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

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Agenda

- Introduction
- Literature review
- Purpose
- Data
- Methodology
- Empirical results
- Scenario Analysis
- Conclusion

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Introduction

There is **growing concern** among **financial regulators** and **central banks** about the **implications of climate change** for credit institutions

2015

In his seminal 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), **emphasised that climate change** could **impact the soundness of financial institutions and pose a threat to global financial stability**.

- **Paris Agreement on climate change**
- 17 **Sustainable Development Goals** (SDGs) adopted by the United Nations

2017

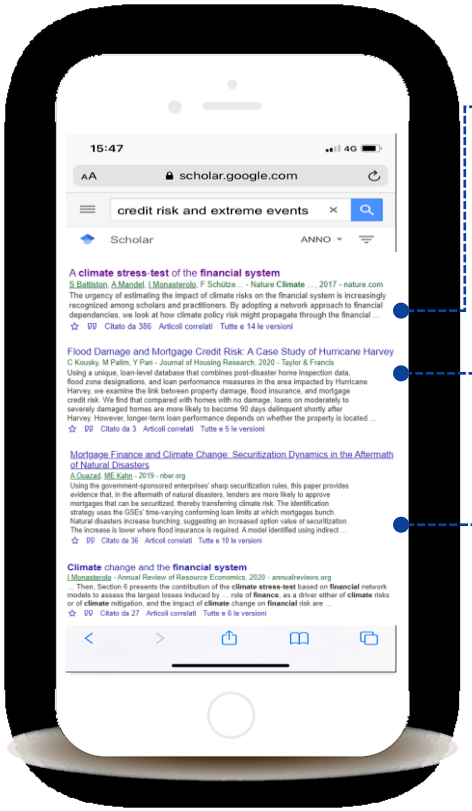
A group of eight central banks and financial regulators formed the **Network for Greening the Financial System** whose core objectives include ``**the development of environment and climate risk management in the financial sector**''.

The Basel Committee on Banking Supervision **is working on the development of a climate risk management framework** for banks and regulators

2021

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.

Literature review | a brief overview



Macro level

- **Credit risks have been assessed at the sectoral or macro levels** on the basis of forward-looking projections of climate impacts (e.g., Dietz et al, 2016; Battiston et al., 2017; Mandel et al., 2021)

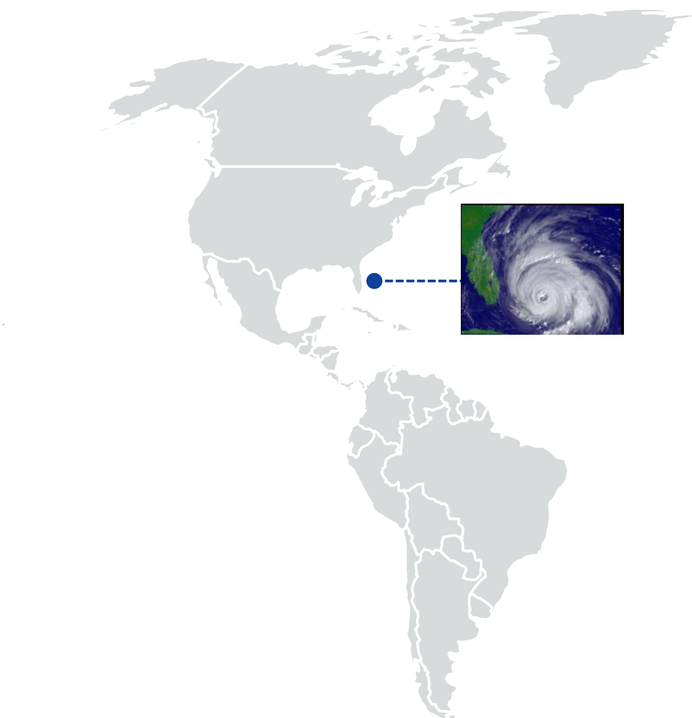
Micro level

- Rossi (2020) finds a substantial impact of **exposure to hurricanes on mortgage default**.
- Kousky et al. (2020) investigate the 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**.
- Ouazad and Kahn (2021) analyse the impact of tropical cyclones on lenders' behaviour on the mortgage market. They find there is a substantial **increase in securitisation activity** in years following a large disaster.

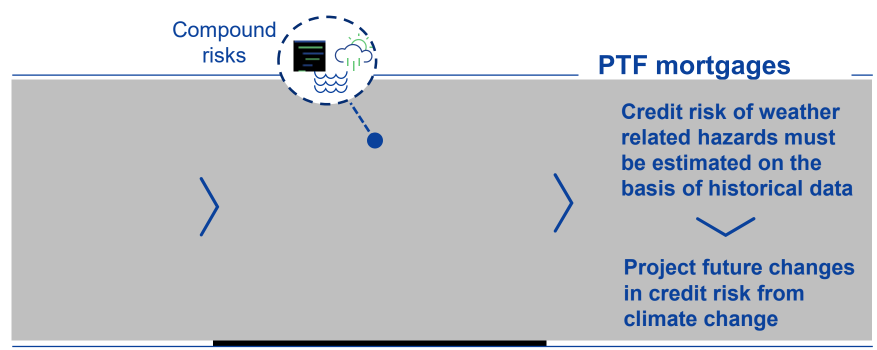
- *Dietz, S., Bowen, A., Dixon, C., and Gradwell, P. (2016). 'Climate value at risk' of global financial assets. Nature Climate Change, 6(7):676–679.*
- *Battiston, S., Mandel, A., Monasterolo, I., Sch¨utze, F., and Visentin, G. (2017). A climate stress-test of the financial system. Nature Climate Change, 7(4):283–288*
- *Mandel, A., Tiggeloven, T., Lincke, D., Koks, E., Ward, P., and Hinkel, J. (2021). Risks on global financial stability induced by climate change: the case of flood risks. Climatic Change*
- *Kousky, C., Palim, M., and Pan, Y. (2020). Flood damage and mortgage credit risk: A case study of hurricane Harvey. Journal of Housing Research, 29(sup1):S86–S120*
- *Rossi, C. (2020). Assessing the impact of hurricane frequency and intensity on mortgage default risk. Working Paper.*
- *Ouazad, A. and Kahn, M. (2021). Mortgage finance and climate change: Securitization dynamics in the aftermath of natural disasters*

Purpose

We study the **impacts of weather extremes (compound risks: tropical cyclones and intense rainfalls)** and climate change on **mortgage <u>default</u>** and **<u>prepayment</u>** in Florida.



- We pilot test our approach on a **portfolio representative of the Florida mortgage market**.
- Mortgages are of particular concern in the context of **climate financial risks because their collateral, composed of immovable assets, is fully exposed to physical risks.**
- To project impacts of climate change on credit risks, we perform a **scenario analysis**.



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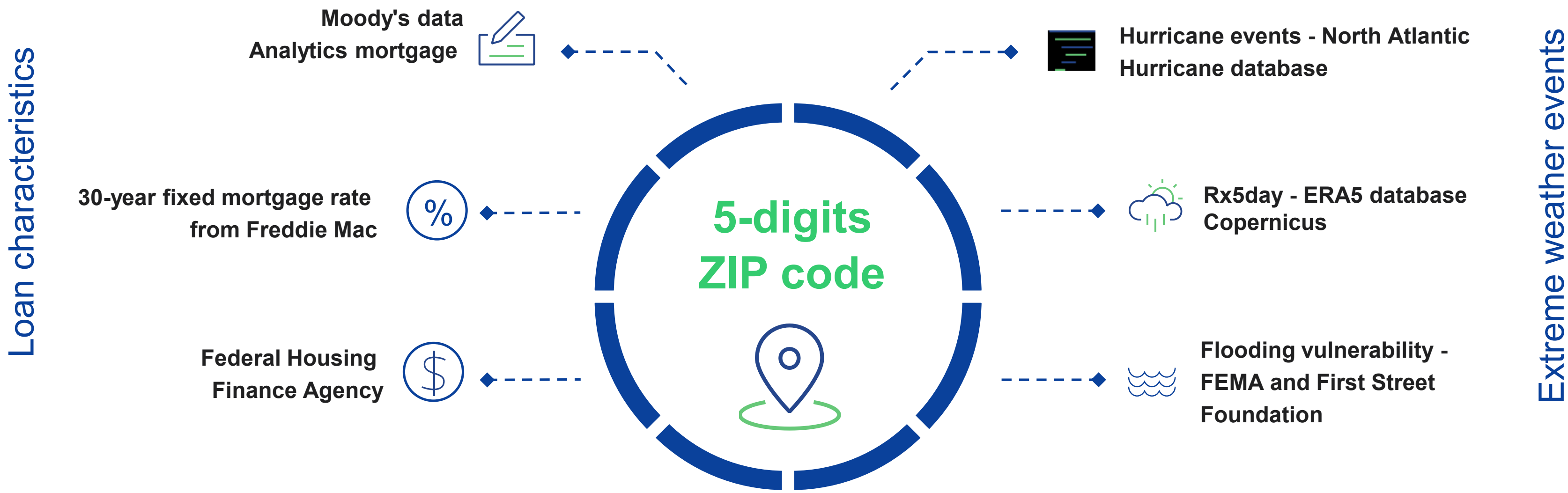
Data

The Moody's mortgage dataset 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, the National Hurricane Center, and Copernicus.



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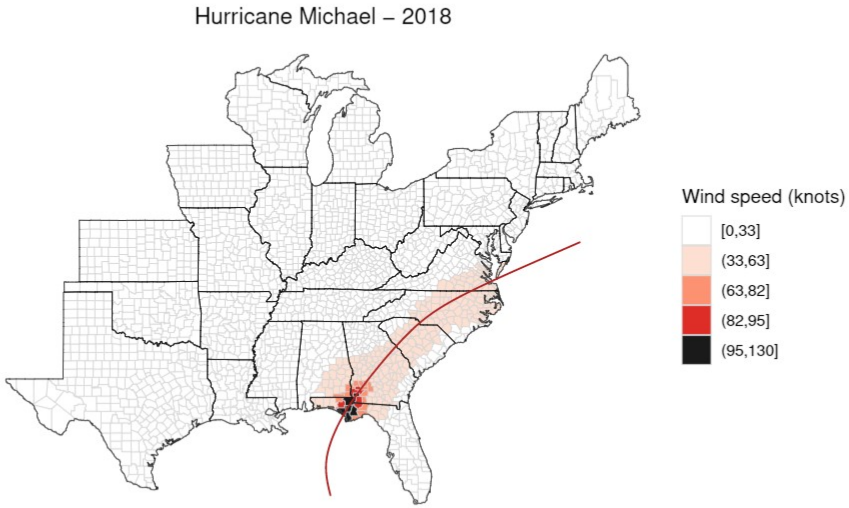
Data | Hurricanes

An example of estimation of wind speed at the local level:



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).

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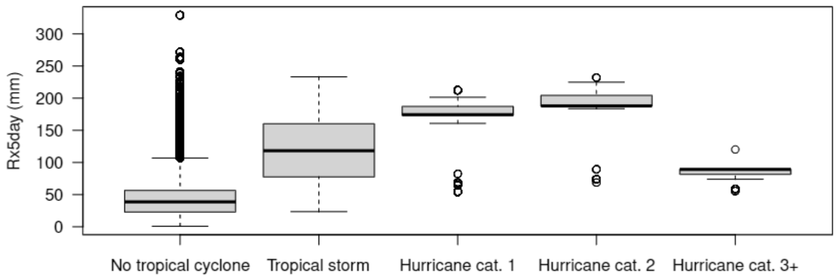
- The data source is the second-generation **North Atlantic hurricane database** (HURDAT2; Landsea and Franklin, 2013) of the National Hurricane Center (it covers the events from 1851)
- It does not provide information on wind speed at the five-digit ZIP code level
- We **estimate** this information by applying the **wind speed model** proposed by Willoughby et al. (2006) and implemented in the *stormwindmodel* R package
- After estimating wind speed for each location, we have used the **Saffir-Simpson hurricane wind scale** to classify the tropical cyclone category
- In the 2010-2019 period, based on the National Hurricane Center classification, Florida was exposed to eight tropical storms and six hurricanes

Data | Intense Rainfalls



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.

- We consider using as a measure of rainfall intensity the monthly **maximum accumulated consecutive 5-day precipitation** (Rx5day) in millimetres (mm). The Rx5day is computed as the max($PREC_{tmy}$), where $PREC_{tmy}$ is the precipitation amount >1 mm 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 are in a **regular latitude-longitude grid of 0.25°×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 between the centroid of the five-digit ZIP code and each grid point.**

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Methodology | Predictors and Target Events

Predictors

- IR = loan rate(%) – Benchmark (%)
- LTV (%)
- Fico score
- Asset type (Prime, Subprime, etc.)
- Purpose type (Cash out refinancing, Purchase, Construction, etc.)

- Occupancy type (Owner occupied, Second home, Vacant, etc.)
- Number of units

- Tropical cyclones
- Rx5day

Target Events

Default

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

1 if borrower is 90+ days delinquent at time *t*

0 otherwise

Prepayment

1 if borrower *i* fully repays the mortgage in advance at time *t*

0 otherwise

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Methodology | Survival Model

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 behaviour of these probabilities over time.

General specification of the survival model

Let z= $(z_1,z_2,\ldots,z_k)'$ 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

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

$\lambda_0(t)$ is a baseline hazard function and the risk function r(*t*,***z***) represents the relationship between the explanatory variables ***z*** and the hazard function.

We consider a data-driven specification…

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Methodology | Additive Cox Model

We consider an additive Cox model specification (Wood, 2017):

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

where $\{\eta_j(\cdot), j = 1, 2, \ldots, k\}$ are unknown smooth functions.

- 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. **If the covariate is a continuous variable, we consider η_j as a penalised 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 damages (FS-2020)** on mortgage default and prepayment, we use a tensor product interaction approach based on the ANOVA decomposition of the smooths (Wood, 2017).
- We consider a low-rank **Gaussian process** smooth based on the Matérn correlation function **to capture the spatial effects** (Wood, 2017).

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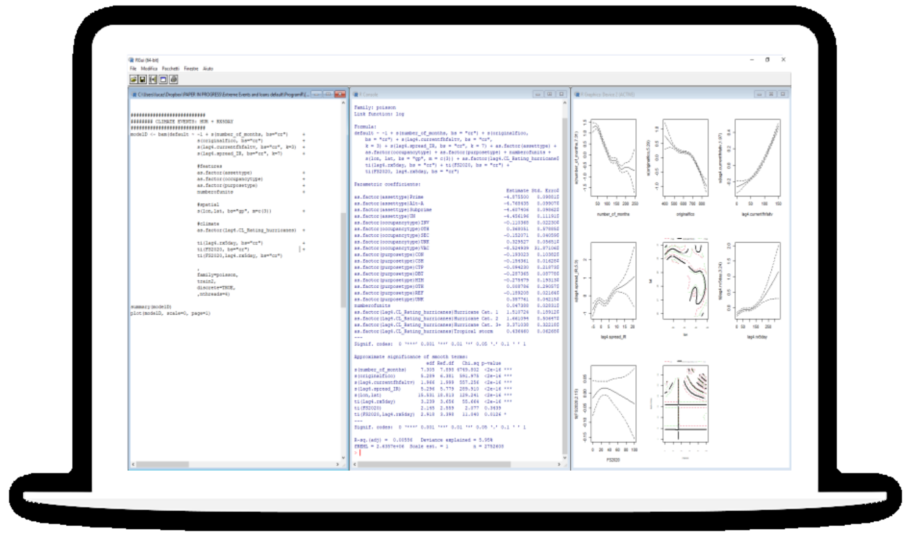
Empirical results

We estimated the models using the R package «*mgcv*»



Model selection measures

	Default		Prepayment	
Base Model+	*AIC*	*BIC*	*AIC*	*BIC*
No Extremes	259,974.1	260,679.7	192,801.1	193,602.8
Cyclone	259,784.3	260,540.2	192,799.2	193,645.1
Rx5day	259,823.0	260,646.1	**192,609.2**	**193,530.9**
Cyclone+Rx5day	**259,696.6**	**260,539.5**	192,603.9	193,581.5

We found no statistically significant relationship between the behaviour of prepayment and tropical cyclone events.

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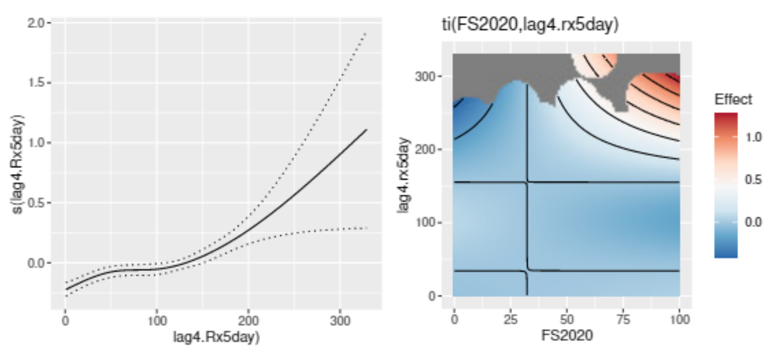
Empirical results | Parameters Estimation

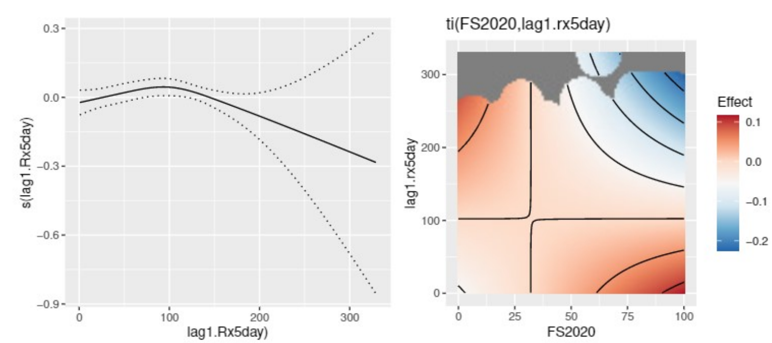
Default

Variables	Base Model+Weather	
	Estimates	Std. Error
Weather variables		
ti(Rx5day$_{t-4}$)	3.199***	
ti(FS2020)	2.101	
ti(FS2020, Rx5day$_{t-4}$)	2.872**	
Tropical cyclone (Base:No event)		
Tropical storm$_{t-4}$	0.438***	0.063
Hurricane of category 1$_{t-4}$	1.504***	0.189
Hurricane of category 2$_{t-4}$	1.659***	0.506
Hurricane of category (3+)$_{t-4}$	3.372***	0.322



Prepayment

Variables	Base Model+Weather	
	Estimates	Std. Error
Weather variables		
ti(Rx5day$_{t-1}$)	2.419***	
ti(FS2020)	3.953	
ti(FS2020, Rx5day$_{t-1}$)	1.030**	



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Empirical results | Model Performance

We compare the **predictive accuracy** of the survival models when excluding or including (extreme) weather events using a **5-fold cross-validation**.

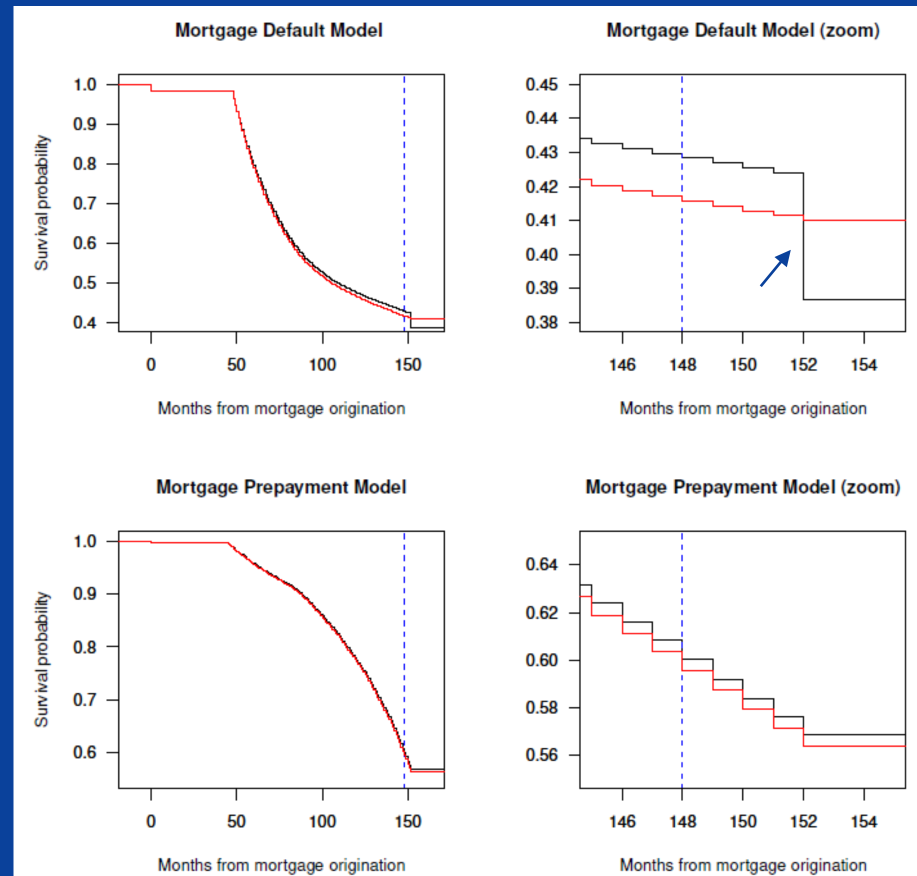
We assess the predictive accuracy using the Area under the ROC Curve (**AUC**), H-measure (**H**), and the Kolmogorov-Smirnoff (**KS**) statistic

	Default model			Prepayment model		
Base Model+	*AUC*	*H*	*KS*	*AUC*	*H*	*KS*
No Extremes	0.7071	0.1217	0.3093	0.7480	0.1600	0.3733
Cyclone	0.7087	0.1227	0.3111	.	.	.
Rx5day	0.7084	0.1226	0.3099	**0.7498**	**0.1622**	**0.3773**
Cyclone+Rx5day	**0.7093**	**0.1235**	**0.3114**	.	.	.

Out-of-sample predictive accuracy measures using 5-fold cross-validation. In bold, we highlight the survival models with the best predictive accuracy

Empirical results | Survival Curves 1/2

Mortgage Characteristics	Mortgage A (Extreme wind)
Property Type	
Occupancy type	Owner
Number of units	1
Mortgage Variables	
N. months from origination to weather event	148
Spread IR	3.0
LTV (%)	71.4
FICO score	719
Weather Variables	
Tropical cyclone	Cat. 3+
Month/Year of event	10/2018
Rx5day (mm)	89.2
FS2020 (%)	13.8



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 climatic event of interest (marked by a blue dashed vertical line). The red line refers to the baseline model, while the black line to the model with extreme weather events.

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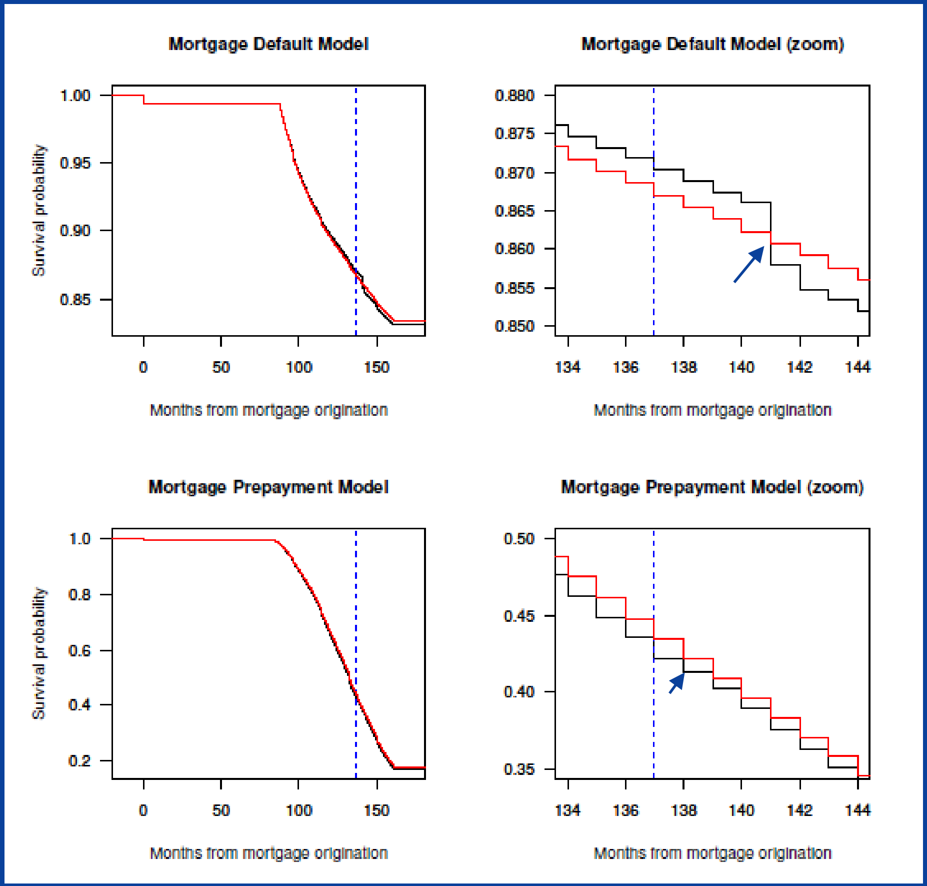
Empirical results | Survival Curves 2/2

Mortgage Characteristics	Mortgage B (Extreme rain)
Property Type	
Occupancy type	Owner
Number of units	1
Mortgage Variables	
N. months from origination to weather event	137
Spread IR	2.9
LTV (%)	86.2
FICO score	798
Weather Variables	
Tropical cyclone	No
Month/Year of event	8/2017
Rx5day (mm)	272.3
FS2020 (%)	93.3



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 climatic event of interest (marked by a blue dashed vertical line). The red line refers to the baseline model, while the black line to the model with extreme weather events.

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Scenario Analysis | Default Probability

- To assess the **potential impact of climate change on mortgage default risk**, we combine our models with projections of climate-induced changes in flood risk from the First Street Foundation Flood Model. The FS model focuses on the **RCP 4.5 scenario.**

Assumptions

Compound extreme weather events in 2050

- Hurricane cat. 3+
- Rx5day 300 mm

	Probability of Default			
Scenario	Median	Mean	95th%	99th%
No events	0.003	0.003	0.005	0.006
FEMA	0.157	0.175	0.340	0.506
FS 2020	0.164	0.189	0.389	0.626
FS 2050	0.173	0.202	0.439	0.695

Key statistics of the distribution of Probability of Default (PD) over the mortgage portfolio for varying exposure to flood risk

- Relative to the current situation (FS-2020), climate-induced changes in exposure (FS-2050) lead to an **increase of the mean and median probability of default by 1 percentage point**.
- The **impact** is much **more stringent in the tail of the distribution** with a 5 percentage points increase in the 95th percentile of the distribution and a 7 percentage points increase at the 99th percentile.
- **These changes** are quantitatively comparable with the increase in risk observed when **shifting from FEMA to FS-2020 exposure**. In this case, the effect is even **more pronounced in the right tail of the distribution with an increase of 12 percentage points at the 99th percentile.**

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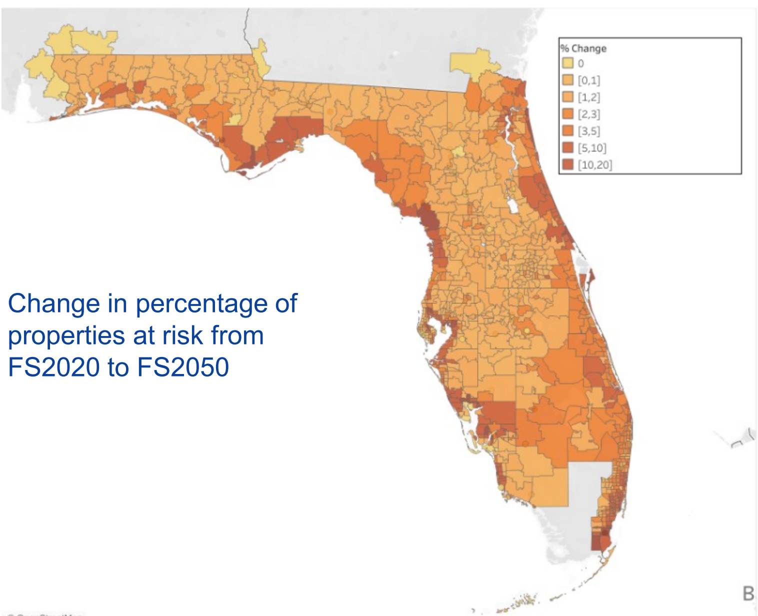
Scenario Analysis | Default Probability

… up to 2050 the largest increase in exposure and in risk **will occur in coastal areas**



Change in percentage of properties at risk from FS2020 to FS2050

Assumptions

Compound extreme weather events in 2050

Hurricane cat. 3+

Rx5day 300 mm

City	ZIP	FS20 Δ PD	City	ZIP	FEMA Δ PD
Tampa	33629	0.14	Tampa	33635	0.36
Port Charlotte	33954	0.13	Cape Coral	33990	0.35
Clearwater	33760	0.12	Cape Coral	33991	0.34
Punta Gorda	33980	0.12	Satellite Beach	32937	0.33
North Port	34287	0.12	Port Charlotte	33952	0.33
Jacksonville	32202	0.11	Cocoa Beach	32931	0.33
Cape Canaveral	32920	0.11	Merritt Island	32953	0.32
Cape Coral	33990	0.11	Merritt Island	32952	0.32
Cape Coral	33909	0.11	Cape Canaveral	32920	0.32
New Smyrna Beach	32169	0.11	North Port	34287	0.31
Palm Harbor	34685	0.11	Fort Myers	33907	0.30
Ponte Vedra Beach	32082	0.10	Tampa	33611	0.29
Cape Coral	33993	0.10	Punta Gorda	33980	0.25
Neptune Beach	32266	0.10	Cape Coral	33904	0.25
Naples	34103	0.10	Port Charlotte	33954	0.25

Top 15 ZIP codes in terms of increase in default probability in the FS-2050 exposure scenario as compared to FS-2020 (ΔPD FS) and FEMA-2020 (ΔPD FEMA)

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Conclusion

- We have **introduced 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 find a statistically significant and non-linear impact of **tropical cyclone intensity on default** as well 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.

- 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 2050** First Street flood model. Insofar as mortgages originated now may still exist in 2050, this analysis illustrates the <u>**need to quantitatively model climate effects on mortgage outcomes**</u>.

- These results <u>**suggest that climate change will lead to substantial changes in risk**</u>, 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, <u>**it seems necessary to systematically account for the impact of extreme weather events in credit risk assessment**</u>. 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.