Adaptation Using Financial Markets: Climate Risk Diversification through Securitization

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Climate Risk Pooling as a Key Tool for Financial Adaptation?

With rising wildfire risk and rising dollars exposed to hurricane risk, an extensive literature estimates the impact natural disasters $\rightarrow$ mortgage credit.

- Wildfires $\rightarrow$ prepayments and defaults (Issler et al. 2020, An et al. 2023, Biswas et al. 2023).
- Hurricanes $\rightarrow$ prepayments and defaults, both in residential and commercial segments (Kousky et al. 2020, Gete & Tsouderou 2022, Holtermans et al. 2023).

The Value-Added of Securitization

What are the **benefits of the securitization technology** in an age where individual mortgage risk can be measured (with uncertainty)? Are wildfires a drop in the ocean of cash flows? A priced risk factor?

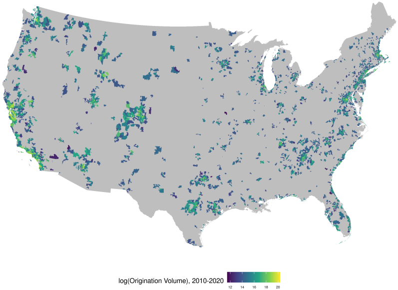
From Mortgage-Level to Deal-Level Cash Flows

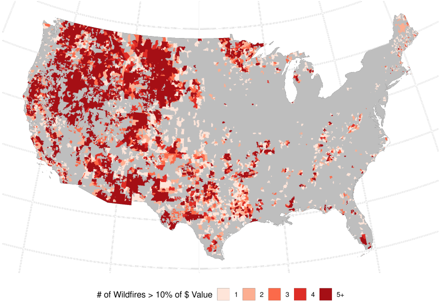
1. **Do wildfires affect prepayment, default, and losses at the mortgage level?**
   - National sample of private label MBSs at monthly frequency.
2. **Do wildfires affect deal-level cash flows when they are geographically diversified?**
   - "Climate Pooling Hypothesis." Depends on the spatial correlation and concentration of risk.
3. **What geographic diversification of an MBS deal achieves a given risk exposure?**
   - Finding $ weights across the US to get moments of cash flows (mean, S.D., tail risk) affected by interest rate and wildfire risk.
4. **Is natural disaster risk exposure priced in Mortgage-Backed Securities over and above Typical Risk Factors?**
   - A wildfire risk beta that captures the correlation between cash flows and the wildfire risk factor.
   - A wildfire risk factor based on weather, climate, land cover, infrastructure data.

Data – The Private-Label MBS Market

- Data set of 1.7 trillion dollars or mortgage originations across the US.
- Transparency: Possible to inspect the location, borrower characteristics, loan characteristics of each mortgage in a deal.
  $\rightarrow$ Gives us a "laboratory" of disaster experiments to assess the empirical impact on cash flows and prices.
- May exhibit significantly more geographic concentration than agency MBSs, which are spread out over a number of states.
- Investors may not require that the balance of the mortgage is guaranteed.
  $\rightarrow$ Pricing of an MBS may account for prepayment, credit, and interest rate risks.

PLS Mortgage Origination and Wildfires – Descriptives



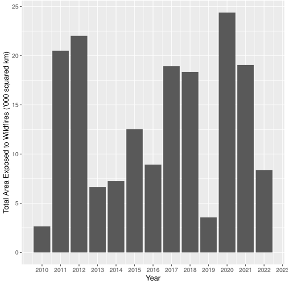


Total log dollar origination volume in the MBS segment (excl. ABS), for the period 2010–2020. Corelogic PLS RMBS data. Number of wildfires affecting more than 10% of the total dollar value of owner-occupied housing units. From Census-wildfire matched sample. Wildfire perimeters from National Interagency Fire Center.

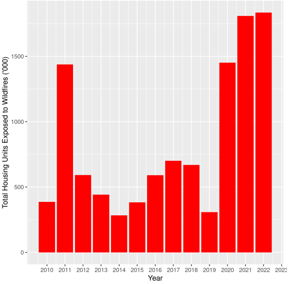
Rising Wildfire Exposure

Surface Area, Housing Units, and Total House Value Affected (From 2010 to 2022)

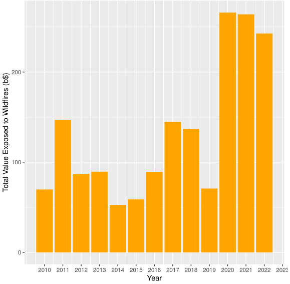
(a) Surface Area Exposed



(b) Housing Units Exposed



(c) Housing Value Exposed



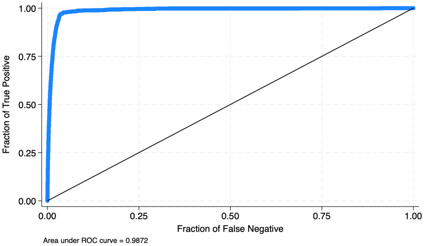
Wildfire Exposure and Mortgage Cash Flows

Propensity of Wildfires by Zip Code

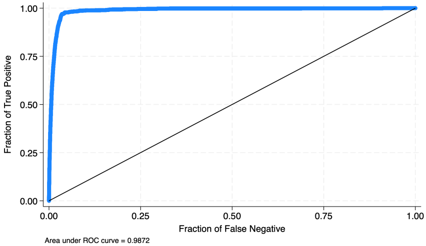
	Wildfire in a ZIP Code (1=Yes)			
	(1) PS0	(2) PS1	(3) PS2	(4) PS3
Abnormal Temperature	0.229***	0.266***	0.265***	0.262***
	(0.009)	(0.011)	(0.011)	(0.011)
Mean Temperature	0.106***	0.062***	0.063***	0.062***
	(0.003)	(0.013)	(0.013)	(0.013)
ln(Drought Index)	0.036***	0.101***	0.051***	0.049***
	(0.011)	(0.007)	(0.009)	(0.009)
× Forest Share	0.003***		0.002***	0.002***
	(0.000)		(0.000)	(0.000)
Forest Share	-0.005***	0.003**	-0.006***	-0.007***
	(0.002)	(0.001)	(0.002)	(0.002)
Developed Area Share	-0.009**			-0.018***
	(0.004)			(0.006)
Electricity Lines (m/m2)	226.911**			357.312***
	(105.138)			(135.263)
Road Length (m/m2)	-72.807**			32.666
	(34.382)			(46.157)
ln(ZIP Code Area)	0.222***	0.828***	0.831***	0.773***
	(0.027)	(0.032)	(0.032)	(0.038)
ln(# of State-Level Past Wildfires)	2.098***			
	(0.031)			
Constant	Yes	Yes	Yes	Yes
Year FE	–	Yes	Yes	Yes
Month FE	–	Yes	Yes	Yes
State FE	–	Yes	Yes	Yes
# of ZIP Code-Months	5,396,580	3,205,692	3,205,692	3,205,692
In-Sample ROC	0.984	0.969	0.969	0.969

Wildfire Exposure and Mortgage Cash Flows

In-Sample and Out-of-Sample ROC Curves



(i) Out-of-Sample ROC of PS0 (No Fixed Effects)



(ii) Out-of-Sample ROC of PS3 (with Fixed Effects)

- Out-of-Sample ROC curves are derived after running the logistic regression of PS3 until 2019 and the curve is obtained for the out-of-sample predictions for 2020 and 2021 without (ROC=0.99) and with fixed effects (ROC=0.95).
- The ROC curve reflects the tradeoff between the fraction of true positive outcome and the fraction of false negative outcome.
- A value of one means a perfect prediction and a value of 0.50 reflects the probability of having heads after tossing a coin.

Wildfire Exposure and Mortgage Cash Flows

Mortgage-Level Default and Prepayment Survival: Data Setup

We create mortgage-level survival data for the mortgages that are pooled into non-agency RMBS from 2010 to 2020 by mortgage-months.

A loan enters the analysis at origination (or the start of sample period, whichever is later), and...

...exits the analysis (the earliest of)...

- at maturity;
- default (foreclosure or REO);
- prepayment;
- the end of sample period

After matching with wildfire data, in our largest specification, we have more than 12 million mortgage-months for more than 300,000 mortgages.

Wildfire Exposure and Mortgage Cash Flows

Mortgage-Level Default and Prepayment Survival: DiD Model

We apply a DiD approach with a two-way fixed effects model. We estimate:

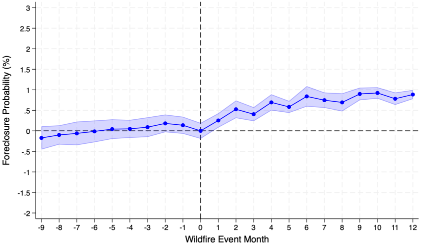
$$MortgageEvent_{i,t} = \alpha_i + \lambda_{i,t} + \beta_1 D_i \times PRE_t + \beta_2 D_i \times POST_t + \epsilon_{i,t} \quad (1)$$

where D_i is a zip-code level wildfire with a 10% fire area coverage in a zip code, α_i are mortgage fixed effects, and $\lambda_{i,t}$ are county $\times$ year-month fixed effects.

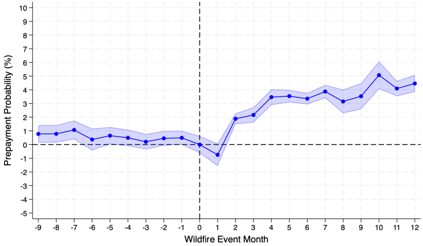
We apply

- alternative fire area coverage (5%, **10%**, and 15%)
- **propensity score weighting** using the likelihood of a wildfire in a zip code based on climatological determinants

Wildfire Exposure and Mortgage Cash Flows
DiD Results for the Likelihood of Foreclosure and Prepayment



(i) Two-Way Fixed-Effects DiD Estimation of Wildfires on Foreclosure



(ii) Two-Way Fixed-Effects DiD Estimation of Wildfires on Prepayment

- Wildfires increase the likelihood of foreclosure and prepayment by 1% and 4%, respectively, within a year following a wildfire.

Wildfire Exposure and Mortgage Cash Flows

Loss in a Foreclosure following Wildfires

	Loss-to-Balance Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Wildfire (1=Yes)	0.052***	0.063***	0.045*	0.038	6.156***	7.033***
	(2.597)	(2.679)	(1.784)	(1.550)	(3.853)	(3.931)
× ln(FICO)					-0.929***	-1.061***
					(-3.818)	(-3.887)
ln(FICO)				-0.652***	0.061*	0.071**
				(-3.356)	(1.905)	(2.566)
Selection Correction		-0.000	0.000	0.000	0.000	-0.000
		(-0.633)	(0.108)	(0.233)	(0.262)	(-0.635)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Mortgage Controls	–	–	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	–
Zip Code FE	–	–	–	–	–	Yes
# of Loans at Foreclosure	50,926	37,417	37,413	37,060	37,060	36,254
Adj. R-squared	0.615	0.622	0.867	0.871	0.873	0.891

- We apply a first stage linear probability model for mortgage foreclosures to predict selection correction following Olsen (1980).
- Following a wildfire, Loss-to-balance ratio increases by 4.5% to 6.3%. So, wildfires can lower the recovery rate to less than 57% – unconditional recovery rate is 63%.
- Lower-FICO mortgages have larger losses after a wildfire.

Wildfire Exposure and Mortgage Cash Flows

The Changing Features of Mortgage Contracts in the Aftermath of Wildfires

	Interest Rate (%)			LTV (%)		
	(1) All	(2) Loans with LTV<80%	(3)	(4) All	(5) Loans with LTV<80%	(6)
Wildfire Last Year (1=Yes)	0.054*** (0.018)	0.054*** (0.009)	0.056*** (0.011)	-3.486* (1.934)	-3.118* (1.610)	-5.969*** (1.519)
LTV (%)	0.001 (0.001)					
LTV<80% (1=Yes)	-0.114*** (0.026)					
Interest Rate (%)				7.729** (3.582)		
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Other Mortgage Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	–	Yes	Yes	–
Zip Code FE	–	–	Yes	–	–	Yes
# of Loan Originations	12,625	8,932	8,596	12,625	8,932	8,596
Adj. R-squared	0.969	0.781	0.808	0.722	0.364	0.540

- Within a year following a wildfire, interest rates of new mortgages in exposed zip codes increase by around 5.5 and LTV decreases by 3.1% to 6%.

Diversifying Risk at Deal Level: Role of Spatial Correlation

The share of the balance of a pool affected by wildfires is a $ weighted average across mortgages:

$$\text{Wildfire}_{jt} = \frac{\text{Balance}_{kjt} \times \text{Wildfire}_{kjt}}{\text{Balance}_{jt}} \in [0,1] \tag{2}$$

$$\begin{aligned}\text{Var}(\widetilde{\text{Wildfire}}_{jt}) \quad = \quad & \underbrace{\rho \left\{ 2 \sum_{i<i'} b_{ijt} b_{i'jt} W_{\ell(i)t}(1 - W_{\ell(i)t}) W_{\ell(i')t}(1 - W_{\ell(i')t}) \right\}}_{\textbf{Pool-level Spatial Correlation of Wildfire Events}} \\ & + \quad \underbrace{\sum_{i=1}^{N_j} b_{ijt}^2 W_{\ell(i)}(1 - W_{\ell(i)})}_{\textbf{Herfindahl of \$ Spatial Concentration}} \end{aligned} \tag{3}$$

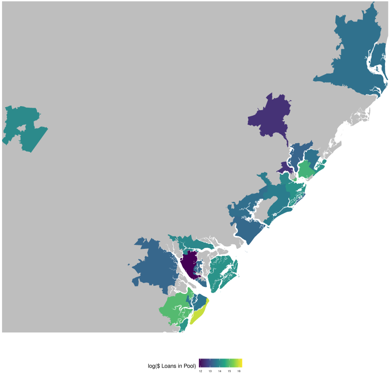
An MBS deal's wildfire exposure depends on

⇒ a **spatial correlation term**;

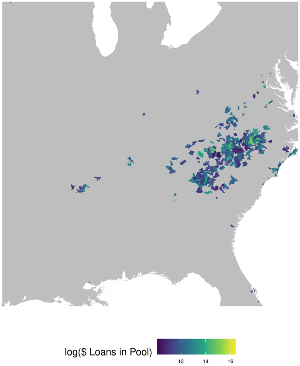
⇒ a **Herfindahl term** of the concentration of dollar originations across ZIPs;

⇒ and also, the time series autocorrelation of wildfire events.

Two Examples of Spatial Correlation: Pools BSRT01-7-4_BUR and SAL03NB1-5_USG



(i) Coast of the Carolinas



(ii) Spatially Diversified Pools

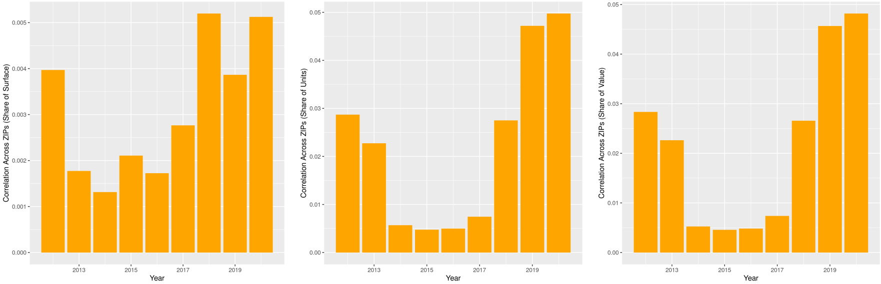
Source: Corelogic PLS RMBS, Tickers from Bloomberg-Corelogic crosswalk

US-Wide Spatial Correlation in Wildfire Occurence

Diversifying Risk at the Deal-Level

Nationwide spatial correlation in wildfire occurrence.

(a) share of surface affected, (b) share housing units affected, (c) share of $ value affected.



5-year window centered on each year from 2012 to 2020.

Correlation below 0.05, suggests substantial benefits to diversification.

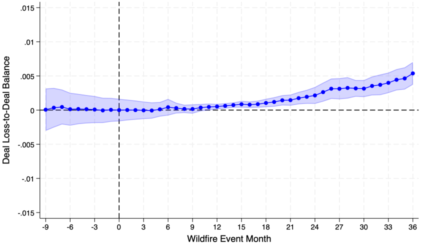
What MBS Deals are Exposed to Wildfires?

Diversifying Risk at the Deal-Level

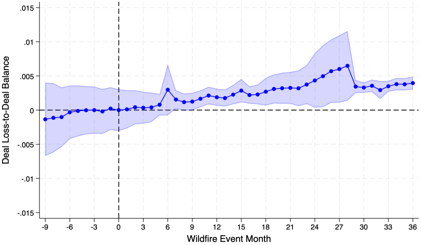
Dependent Variables:	Max. UPB Exposed to Wildfires $\in [0, 1]$	Treated MBS Deal $= 0, 1$	log(Herfindahl) $\in (-\infty, 0]$	Within Deal Spatial Correlation $\in [-1, 1]$	
Model:	(1)	(2)	(3)	(4)	(5)
Constant	0.1423***	-2.044***	2.633***	-1.227***	-0.7643***
	(0.0517)	(0.4037)	(0.2243)	(0.1212)	(0.0617)
Within-Deal Spatial Correlation	0.0854*** (0.0109)	0.4011*** (0.0852)			
log(Herfindahl)	0.0076***	0.0797***			
	(0.0023)	(0.0179)			
log(# ZIPs in Deal)	-0.0228***	-0.1686***	-0.6716***	-0.0508***	
	(0.0048)	(0.0373)	(0.0116)	(0.0115)	
log(Deal Balance) at Origination	0.0041 (0.0035)	0.1848*** (0.0276)	-0.1226*** (0.0121)	0.0704*** (0.0085)	0.0350*** (0.0029)
Fit statistics					
Observations	1,550	1,550	1,786	1,550	1,550
R^2	0.16081	0.07452	0.78389	0.09742	0.08599
Adjusted R^2	0.15864	0.07213	0.78365	0.09625	0.08540

Impact on Share of Losses as % Balance

Shock of the First Wildfire Event on a Deal



(i) Deals Affected by at least 2% of Deal Balance



(ii) Deals Affected by at least 5% of Deal Balance

- Losses in individual mortgages due to wildfires are carried to deals.

The important question is whether deals can help diversify to mitigate losses due to climate events.

Motivation

Trade-Offs and Wildfire Exposure

- How should we **design MBSs to target** the expected cash flow, the standard deviation, skewness, and kurtosis of cash flows?
  - **Choosing dollar weights** of notional **invested** in each 5-digit ZIP code of the US. $\rightarrow$ A demand system (Koijen and Yogo, JPE)

$\Rightarrow$ **Trade-off** in wildfire exposure as wildfire-exposed ZIP codes have lower prepayment and foreclosure rates.

A Portfolio Problem: Incorporating Wildfire Risk

The monthly stochastic return of the pool is due to (i) the decline of the notional, due to prepayments and foreclosures and (ii) the cash flow of the pool:

$$\tilde{r}_t(\boldsymbol{w}_0) = \frac{\widetilde{N}_t - \widetilde{N}_{t-1}}{\widetilde{N}_{t-1}} + \frac{\widetilde{\mathrm{CF}}_t}{\widetilde{N}_{t-1}} \tag{4}$$

Cash flow of the deal (CF_t) is the sum of the cash flows of individual mortgages:

$$\widetilde{\mathrm{CF}}_t = \sum_{j=1}^{J} w_{j,0} \underbrace{(\widetilde{N}_{j,t} c_j + \widetilde{\lambda}_{j,t} \alpha_{j,t} I_{j,t})}_{\text{Cash Flow } \widetilde{\mathrm{CF}}_{j,t} \text{ at Location } j} \tag{5}$$

$\widetilde{N}_{j,t}$ is the dollar notional. c_j is the coupon rate in j. $\widetilde{\lambda}_{j,t} \in [0,1]$ is the hazard rate of prepayment and foreclosure. $\alpha_{j,t} \in [0,1]$ is the *recovery rate*.

Weight $(w_{j,0})$ of location j in the deal at $t = 0$ (in logs) is expressed as a function of the wildfire propensity score and a vector of covariates for the location:

$$\frac{w_{j,0}}{w_{0,0}} = \exp\left(\omega^w \mathrm{Wildfire\ PS}_j + \mathrm{x}_j \boldsymbol{\omega}\right) \varepsilon_{j,0} \tag{6}$$

Simulation of MBSs

We simulate 1,000 MBSs across 50 simulations of interest rate paths and wildfires.

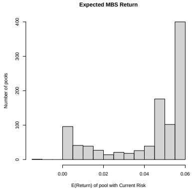
Level	10th Percentile	1st Quartile	Mean	Median	3rd Quartile	90th Percentile
Average Monthly Return (Annualized)						
ZIP Level	-0.18	0.85	10.05	1.45	2.26	3.39
MBS Level	0.51	3.16	4.22	5.03	5.71	5.77
S.D. Monthly Return (Annualized)						
ZIP Level	4.14	6.19	7.65	7.71	8.80	10.46
MBS Level	2.79	2.88	3.72	3.18	4.90	5.28
Sharpe Ratio of Monthly Returns						
ZIP Level	-2.70	-1.27	1.19	-0.41	1.07	3.80
MBS Level	-0.22	0.30	0.84	1.04	1.35	1.45

⇒ The table displays the distribution of the returns for our simulated MBS deals across different portfolio weights (rows 2, 4, 6), alongside the distribution of ZIP-level returns (rows 1, 3, 5).

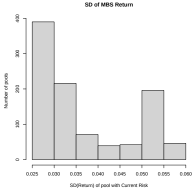
Designing MBS

Simulated Pools and their Performance

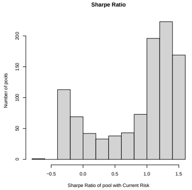
(a) Baseline Distribution of E(Returns) Across Simulated MBSs



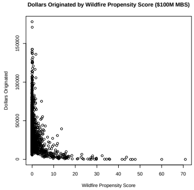
(b) Baseline Distribution of SD(Returns) Across Simulated MBSs



(c) Baseline Distribution of Sharpe Ratios Across Simulated Pools

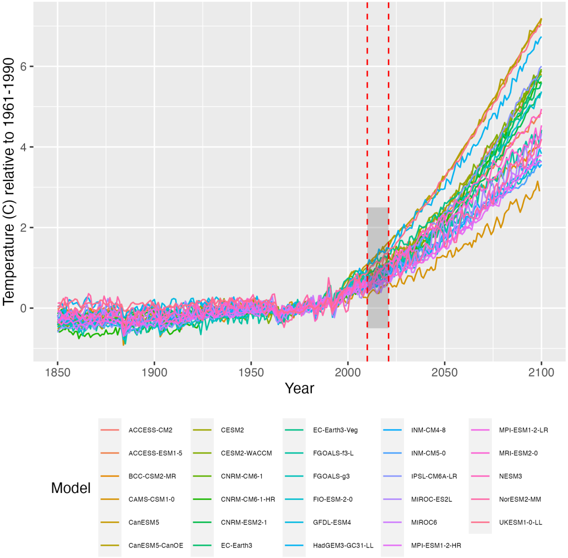


(d) Dollars Invested by Wildfire PS for the Sharpe Ratio Maximizing MBS



Designing MBS Deals with Evolving Risk

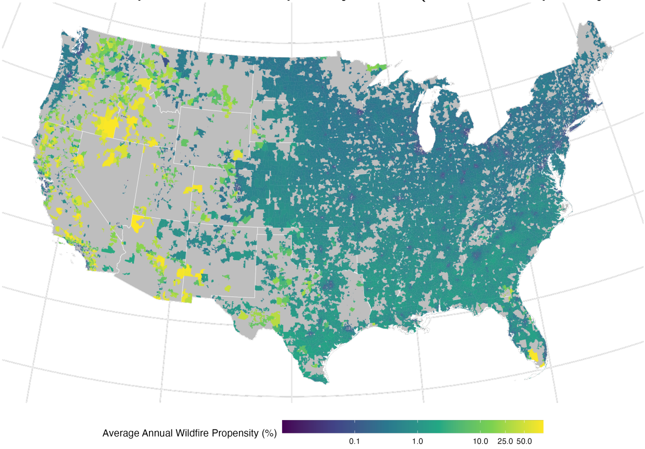
Global Surface Temperature Forecasts



Designing MBS Deals with Evolving Risk

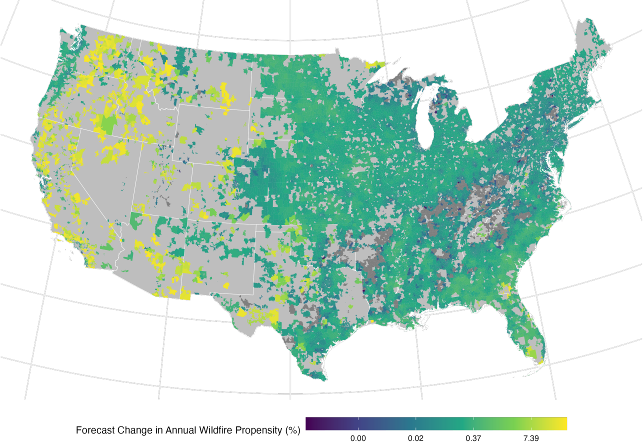
Evolution of the Wildfire Propensity Score

(a) Initial In Sample Wildfire Propensity Score (Wildfire Propensity Model)



Designing MBS Deals with Evolving Risk
Evolution of the Wildfire Propensity Score

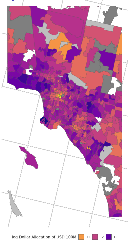
(a) Projected Change in the Wildfire Propensity Score (CMIP6 Forecast + Wildfire Propensity Model)



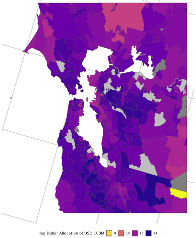
Designing MBSs

Sharpe Ratio Maximization and Resilience to Climate Change

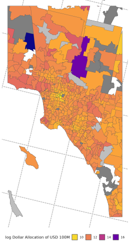
(a) Los Angeles



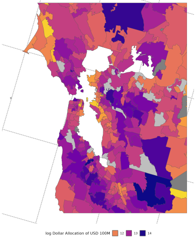
(b) San Francisco



(c) Los Angeles (by 2050)



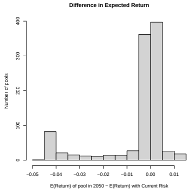
(d) San Francisco (by 2050)



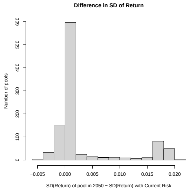
Designing MBS

Simulated Pools and their Performance, with Rising Temperatures

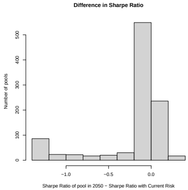
(a) 2050-Now Distribution of E(MBS Returns)



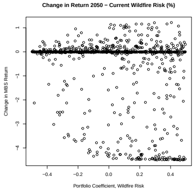
(b) 2050-Now Distribution of SD(MBS Returns)



(c) 2050-Now Distribution of Pool-Level Sharpe Ratios



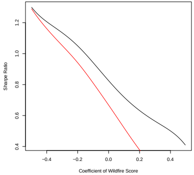
(d) 2050-Now Evolution of Expected Return by Wildfire Weight in Portfolio 2050



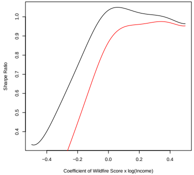
Designing MBSs

Portfolio Coefficients and MBS Sharpe Ratio with Current Wildfire Risk (Black) and with Wildfire Risk in 2050 (Red)

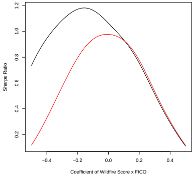
(a) No Interaction



(b) Interacted with Household Income



(c) Interacted with FICO



Beta of Return w.r.t. Wildfire Risk Propensity

Step 1: Deal by Deal, Beta of returns w.r.t. wildfire propensity

For each deal, estimate $\beta_d^{wildfire}$, the sensitivity of cash flows/balance to wildfire propensity:

$$\mathrm{r}_{dt}^{CF} = \beta_d^{w}\text{Wildfire Propensity}_{dt} + \beta_d^{1m}\text{One Month}_t + \beta_d^{p}\text{Term Premium}_t + x_{dt}\beta_d^{x} + \varepsilon_{dt} \quad (7)$$

$\mathbf{Return}_{dt}$: Return of an amortizing bond, which includes interest and principal payments, losses, price changes.

Cross-Sectional Pricing of the Wildfire Beta
Sensitivity of Returns

Use a second step akin to Fama and MacBeth (1973) and Cochrane (2009).

The cross-sectional regression estimates a parameter γ_t by running a cross-sectional regression separately for each t, using either of the following approaches:

Step 2: In the Cross-Section, Pricing of Wildfire Beta

$$y_{dt} = \gamma_0 + \gamma_t^w \widehat{\beta}_{d(\tau)}^w + \gamma_t^{\mathrm{1m}} \widehat{\beta}_{d(\tau)}^{\mathrm{1m}} + \gamma_t^{\mathrm{p}} \widehat{\beta}_{d(\tau)}^{\mathrm{p}} + \eta_{dt} \tag{8}$$

with y_{dt} either equal to the price of the deal, p_{dt} (first approach), to the Return_{dt} of the MBS (second approach).

MBS Pricing Analysis – log Price

β of Cash Flows w.r.t. Wildfire Propensity Score 0				
Sample	Estimate	S.E.	t statistic	p value
All tranches	−0.330	0.275	−1.198	0.233
Tranche rank <0.5 (senior tranches)	−0.190	0.243	−0.784	0.435
Tranche rank >0.5 (junior tranches)	−0.283	0.236	−1.199	0.233
Most junior tranche	−0.484	0.176	−2.750	0.007
β of Cash Flows w.r.t. Wildfire Propensity Score 1				
Sample	Estimate	S.E.	t statistic	p value
All tranches	−1.631	0.487	−3.351	0.001
Tranche rank <0.5 (senior tranches)	−0.489	0.212	−2.302	0.023
Tranche rank >0.5 (junior tranches)	−1.436	0.473	−3.034	0.003
Most junior tranche	−0.845	0.215	−3.928	0.000
β of Cash Flows w.r.t. Wildfire Propensity Score 2				
Sample	Estimate	S.E.	t statistic	p value
All tranches	−1.594	0.508	−3.138	0.002
Tranche rank <0.5 (senior tranches)	−0.489	0.227	−2.151	0.033
Tranche rank >0.5 (junior tranches)	−1.421	0.491	−2.892	0.005
Most junior tranche	−0.881	0.198	−4.443	0.000
β of Cash Flows w.r.t. Wildfire Propensity Score 3				
Sample	Estimate	S.E.	t statistic	p value
All tranches	−1.160	0.374	−3.104	0.002
Tranche rank <0.5 (senior tranches)	−0.222	0.153	−1.445	0.151
Tranche rank >0.5 (junior tranches)	−0.955	0.347	−2.747	0.007
Most junior tranche	−0.621	0.125	−4.976	0.000

MBS Pricing Analysis – log Price Changes

β of Cash Flows w.r.t. Wildfire Propensity Score 0				
Sample	Estimate	S.E.	t statistic	p value
All tranches	0.108	0.016	6.793	0.000
Tranche rank <0.5 (senior tranches)	0.165	0.031	5.395	0.000
Tranche rank >0.5 (junior tranches)	0.087	0.024	3.610	0.000
Most junior tranche	−0.004	0.016	−0.218	0.828
β of Cash Flows w.r.t. Wildfire Propensity Score 1				
Sample	Estimate	S.E.	t statistic	p value
All tranches	0.685	0.752	0.910	0.364
Tranche rank <0.5 (senior tranches)	0.281	0.135	2.079	0.040
Tranche rank >0.5 (junior tranches)	0.174	0.086	2.032	0.044
Most junior tranche	−0.031	0.038	−0.831	0.408
β of Cash Flows w.r.t. Wildfire Propensity Score 2				
Sample	Estimate	S.E.	t statistic	p value
All tranches	0.370	0.265	1.396	0.165
Tranche rank <0.5 (senior tranches)	0.273	0.131	2.091	0.039
Tranche rank >0.5 (junior tranches)	0.144	0.065	2.227	0.028
Most junior tranche	−0.036	0.037	−0.963	0.338
β of Cash Flows w.r.t. Wildfire Propensity Score 3				
Sample	Estimate	S.E.	t statistic	p value
All tranches	0.311	0.229	1.357	0.177
Tranche rank <0.5 (senior tranches)	0.206	0.102	2.024	0.045
Tranche rank >0.5 (junior tranches)	0.122	0.059	2.052	0.042
Most junior tranche	−0.022	0.028	−0.793	0.429

Concluding Remarks

- Wildfires have an economically and statistically significant impact on mortgage-level cash flows, yet these effects are muted, when deals are geographically diversified.
- **Three measures of climate risk diversification:**
  - Average MBS-level dollar weighted wildfire propensity score.
  - Spatial correlation of dollar weighted wildfire propensity score.
  - Herfindahl index of the distribution of dollar originations across ZIP codes.
- Sharpe-Ratio Optimal MBSs include mortgages located in wildfire-exposed areas.
- Markets are ex-ante pricing of wildfire risk and a Fama McBeth risk premium of wildfires.
- Evidence that the wildfire beta w.r.t cash flows is correlated with price levels and capital gains.

The key role of the securitization market in risk-sharing between risk averse borrowers and investors looking for yield.