance increases to 0.05. We can observe that intense rainfalls increase the probability of default when occurring in the area where properties are most exposed to flood risk. Intense rainfalls in areas not exposed to flood risk do not have an impact on the survival probability of the mortgage.

We find some interesting results for the mortgage and property characteristics. Specifically, we observe a non-linear positive highly significant relationship between the LTV ratio and the default probability (Figure 5) that suggests how borrowers with less home equity (larger LTV) are more likely to default. Loans taken out as the result of refinancing activities are less likely to default compared to the baseline group of new purchase mortgages. The default probability rises with the riskier categories so that Alt-A loans are more likely to default than prime loans, subprime loans are more likely to default than Alt-A, and the unknown category is the most likely to default. Mortgages for second homes or investment properties (non-owner-occupied) are less likely to default when compared to the baseline group of owner-occupied properties. Note that both of these categories have higher underwriting standards. The variable FItakeup_{t-4} measuring the flood insurance coverage has a significant non-linear inverse relationship with the default probability. This suggests that flood insurance protects mortgage borrowers against credit risk, in line with Kousky et al. (2020). Coherently with the expectations and the literature (Bellotti and Crook, 2009; Tian et al., 2016) we obtain that the unemployment rate has a significant direct effect on the default probability. The spatial components are highly significant, as shown by previous studies (Calabrese and Crook, 2020). Some heterogeneous spatial effects are captured and displayed in the map of Florida and reported in Figure 5. We can observe how mortgages for properties located mainly in the western coastal areas show the highest probability of default.

5.3 Estimation Results for Mortgage Prepayment

In the prepayment survival model, the categorical variables for storm classification are omitted as Table 1 shows that when they are included in the model, the AIC and BIC increase. These variables are also not statistically significant. One additional difference between the prepayment model and the default model is that the dynamic predictor variables are only one month lagged, since the observation of prepayment is immediate compared to the 90-day lag built into the default definition described in Section 3.2.

Table 3 shows that mortgages for non-owner-occupied (investment) properties are less likely to prepay. From the mortgage characteristics, higher prepayment penalties lower the probability of prepayment. For loan purpose, our baseline group is new purchase loans. Loans resulting from refinancing activity are less likely to prepay, whereas construction to permanent loans are more likely to prepay, albeit this is only marginally significant. Conversely, regular construction loans are less likely to prepay. In regard to the asset type or risk class of the mortgages, the negative

	Base Model		Base Model+Weather	
Variables	Estimates	Std. Error	Estimates	Std. Error
Occupancy Type (Base:Owner)				
Second Home	-0.126^{***}	0.041	-0.126^{***}	0.041
Vacant	-9.583	52.390	-9.559	52.332
Other	-0.007	0.580	-0.026	0.580
Non-Owner Occupied	-0.101^{***}	0.023	-0.102^{***}	0.023
Unknown	0.317^{***}	0.059	0.318^{***}	0.057
Number of Units	0.054^{*}	0.028	0.053^{*}	0.028
Mortgage Characteristics				
Loan Purpose (Base: Purchase)				
Construction	-0.122	0.105	-0.124	0.105
Cash Out Refinancing	-0.112^{***}	0.016	-0.113^{***}	0.016
Construction to Permanent	0.032	0.219	0.032	0.219
Debt Consolidation	-0.221^{**}	0.090	-0.222^{**}	0.090
Home Improvement	-0.357^{*}	0.193	-0.356^{*}	0.193
Refinancing	-0.158^{***}	0.022	-0.158^{***}	0.022
Other	-0.126	0.292	-1.128	0.292
Unknown	0.347^{***}	0.043	0.346^{***}	0.043
Loan Class (Base: Prime)				
Alt-A	0.052^{**}	0.023	0.051^{**}	0.023
Subprime	0.161^{***}	0.031	0.160^{***}	0.031
Unknown	0.340^{***}	0.058	0.339^{***}	0.058
	Edf		Edf	
s(LTV_{t-4})	1.987^{***}		1.987^{***}	
s(FICO)	4.781^{***}		4.781^{***}	
Macroeconomics + Insurance				
s(FItakeup_{t-4})	1.002^{***}		1.411^{***}	
s(Spread IR_{t-4})	5.273^{***}		5.258^{***}	
s(Unemployment Rate_{t-4})	1.993^{***}		1.992^{***}	
Spatial Component				
s(lat,lon)	15.548^{***}		15.172^{***}	
Weather Variables				
ti(Rx5day_{t-4})			3.236^{***}	
ti(FS2020)			1.617^{*}	
ti(FS2020, Rx5day_{t-4})			2.839^{**}	
			Estimates	Std. Error
Tropical Cyclone (Base: No event)				
Tropical storm_{t-4}			0.469^{***}	0.063
Hurricane of category 1_{t-4}			1.474^{***}	0.189
Hurricane of category 2_{t-4}			1.657^{***}	0.507
Hurricane of category $(3+)_{t-4}$			3.347^{***}	0.324
Deviance explained	6.30%		6.45%	
Loan-month observation count	$2.75M$		$2.75M$	

Table 2: Estimates for the default probability. For the parametric components, we report the parameter estimates, the standard error, and the statistical significance. For the smooth function components ($s(\cdot)$ or $ti(\cdot)$), we report the *edf* (estimated degrees of freedom) and the associated approximate significance. We include the number of months from origination and fixed effects for the MBS lead manager. P-value: $^{***} < 0.01, ^{**} < 0.05, ^{*} < 0.10$.

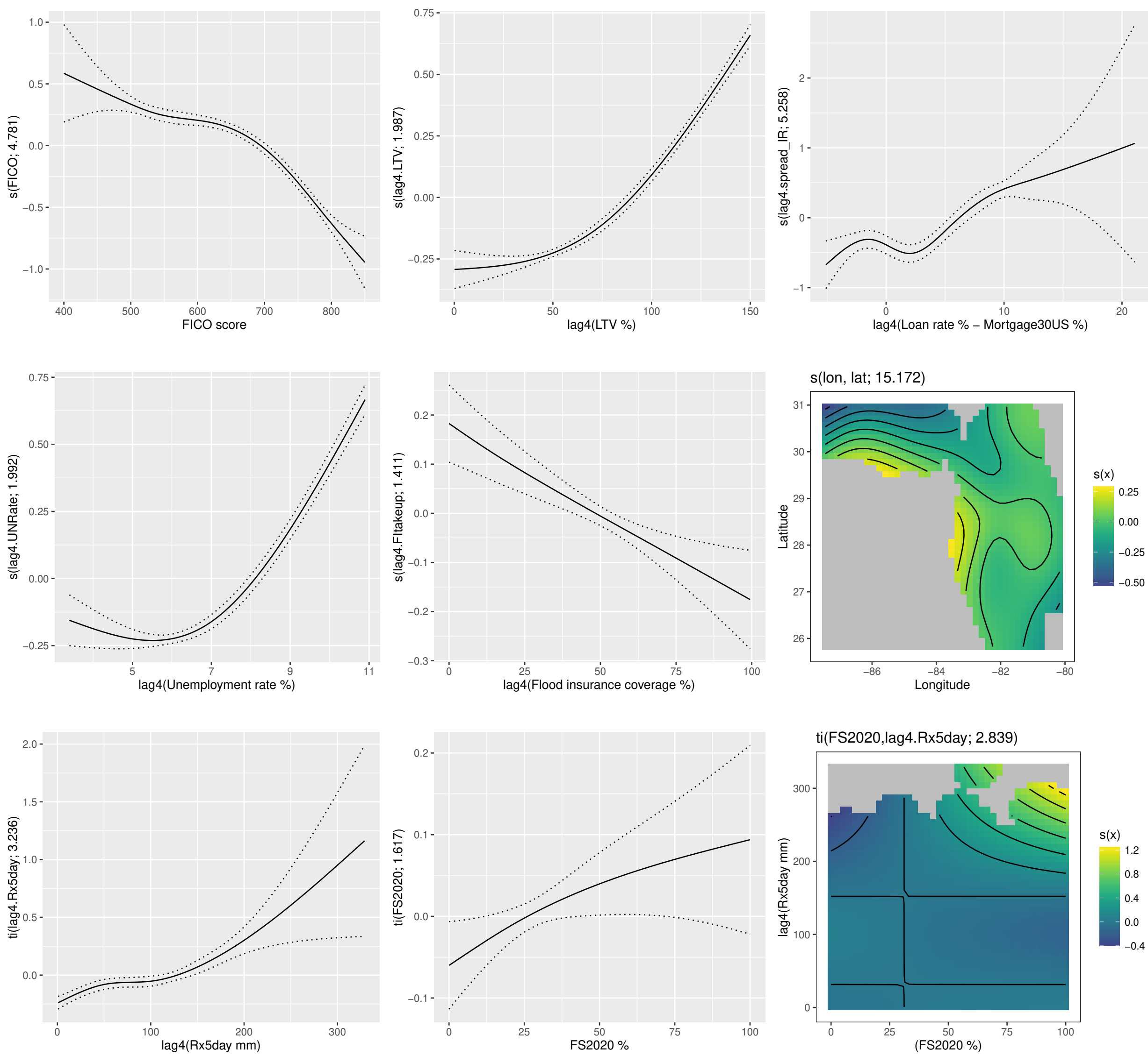


Figure 5: Estimated smooth components for the continuous variable in the default model. The results are on the scale of the respective linear predictors. Dashed lines represent 95% Bayesian credible intervals. We report the estimated degrees of freedom on the Y-axis in round brackets.

estimate for Alt-A is not significant relative to the baseline of prime loans. Subprime mortgages exhibit significance with their lower prepayment risk compared to prime loans. This may naturally follow from prime loans generally being for larger dollar amounts, and thus, the benefits from refinancing to a lower rate are greater for these larger loans.

Coherently with the expectations, higher flood risk is associated with a lower probability of prepayment, as Figure 6 shows. From the same Figure we can note that borrowers with higher FICO score and lower LTV_{t-1} are more likely to prepay their loans. Higher credit scores are usually associated with more financially literate borrowers (e.g. Duca and Kumar, 2014; Bajo and Barbi, 2018).

In line with Quercia et al. (2016), higher unemployment rates are associated with a higher probability of repayment. Analogously to the probability of default, the spatial component is also highly significant for the probability of prepayment. However, we note that weather variables show different behaviors for the two probabilities. For example, the interaction between $\mathrm{Rx5day}_{t-1}$ and FS2020 is not significant for the probability of prepayment but it is for explaining the default event. Both the weather variables $\mathrm{Rx5day}_{t-1}$ and FS2020 are significant but their interaction is not. Some non-linear spatial effects are reported in the map of Florida in Figure 6. We can observe how, after controlling for several factors, prepayment is most likely in the northern part of the Florida panhandle.

5.4 Model Performance

To assess the performance of our survival model, we compare its predictive accuracy with a logistic regression approach and an extreme gradient boosting tree approach (see online Appendix A for details on these models). The logistic approach is widely used in the banking industry (Thomas et al., 2017). The XGBoost approach has recently been put forward as a method of choice for credit risk assessment (Chang et al., 2018) and credit scoring (Gunnarsson et al., 2021; Xia et al., 2017).

We compare predictive accuracy between these approaches and our survival model (5) when excluding or including weather-related variables using a five-fold out-of-sample cross-validation and a five-fold out-of-time cross-validation. We assess the predictive accuracy using the Area under the ROC Curve (AUC), H-measure (H), and the Kolmogorov-Smirnoff (KS) statistic analogously to Calabrese and Crook (2020).

In Table 4, we report the results of the five-fold out-of-sample cross-validation. We observe that all the models estimating the probability of default and including the weather variables tend to outperform the models without weather-related variables. As discussed in Section 5.3, the tropical cyclone event has no statistically significant impact on prepayment probability. Therefore, we consider only Rx5day as a weather-related variable in the GAM survival and GAM logistic for prepayment. The XGBoost outperforms the survival and logistic models for both default and prepayment. However, some measures show only a small improvement.

To further investigate the model performance, in Figure 15 in Appendix D, we compare the observed percentage of default and the predicted one, estimated by including and excluding the weather-related variables, over time in the out-of-sample. Figure 16 in Appendix D reports a similar time series for the probability of prepayment. We note that the survival and logistic GAMs show similar results for the default probability. If we include weather-related variables in these models, this helps in capturing some important spikes in the time series.

Both Figures 15 and 16 show that the XGBoost, with or without including weather events,

	Base Model		Base Model+Weather	
Variables	Estimates	Std. Error	Estimates	Std. Error
Occupancy Type (Base: Owner)				
Second Home	0.059	0.037	0.060	0.037
Vacant	0.861	0.709	0.807	0.709
Other	−8.354	43.857	−9.264	72.190
Non-Owner Occupied	−0.250***	0.023	−0.241***	0.023
Unknown	0.434***	0.062	0.441***	0.062
Number of Units	−0.154***	0.028	−0.150***	0.028
Mortgage Characteristics				
Prepayment Penalty	−0.620***	0.171	−0.616***	0.171
Loan Purpose (Base: Purchase)				
Construction	−0.537***	0.202	−0.545***	0.202
Cash Out Refinancing	−0.220***	0.019	−0.217***	0.019
Construction to Permanent	0.274*	0.161	0.267*	0.162
Debt Consolidation	−0.300*	0.169	−0.280*	0.169
Home Improvement	−0.275	0.230	−0.276	0.230
Refinancing	−0.074***	0.023	−0.070***	0.023
Other	−0.378	0.322	−0.376	0.322
Unknown	0.058	0.057	0.058	0.057
Loan Class (Base: Prime)				
Alt-A	−0.017	0.023	−0.017	0.023
Subprime	−0.076**	0.036	−0.075**	0.036
Unknown	−0.378***	0.074	−0.378***	0.074
	Edf		Edf	
s(LTV $_{t-1}$)	1.983***		1.983***	
s(FICO)	4.405***		4.398***	
Macroeconomics + Insurance				
s(FItakeup$_{t-1}$)	6.471***		6.346***	
s(Spread IR$_{t-1}$)	5.046***		4.991***	
s(Unemployment Rate$_{t-1}$)	3.713***		3.742***	
Spatial Component				
s(lat,lon)	20.069***		18.744***	
Weather Variables				
ti(Rx5day$_{t-1}$)			2.383*	
ti(FS2020)			3.900***	
ti(FS2020, Rx5day$_{t-1}$)			1.012	
Deviance explained	8.57%		8.64%	
loan-month observation count	2.91M		2.91M	

Table 3: Estimates for the prepayment probability. For the parametric components, we report the parameter estimates, the standard error, and the statistical significance. For the smooth function components ($s(\cdot)$ or $ti(\cdot)$), we report the *edf* (estimated degrees of freedom) and the associated approximate significance. We include the number of months from origination and fixed effects for the MBS lead manager. P-value: $^{***} < 0.01$,$^{**} < 0.05$,$^{*} < 0.10$.

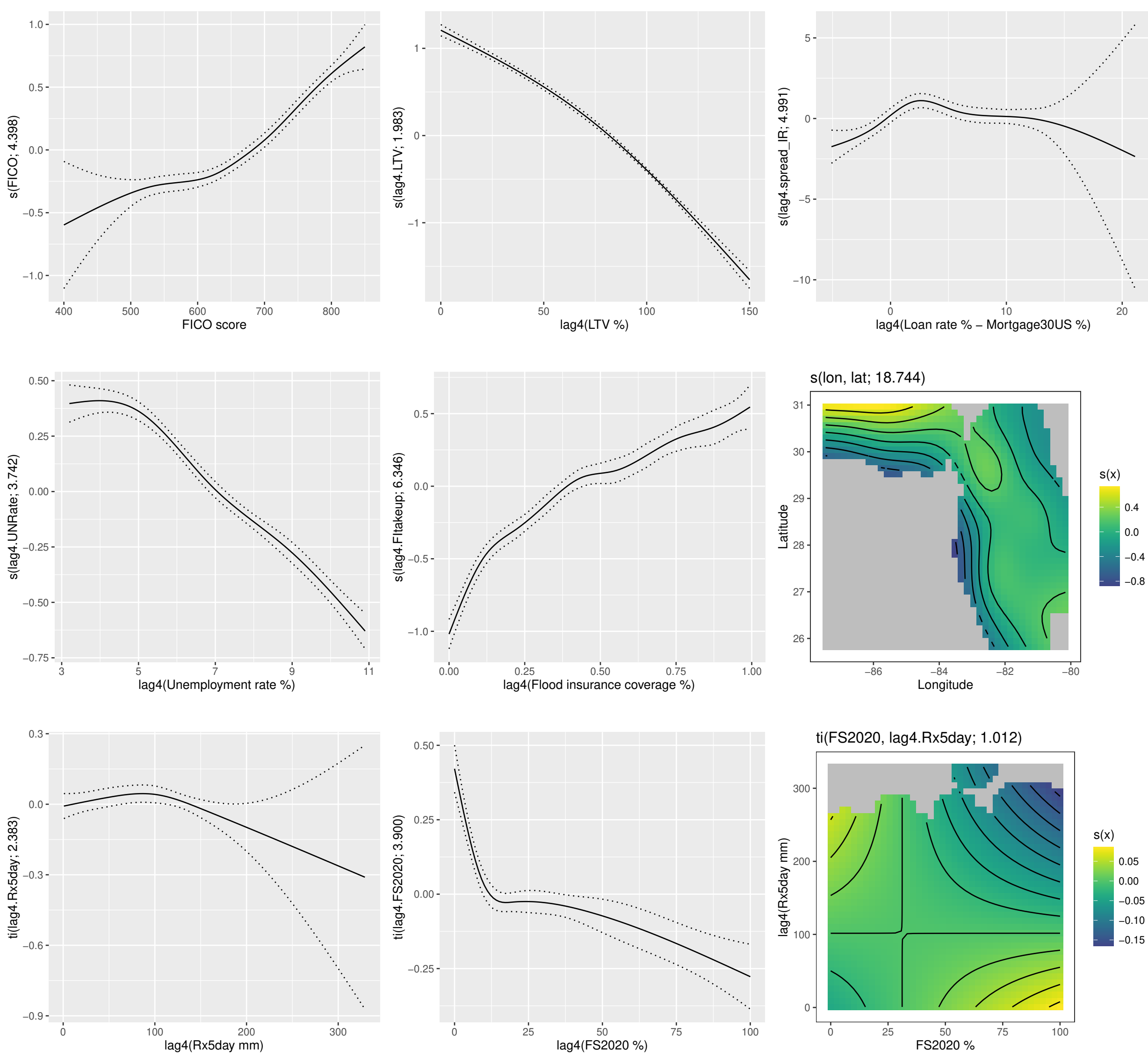


Figure 6: Estimated smooth components for the continuous variable in the prepayment model. Results are on the scale of the respective linear predictors. Dashed lines represent 95% Bayesian credible intervals. We report the estimated degrees of freedom on the Y-axis in round brackets.

		Default model			Prepayment model		
Model	Base Model+	*AUC*	*H*	*KS*	*AUC*	*H*	*KS*
GAM	No Extremes	0.7117	0.1280	0.3199	0.7504	0.1637	0.3800
Survival	Cyclone	0.7134	0.1291	0.3221	.	.	.
	Rx5day	0.7131	0.1291	0.3199	**0.7512**	**0.1645**	**0.3798**
	Cyclone+Rx5day	**0.7140**	**0.1300**	**0.3214**	.	.	.
GAM	No Extremes	0.7115	0.1268	0.3204	0.7528	0.1654	0.3855
Logistic	Cyclone	0.7132	0.1279	0.3214	.	.	.
	Rx5day	0.7130	0.1277	0.3193	**0.7535**	**0.1664**	**0.3863**
	Cyclone+Rx5day	**0.7139**	**0.1285**	**0.3211**	.	.	.
XGBoost	No Extremes	0.7249	0.1412	0.3380	0.7787	0.2083	0.4288
Logistic	Cyclone+Rx5day	**0.7252**	**0.1413**	**0.3389**	**0.7807**	**0.2122**	**0.4308**

Table 4: The average predictive accuracy measures on five-fold out-of-sample cross-validation. The sample size of each fold is about 743,990 loan-month observations. The models with the best predictive accuracy are in bold.

better captures the spikes in the time series than the GAM models. This is because this algorithm sequentially combines base models to achieve the best predictive accuracy.

We also perform a five-fold out-of-time cross-validation. Table 5 reports the results of the predictive accuracy measures. Analogously to the results observed for the out-of-sample cross-validation, all the models estimating the probability of default and prepayment and including the weather variables tend to outperform the models without weather-related variables. We also confirm again that the XGBoost outperforms the survival and logistic models for both default and prepayment. However, as a point of attention in interpreting the results of defaults, we point out that in the period used for training the models (2010-2017), we do not observe the most acute events of hurricanes (categories greater than two) that we observe instead in the out-of-time sample. Therefore, when evaluating the predictive accuracy of the models, it is likely that they could suffer from some under-performance. We do not report the Figures of the percentage of observed default and predicted one over time, as we obtain qualitative similar evidence as observed for Figures 15 and 16, but restricted to the out-of-time sample.

Overall, for all models, the inclusion of weather-related variables improves predictive accuracy. In terms of relative performance, the XGBoost approach has the best predictive accuracy. However, the next session shows that the XGBoost approach leads to incoherent results when used for future projections and scenario analysis.

Further to this performance analysis, we highlight, in online Appendix C, the impact of the inclusion of extreme weather events on the survival curves for two representative mortgages from our dataset.

		Default model			Prepayment model		
Model	Base Model+	AUC	H	KS	AUC	H	KS
GAM	No Extremes	0.6121	0.0520	0.1956	0.5978	0.0367	0.1493
Survival	Cyclone	0.5933	0.0491	0.1581	.	.	.
	Rx5day	0.6128	0.0611	0.1918	**0.6002**	**0.0369**	**0.1538**
	Cyclone+Rx5day	**0.6348**	**0.0654**	**0.2201**	.	.	.
GAM	No Extremes	0.6137	0.0479	0.1879	0.5974	0.0351	0.1472
Logistic	Cyclone	0.5906	0.0441	0.1484	.	.	.
	Rx5day	0.6145	0.0569	0.1876	**0.5996**	**0.0360**	**0.1517**
	Cyclone+Rx5day	**0.6317**	**0.0623**	**0.2121**	.	.	.
XGBoost	No Extremes	0.5981	0.0363	0.1656	0.5925	0.0431	0.1344
Logistic	Cyclone+Rx5day	**0.6523**	**0.0911**	**0.2275**	**0.6042**	**0.0486**	**0.1523**

Table 5: The average predictive accuracy measures on five-fold out-of-time cross-validation. The training sample covers the period from 2010 to 2017, while the test sample the period from January 2018 to August 2019. The sample size of each test set fold is about 57,660 loan-month observations. The models with the best predictive accuracy are in bold.

5.5 Scenario analysis

To assess the potential impact of extreme climate events on mortgage default risk, we project the probability of default due to climate-induced changes in exposure to flooding from the First Street Foundation (FS) Flood Model.

The FS model provides high-resolution probabilistic projections of the exposure to flooding in the contiguous United States due to rainfall (pluvial), riverine (fluvial), and coastal surge flooding (First Street Foundation, 2020; Bates et al., 2021). More precisely, it applies global climate model projections to forecast how exposure to flood risk will change over the next 30 years through changing environmental factors including sea-level rise, increasing cyclonic intensity, higher probabilities of cyclone landfall locations at higher latitudes, shifting precipitation patterns, and shifts in river discharge. The FS model focuses on the RCP 4.5 scenario, which corresponds to *We thank the reviewer for this comment and we add a part in the conclusions where we address the main limitations of the paper.* at $4.5W.m^{-2}$ after 2100 and to a likely range of global mean surface temperature increase between 1.1 and 2.6°C in 2100 (IPCC, 2013). The key inputs of the FS-model to our analysis are the share of properties estimated at risk of flooding per ZIP code under current climate conditions in 2020 (FS2020) and under the RCP4.5 climate change scenario in 2050 (FS2050).

To analyze the impact of climate-induced changes on default risk, we performed a scenario analysis on the portfolio of mortgages active in January 2019. We consider hurricanes and heavy rains as extreme weather events. We analyse two scenarios of weather events: (i) 300mm precipitation (Rx5day) without a tropical storm and an (ii) 200mm precipitation (Rx5day) with a category two hurricane. The properties' exposure to flood risk are by (*) the FS-model with current climate conditions (FS2020) and (**) the FS-model with RCP 4.5 2050 climate conditions (FS2050). The comparison of these two estimates allows us to compare the change in mortgage default risk due to climate change. We use the XGBoost and the survival model as scoring models.

Figure 7 shows the percentage change in the default probability under the FS2050 and the FS2020 flood risk for the scenario (i) (300mm precipitation and no hurricane).[18] The left plot on the left hand side in Figure 7 shows the results for the XGBoost and the one on the right hand side for the survival model. These results highlight that the XGBoost generates incoherent estimates for the default probability as the default risk decreases when the exposure to flooding risk increases from FS2020 to FS2050. On the contrary, the survival approach shows a systematic increase in risk as one shifts from FS2020 to FS2050 as well as a default probability differential increasing with the flooding risk differential (see the right panel of Figure 7).

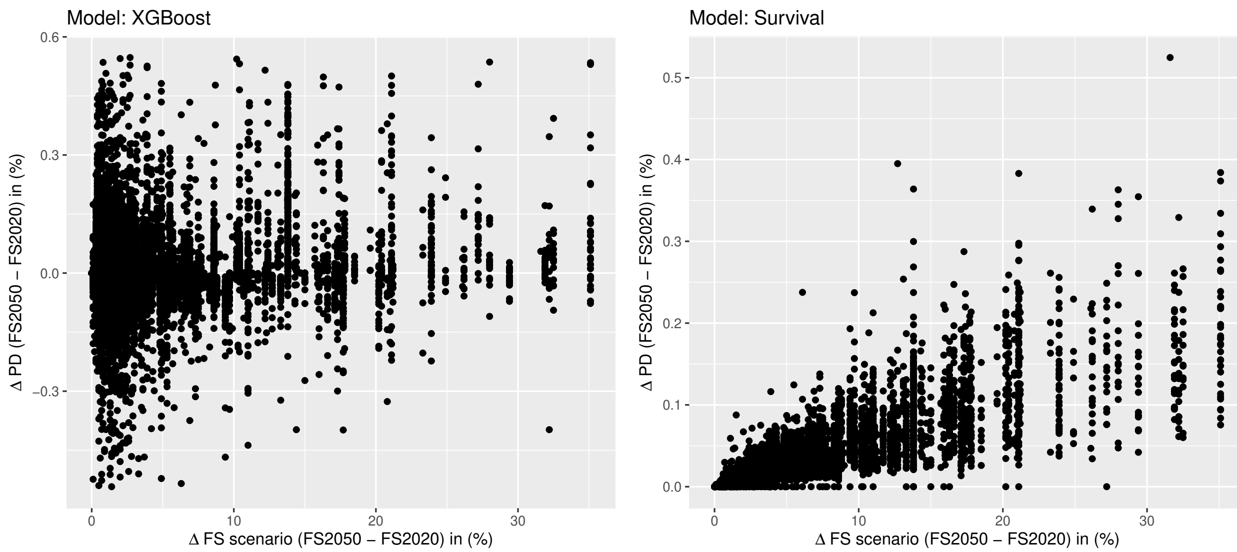


Figure 7: Scatter plots of the percentage change in the default probability under the FS2050 compared to FS2020 flood risk for the scenario (i) (300mm precipitation and no hurricane).

Table 6 shows some descriptive statistics of the default probability distribution for the scenario (i) with the 300mm precipitation event without a tropical cyclone. Focusing on results from the survival model, one observes an increase in the mean of 2 basis points as one shifts from FS2020 to FS2050 exposure. The impact is more apparent in the tail of the distribution where the default probability at the 99th percentile increases by 9 basis points as one shifts from FS2020 to FS2050 exposure. This represents a 5% increase in relative terms.

Table 7 focuses on the scenario (ii) with category two hurricane and 200mm precipitation event. In this setting, we observe an increase of 3 basis points as one shifts from FS2020 to FS2050 exposure, with a more pronounced impact in the tail of the distribution. It is worth pointing out that RCP 4.5 is a relatively mild climate scenario and that impacts could be substantially more stringent in unmitigated scenarios such as RCP 8.5. Furthermore, if properties become more exposed to extreme weather events due to climate change, insurers will likely demand higher insurance premiums. This may lower the value of housing and thus increase the loan-to-value ratio with an associated higher probability of default.

[18]The results for the scenario (ii) are available upon request to the authors. We do not report them as they are consistent with those of scenario (i).

Scenario FS	XGBoost				Survival model			
	Mean	Median	95^{th} percentile	99^{th} percentile	Mean	Median	95^{th} percentile	99^{th} percentile
Base model	0.30	0.25	0.64	1.20	0.32	0.30	0.61	0.81
FS2020	0.79	0.59	1.97	3.42	0.64	0.58	1.22	1.67
FS2050	0.80	0.60	2.00	3.43	0.66	0.60	1.28	1.76

Table 6: Some descriptive statistics of the default probability (PD, in percentage points) distribution for the scenario (i) (300mm precipitation and no hurricane). The *Base model* does not include weather related variables.

Scenario FS	XGBoost				Survival model			
	Mean	Median	95^{th} percentile	99^{th} percentile	Mean	Median	95^{th} percentile	99^{th} percentile
Base model	0.30	0.25	0.64	1.20	0.32	0.30	0.61	0.81
FS2020	1.12	0.84	2.85	4.75	2.14	1.97	4.03	5.32
FS2050	1.14	0.85	2.88	4.89	2.17	2.00	4.11	5.42

Table 7: Some descriptive statistics of the default probability (PD, in percentage points) distribution for the scenario (ii) (200mm precipitation and with a category two hurricane). The *Base model* does not include weather related variables.

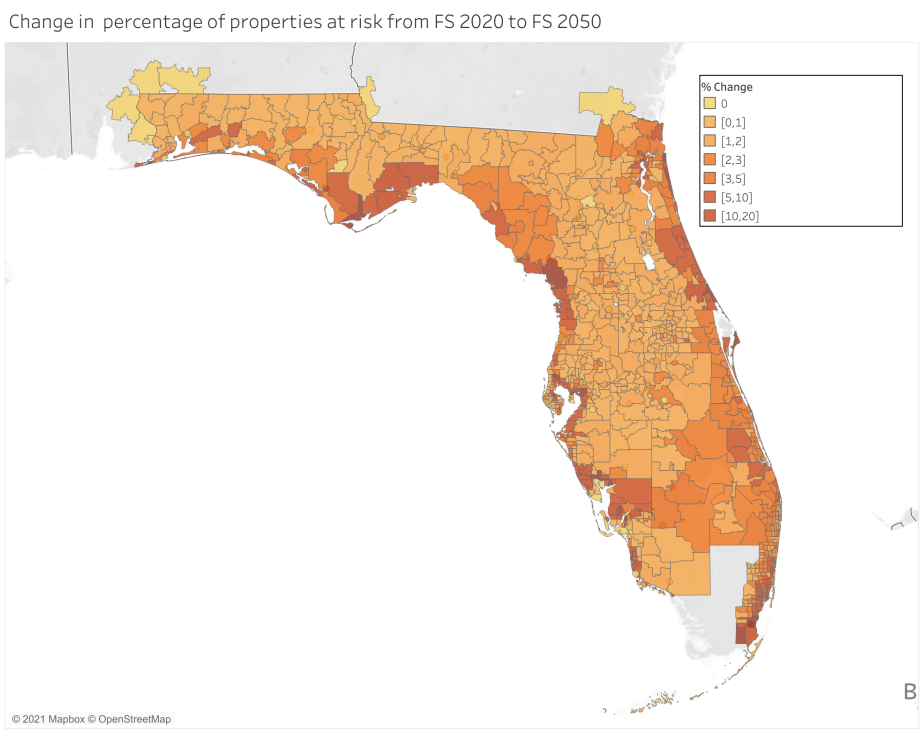


Figure 8: Evolution of exposure to flood risk in the shift from FS2020 to FS2050. The map displays the increase in the share of properties at risk of flooding between FS2020 and FS2050.

City	ZIP	scenario (i)	City	ZIP	scenario (ii)
Cape Coral	33909	36.11	Cape Coral	33909	16.97
Jacksonville	32202	30.90	Jacksonville	32202	14.21
Neptune Beach	32266	29.36	Edgewater	32132	12.82
Atlantic Beach	32233	28.66	Neptune Beach	32266	12.43
Ponte Vedra Beach	32082	27.17	Atlantic Beach	32233	12.11
Edgewater	32132	26.88	North Port	34286	10.90
North Port	34286	22.96	Ponte Vedra Beach	32082	10.67
Port Charlotte	33954	22.80	Palm Harbor	34685	10.27
Tampa	33629	22.37	North Port	34288	9.19
Palm Harbor	34685	21.94	Fleming Island	32003	9.08
New Smyrna Beach	32169	20.47	Port Charlotte	33954	8.82
Clearwater	33760	20.06	Jacksonville	32204	8.11
Naples	34103	19.22	Tampa	33629	7.79
Jacksonville	32204	18.27	New Smyrna Beach	32169	7.64
Tampa	33619	17.72	Jacksonville	32217	7.63

Table 8: Top 15 ZIP codes in terms of increase in default probability following a change in exposure from FS 2020 to FS2050. Results are reported for extreme event scenarios (i) and (ii) and are based on the survival models. Results are expressed as variations in percentage terms.

From a geographical perspective, Figure 8 illustrates that up to 2050 the largest increase in exposure and in risk will occur in coastal areas. Table 8 highlights this fact from a more quantitative perspective. There is a substantial increase in risk in some of the largest coastal cities of Florida when considering the shift in exposure from FS2020 to FS2050 [19]. In scenario (i), the default probability increases up to 36 percentage points in certain ZIP codes in Cape Coral, 30 percentage points in Jacksonville and 22 percentage points in Tampa. In scenario (ii), the default probability increases up to 17 percentage points in certain ZIP codes in Cape Coral, 14 percentage points in Jacksonville and 7 percentage points in Tampa. These results strongly echo recent results in the hydrological literature that emphasize the vulnerability of US coastal cities to compound flooding events involving storm surges and heavy rainfall (Wahl et al., 2015; Zscheischler et al., 2018). This literature also highlights sea-level rise as the major driver of long-term increase in risk under climate change. The risk is also highly influenced by local geographical characteristics and exhibits large heterogeneity even at the very local scale. For example, in Jacksonville, certain ZIP codes exhibit no increase in risk while others are among the most strongly affected.

6 Conclusion

We use an additive Cox proportional hazard model with time-varying covariates, including spatio-temporal characteristics of weather events, to study the impact of weather extremes (heavy rains and tropical cyclones) on the probability of mortgage default and prepayment. The model is estimated on a portfolio of non-agency mortgages in Florida consisting of 69,046 loans and 3,707,831

[19] Miami is absent from the sample due to missing data on LTV ratios.

loan-month observations with localization data at the five-digit ZIP code level.

We find a statistically significant and non-linear impact of tropical cyclone intensity on default as well as a significant impact of heavy rains on default in areas with large exposure to flood risks. We do not identify a significant impact of tropical cyclones, per se, on prepayment but find that heavy rain has a negative impact on prepayment when interacting with a large exposure to flood risks. These findings confirm existing results in the literature and also provide estimates of the impact of the extreme event characteristics on mortgage risk, e.g. the impact of tropical cyclones more than doubles in magnitude when moving from a hurricane of category two to a hurricane of category three or more.

We further build on the identified effect of exposure to flood risk (in interaction with heavy rainfall) on mortgage default to perform a scenario analysis of the future impacts of climate change using the metrics from the 2050 First Street flood model. Namely, we compare the distribution of default probabilities relative to the mortgage probability under current exposure to flood risks and relative to the projected exposure at the horizon 2050 for the RCP 4.5 scenario. We find a systematic increase in risk with a more pronounced effect in the tail of the distribution and large spatial heterogeneity. The largest increase in risk occurs in coastal areas, in line with recent results in the hydrological literature that emphasise the vulnerability of US coastal cities to compound flooding events involving storm surge and heavy rainfall.

We compare the results of our survival model with those obtained using (a) a generalized additive logistic model and (b) an extreme gradient boosting approach (XGBoost) with a logistic link. The XGBoost model exhibits high predictive accuracy consistently with previous findings in the literature. However, the XGBoost also provides incoherent results in the scenario analysis. Hence, overall, the survival approach appears as best fitted to our final objective, which is to predict the impact of future climate change on credit risk. The survival approach also has a temporal component, which provides more precise information to financial institutions as the loss faced by a bank depends not only if a borrower defaults on the loan, but also when this happens.

Overall, our results suggest that climate change will lead to substantial changes in risk, considering in particular that RCP 4.5 is a relatively mild scenario and that impacts will increase substantially more in the second half of the 21st century. Against this background, it seems necessary to systematically account for the impact of extreme weather events in credit risk assessment. Ours is an early contribution in that direction but substantial efforts are required to obtain a comprehensive assessment of climate risks over all asset classes and geographies so as to integrate climate-related risks in portfolio selection (Sirignano et al., 2016).

This study faces some main limitations. This manuscript analyzes the non-agency US mortgage market, but different results could be obtained for agency mortgages provided by Freddie Mac and Freddie Mae. Furthermore, our analysis considers a limited number of extreme events, such as tropical cyclones of category 2 and above. Therefore, the potential effects of natural disasters could be underestimated. Even if some areas have not been affected by tropical hurricanes, they could be subjected in the future. As for the scenario analysis, an extension of the present study might be considering climate models to generate (compound) scenarios of extreme events and evaluate their impacts on credit risk.

To have a time horizon long enough to study the default event, we consider only loans originated before 2010, in line with the literature (see, e.g., Medina-Olivares et al., 2023b,a). When more data is available, a future analysis could also consider mortgages originated after 2010. Finally, the impacts of different extreme weather events, such as wildfire and flooding, on mortgage defaults could also be studied.

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Supplementary material: Impacts of extreme weather events on mortgage risks and their evolution under climate change: A case study on Florida

Appendix A: Alternative modeling approaches

Generalized additive logistic model

We compare our proposal (6) with a widely used logistic regression model (Thomas et al., 2017). Previous studies in the credit scoring literature showed that a Generalized Additive Model (GAM) usually achieves higher predictive accuracy than a Generalized Linear Model (GLM) (e.g. Berg, 2007; Calabrese et al., 2015; Lohmann and Ohliger, 2019) for its flexibility. Based on these results, we compare the semiparametric survival framework with an additive logistic regression model defined as

$$Y_i = \begin{cases} 1 & Y_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where Y_i is the binary dependent variable and Y_i^* is the latent variable described as

$$Y_i^* = \sum_{j=1}^{k} \eta_j[\boldsymbol{Z}_i] \tag{10}$$

and $\{\eta_j(\cdot), j = 1,2,...,k\}$ are unknown smooth functions already considered in the additive Cox model (7). Analogously to section (4), we use the PIRLS method to estimate the splines $\{\eta_j(\cdot), j = 1,2,...,k\}$ as suggested by Wood et al. (2017).

The estimates of the additive logistic models are available upon request to the authors and they are similar to those obtained for the additive survival models.

Extreme gradient boosting (XGBoost)

A boosting approach assigns a weight to each observation that is then changed after a classifier is trained on the data. Particularly, the weights for the correctly classified observations are reduced and those for the wrongly classified observations are increased. In particular, Friedman (2001) proposes the gradient boosting method where the weights are estimated based on the gradient reduction of the loss function. This approach is then combined with a regression tree in an iterative algorithm of decision trees. This is a tree ensemble method that implements a decision tree at each step by fitting the gradients of the residuals of the previous tree in the previous step. This method is known as a gradient boosting decision tree (GBDT).

Chen and Guestrin (2016) suggested the extreme gradient boosting tree (XGBoost) where the loss function is normalized to decrease the complexities of modeling and the model variances. If the GBDT approach used the first derivative, the XGBoost improves the estimation of the loss function using the Taylor expansion. This increases the level of complexity but the normalization avoids over-fitting. Another important difference is that GBDT uses decision trees as a classification basis, while XGBoost considers linear classifiers. Moreover, the objective function also includes a penalty term to avoid overfitting.

Base Model		Base Model+Weather	
Variables	Gain	Variables	Gain
Unemployment Rate$_{t-4}$	0.313	Unemployment Rate$_{t-4}$	0.284
LTV$_{t-4}$	0.193	LTV$_{t-4}$	0.171
FICO	0.144	FICO	0.131
Spread IR$_{t-4}$	0.124	Spread IR$_{t-4}$	0.107
FItakeup$_{t-4}$	0.085	Rx5day$_{t-4}$	0.074
Loan purpose (Unknown)	0.008	FItakeup$_{t-4}$	0.067
Loan purpose (Purchase)	0.007	FS2020	0.039
MBS lead manager (BOA)	0.007	Loan Purpose (Unknown)	0.008
Occupancy type (Owner)	0.006	MBS lead manager (BOA)	0.007
Occupancy type (Non-Owner Occupied)	0.005	MBS lead manager (Unknown)	0.006

Table 9: Feature importance for mortgage default based on XGBoost. We report the first ten most important features based on the gain value.

Base Model		Base Model+Weather	
Variables	Gain	Variables	Gain
LTV$_{t-1}$	0.313	LTV$_{t-1}$	0.291
Unemployment rate$_{t-1}$	0.154	Unemployment rate$_{t-1}$	0.139
Spread IR$_{t-1}$	0.120	FICO	0.108
FICO	0.119	Spread IR$_{t-1}$	0.106
FItakeup$_{t-1}$	0.116	FItakeup$_{t-1}$	0.098
MBS lead manager (BOA)	0.018	Rx5day$_{t-1}$	0.056
Occupancy type (Non-Owner Occupied)	0.017	FS2020	0.044
Loan purpose (Cash Out Refinancing)	0.009	MBS lead manager (BOA)	0.017
Loan class (Alt-A)	0.009	Occupancy type (Non-Owner Occupied)	0.016
Loan class (Prime)	0.008	Loan purpose (Cash out refinancing)	0.009

Table 10: Feature importance for mortgage prepayment based on XGBoost. We report the first ten most important features based on the gain value.

Following Zanin (2020), we trained the XGBoost by setting the logistic regression for binary classification as an objective function and the AUC as the evaluation metric of the out-of-sample predictive performance[20]. Table 9 shows the ten most important features for the probability of default excluding (Base Model) and including the weather variables (Base Model+Weather). Table 10 instead shows the results for the probability of prepayment. The higher the gain value, the higher the importance of the feature for the prediction.

If we compare the Base model and the model with weather variables in Table 9, we notice that Unemployment Rate$_{t-4}$, LTV$_{t-4}$, FICO and Spread IR$_{t-4}$ are the four most important features for both models. When we include the weather characteristics, Rx5day$_{t-4}$ has a stronger contribution to the outcome prediction than the hurricane variables. We observe different results in the

[20] For tuning parameters, we set the learning rate equal to 0.1 to avoid over-fitting, the maximum depth of a tree equal to 5, and the number of boosting iterations stops when the performance did not improve for 50 rounds. We use the default setting in the R package XGBoost (Chen et al., 2022) for the other tuning parameters.

survival additive model for time-varying covariates and in the generalized additive logistic models. Furthermore, the insurance coverage is an important feature for both the models in Table 9.

The five most important variables for the base model for default and prepayment are the same. These are also the most important variables when we add the weather-related variables, as Table 10 shows. Similar to default, the most important weather-related variable also for prepayment is Rx5day$_{t-4}$. Coherently with survival and semiparametric logistic models, the variables on hurricanes do not have a strong impact on mortgage prepayment.

Appendix B: Descriptive analyses

Variables	Min	Max	Mean	Median
Borrower/loan characteristics				
LTV (%)	0.00	150.00	80.40	79.62
FICO score	400	850	674.25	676
N. months from mortgage origination	20	246	96.66	93
Prepayment penalty	0	1	0.01	0
Information on property				
Number of Units	1	4	1.05	1
Macroeconomic variables				
Spread IR (%) (3)	−5.09	21.20	2.55	2.51
Unemployment Rate (%)	3.20	10.90	7.77	8.00
Weather + Exposure + Insurance				
Rx5day (mm)	0.76	329.08	44.21	39.11
FS2020 (%)	0.00	100.00	18.94	10.50
FS2050 (%)	0.00	100.00	22.74	12.90
FItakeup (%) (4)	0.00	99.43	12.07	5.53
Observation counts: 69,044 unique loans, 3,707,779 loan-month observations				

Table 11: Descriptive statistics for continuous and count variables.

Variables	Frequency	Percentage
Static Loan Characteristics	**69,044**	**100.00**
Occupancy Type		
Owner Occupied	55,560	80.47
Non Owner Occupied	9,981	14.46
Second Home	2,506	3.63
Vacant	8	0.00
Other	5	0.00
Unknown	984	1.43
Purpose Type		
Cash Out Refinancing	32,432	46.97
Purchase	23,245	33.67
Refinancing	10,860	15.73
Construction	211	0.31
Construction to Permanent	94	0.14
Debt Consolidation	302	0.44
Home Improvement	87	0.13
Other	35	0.00
Unknown	1,778	2.58
Asset Type		
Prime	30,994	44.89
Subprime	20,975	30.38
Alt-A	16,108	23.32
Unknown	967	1.40
Dynamic Variables	**3,707,779**	**100.00**
Prepayment Penalty	48,721	1.31
69,044 unique loans, 3,707,779 loan-month observations		

Table 12: Descriptive statistics for categorical variables.

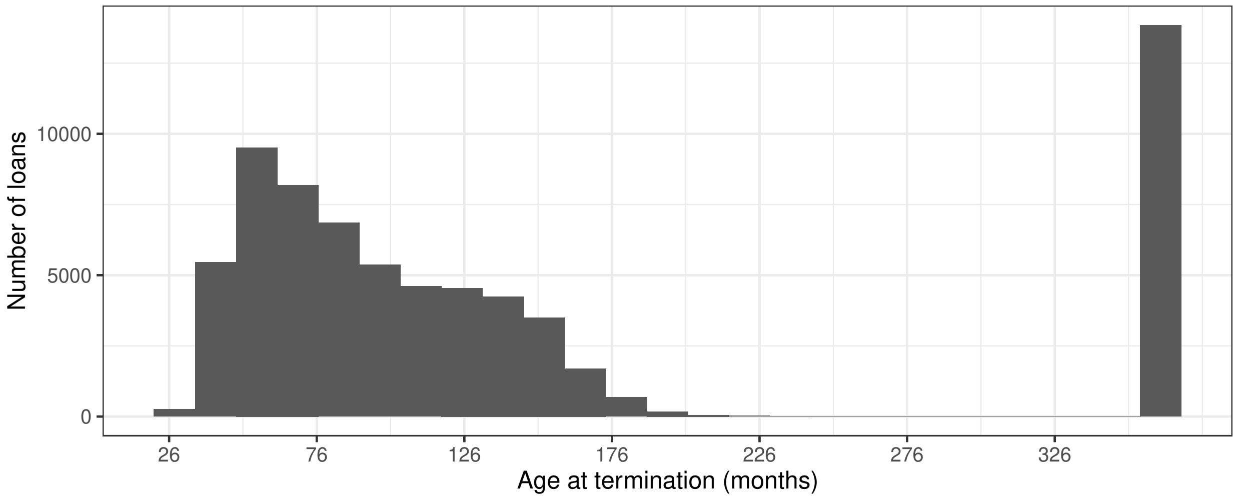

Figure 9: Distribution of loan ages at termination. Loans that remained active throughout the entire sample period are assigned 360 months.

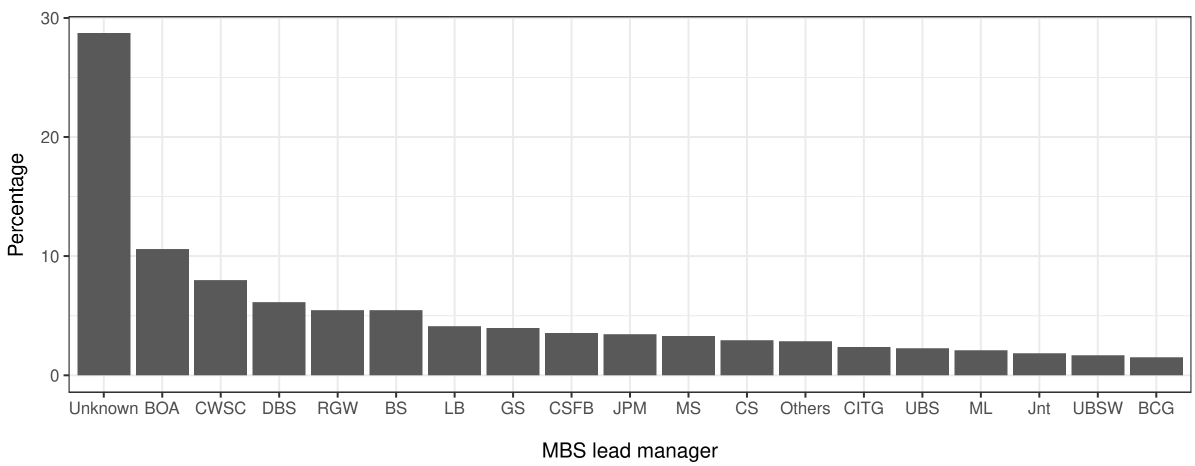

Figure 10: Percentage distribution of MBS lead manager.

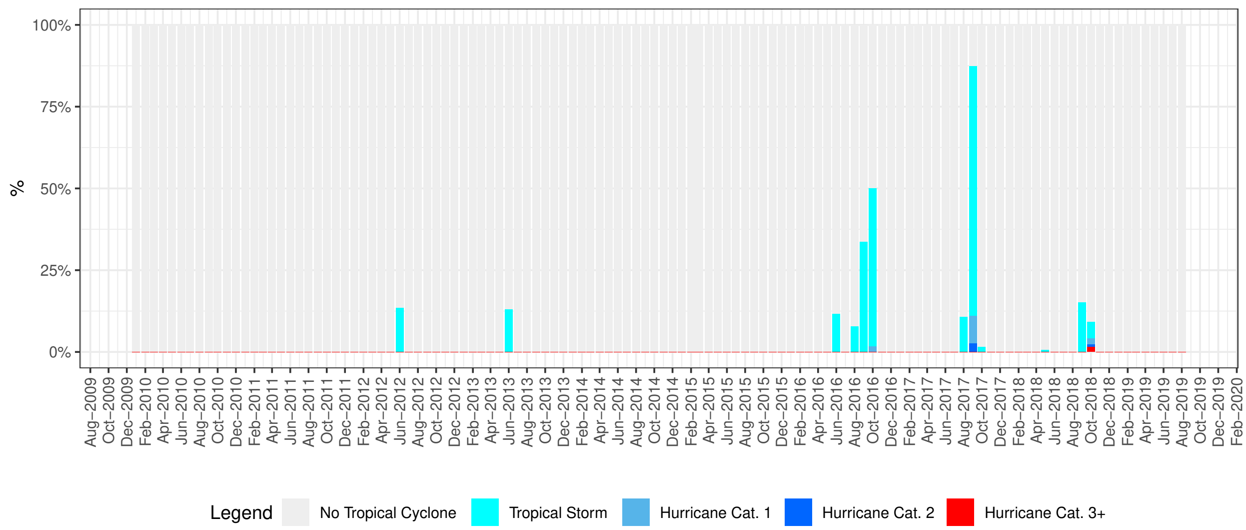

Figure 11: Percentage of unique five-digit zipcodes over time exposed to tropical cyclone events. We only report the events that affected the zipcodes associated to at least a mortgage in our sample.

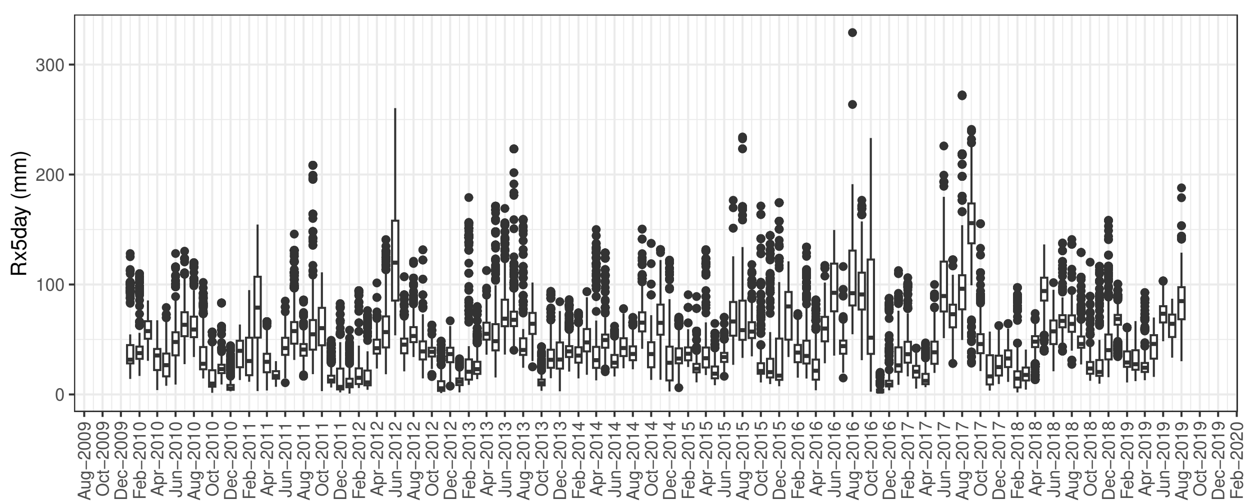

Figure 12: Boxplot distribution of the Rx5day (mm) observed in unique five-digit zipcodes over time. We only report the events that affected the zipcodes associated to at least a mortgage in our sample.

Variables	Default	Prepayment
Borrower/loan characteristics		
lag(.) LTV (%)	1.145	1.153
FICO score	1.633	1.635
Prepayment penalty	.	1.026
Occupancy type	1.038	1.038
Purpose type	1.023	1.024
Asset type	1.175	1.175
MBS lead manager	1.006	1.007
Information on property		
Number of Units	1.041	1.040
Macroeconomic + Insurance		
lag(.) Spread IR (3)	1.038	1.154
lag(.) Unemployment Rate (%)	1.136	1.152
lag(.) FItakeup	1.508	1.510
Weather + Flood exposure		
lag(.) Hurricane category	1.016	1.015
lag(.) Rx5day	1.062	1.063
FS2020	1.485	1.486

Table 13: Generalized Variance Inflation Factor (GVIF) analysis results to detect possible multicollinearity issues. Specifically, we report as a metric the $GVIF^{[1/(2\times Df)]}$ to make $GVIFs$ comparable across dimensions. Df is the degree of freedom. lag(.) indicates that the variable enter into the model with a lag. This lag(.) is equal to four for the default model, and it is equal to one for the prepayment model.

Appendix C: Example Survival Curves

We use the estimated models for mortgage default and prepayment to provide examples of survival curves when the borrower is exposed to extreme weather events. Specifically, we show differences (if any) in the survival curves when weather events are included or not in the models. To achieve this aim, we selected two mortgages from the dataset as case-study. One case takes into account a borrower exposed to an event of extreme wind speed (Mortgage A), while the other case is represented by a borrower exposed to an event of extreme rainfall (Mortgage B). In Table 14, we describe the main characteristics of the two selected mortgages.

Mortgage Characteristics	Mortgage A (Extreme wind)	Mortgage B (Extreme rain)
Property Type		
Occupancy type	Owner	Owner
Number of units	1	1
Mortgage Variables		
N. months from origination to weather event	148	137
Spread IR	3.0	2.9
LTV (%)	71.4	86.2
FICO score	719	798
Macroeconomics + Insurance		
Unemployment Rate (%)	3.0	4.2
FItakeup (%)	21.4	18.9
Weather Variables		
Month/Year of event	10/2018	8/2017
Tropical cyclone	Cat. 3+	No
Rx5day (mm)	89.2	272.3
FS2020 (%)	13.8	93.3

Table 14: We selected two mortgages from the dataset characterised by the exposition to extreme weather events. We rename the identifier of the mortgage for privacy reasons.

Figure 13 shows the estimated survival curves for the Mortgage A. Focusing on climate events, the borrower is characterised by exposure in October 2018 to Hurricane Michael of category 3+, but not extreme precipitation in terms of Rx5day (89.2mm). Moreover, the property is not located in an area at high risk of flood damages (FS2020 equals 13.8%). Thereby, in this case, we expect that is the high wind speed the main cause of damages to the property.

The graph at the bottom right provides a zoom of the prepayment probability. We can note some minor differences between the estimates when including or excluding the climate events. As discussed in Section 5, hurricanes have no statistically significant impact on prepayment, while Rx5day has a negative impact on the outcome, especially if the borrower has the property in a five-digit ZIP code at high risk of flood damages.

In the first graph at the top right, we provide a zoom of the default probability around the extreme climate event of interest. The estimated model suggests that the borrower's exposure to the hurricane of category 3+ reduces his/her the survival probability of the mortgage (with a lag of four months from the event as studied in the estimated model) from 0.51 to 0.47. This jump-down was not captured by the model that excludes the extreme weather events. So, using this last model, banks do not consider the severity of some extreme weather events in the evaluation of the default probability. After this extreme weather event, the servicer has registered a default of the Mortgage A.

Figure 14 shows the estimated survival curves for the Mortgage B. In August 2017, the property associated with the mortgage was exposed to an event of intense rainfall (Rx5day equal to 272.3mm) in an area where FS2020 indicates that 93.3% of properties are at risk of flood damages. The graph at the bottom right provides a zoom of the survival curve related to prepayment probability. In the month following the climate event, we observe a slight slowdown in the descent pattern of the survival curve. This could arise because exposure to intense rainfalls may reduce the borrower's incentive to prepay the mortgage as a homeowner without a loan has only insurance to protect their equity in the event of a disaster, and many borrowers have difficulty getting insurers to pay after a disaster. However, borrowers with a loan always have the option to default if insurance fails to pay. Therefore, borrowers have incentives to keep a loan (not prepay) as this can limit their loss and shift it to the lender. Also, increased expenses stemming from the disaster could reduce the liquidity of individuals and thus their desire to fund prepayment. Finally, most prepayment comes from the sale of a house and these sales may be affected by the disaster. In terms of default, the intensity of rainfalls and the economic shock due to disaster recovery expenses may increase in the probability of default. In this case, as we can see from the first graph at the top right, we observe an estimated decrease in the survival probability – from about 0.88 to 0.87 – that is not captured by the baseline model.

We expect a stronger impact on risk measures than observed in these two cases when there is a combination of extreme weather events like intense rainfalls and tropical cyclones. This is because the rate of increase in damage is much higher than when only one acute event occurs (see also the documentation on the National Weather Service[21]). The evidence that emerges from the case studies illustrated above emphasises the importance for financial institutions to include opportune climate-adjusted measures of risk in their risk management framework.

[21] `https://www.weather.gov/jetstream/tc_potential`.

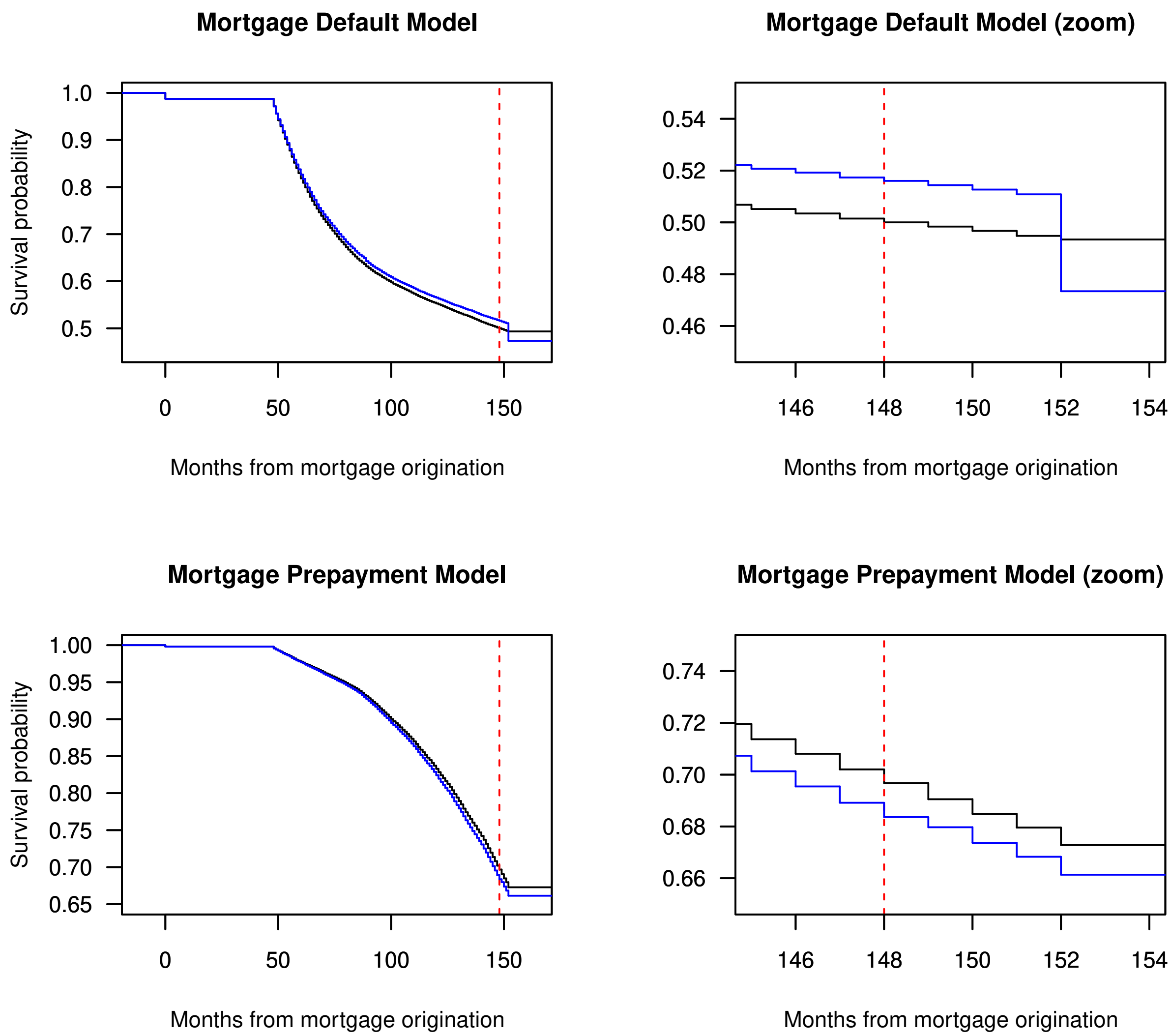

Figure 13: Survival curves for the Mortgage A. The left column plots show the entire survival curve as a result of the application of the default and prepayment models. The right column plots show a zoom around the extreme weather event of interest (marked by a red dashed vertical line). The black line refers to the baseline model, while the blue line to the model with extreme weather events.

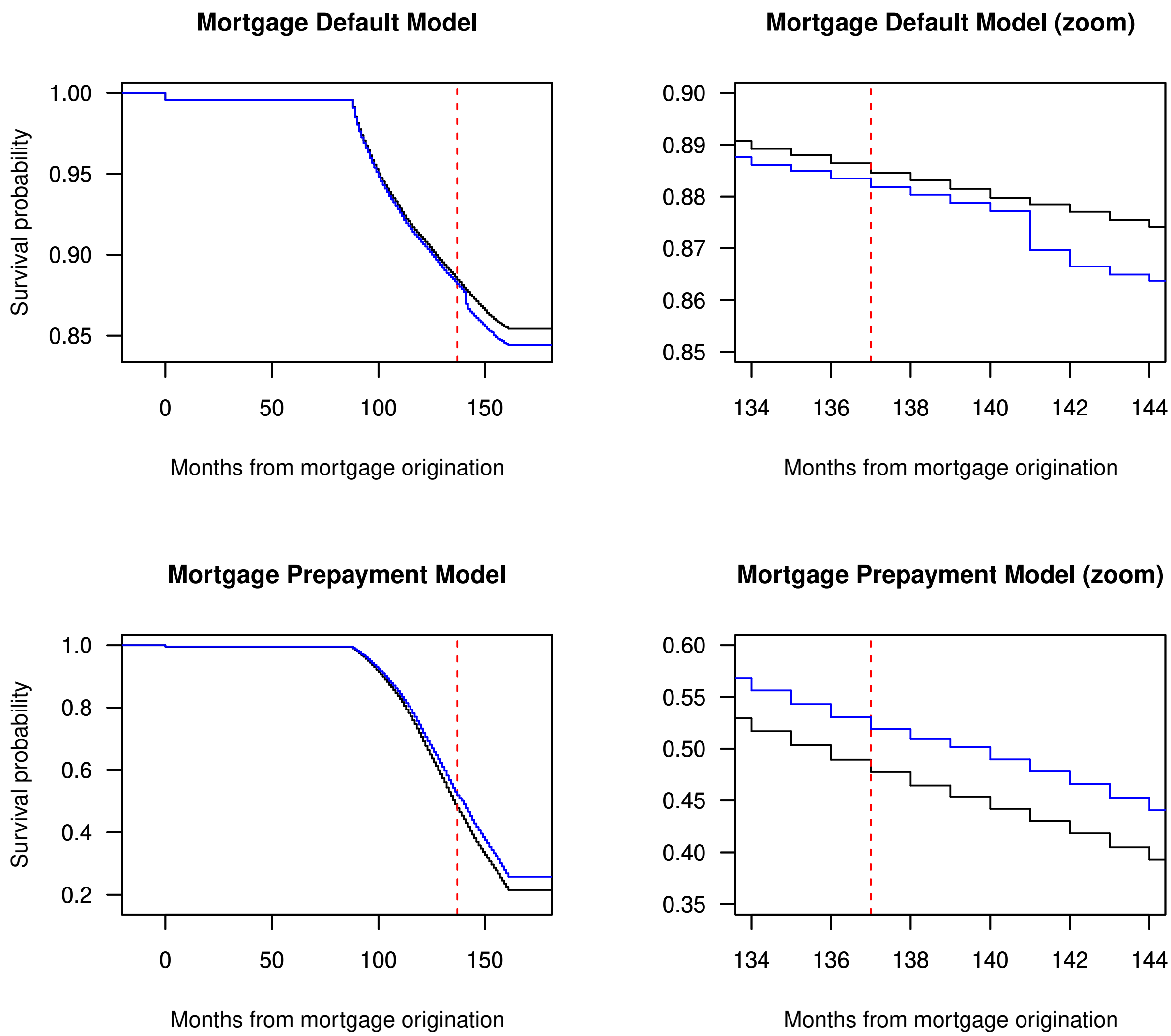

Figure 14: Survival curves for the Mortgage B. The left column plots show the entire survival curve as a result of the application of the default and prepayment models. The right column plots show a zoom around the extreme weather event of interest (marked by a red dashed vertical line). The black line refers to the baseline model, while the blue line to the model with extreme weather events.

Appendix D: Supplementary figures

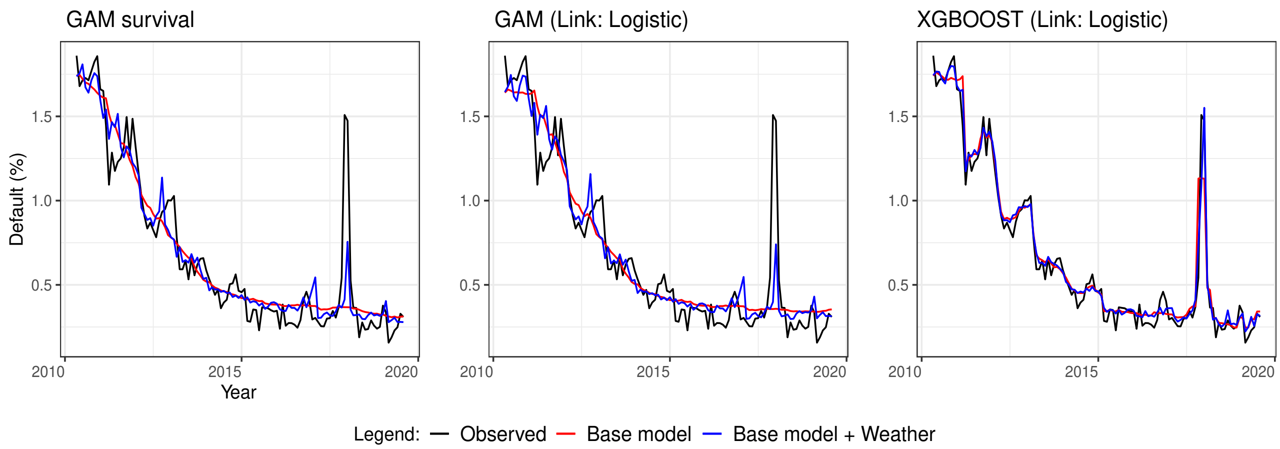

Figure 15: Time series of the percentage of defaults and average predicted probability of default for the three type of models considered (survival, logistic and XGboost), for each point in time of the out-of-sample .

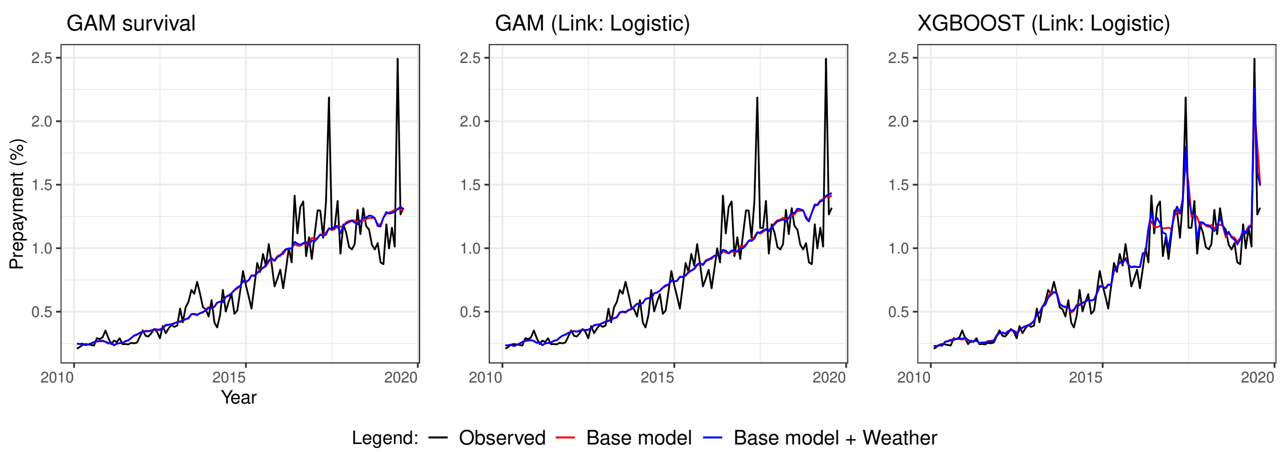

Figure 16: Time series of the percentage of prepayments and average predicted probability of prepayment for the three type of models considered (survival, logistic and XGboost), for each point in time of the out-of-sample.