Premiums or Peril? The Impact of Weather Risk on Residential Real Estate Markets in Florida

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Motivation & Research Question

Motivation

- Home prices combine information on home quality and local amenities
- We expect home prices to also reflect expectations of future catastrophe risk losses
- Mispriced risk could lead to:
  - Over-development in high-risk areas
  - Excess price volatility

Research Question: Are house prices sensitive to hurricane risk exposures?

Key Findings & Contribution

Preview of Findings

- Property-level expected weather losses negatively affect home prices, consistent with rational discounting of future expected weather losses
- Home buyers in Florida seem to be well-informed about and sensitive to risk exposure

Contribution

- Analyze impact of expected non-flood weather risk on home prices
  - Kousky (2010), Bin et al. (2008), MacDonald et al. (1987), Bernstein et al. (2019), Gallagher (2014)
- Consider ex ante expected losses, ex post hurricane exposure, and insurance premiums
- Novel application of double-debiased machine learning with property-level data to control for amenities and property features

Data

Data Sources

- **Property Data (CoreLogic):**
  - *Owner Transfer:* Sale price, date, location
  - *Historical Property Basic:* Home characteristics (e.g., square footage, year built, bedrooms, bathrooms)
  - *Resilience:* Expected annual non-flood disaster losses
- **ICE/McDash Insurance:** Premiums, deductibles, coverage limits
- **NOAA HURDAT2:** Hurricane tracks and wind speeds
  - Between 2012 and 2024, six named storms hit Florida

Final sample: 465,203 sales across 445,654 homes

- Arms-length transactions of single-family homes in Florida with a mortgage, 2012-2024

Summary Statistics

Variable	Median	Mean
Sale amount[1]	$318,687	$396,562
Year built	1989	1986
Monthly premium[1]	$154	$195
Coverage amount[1]	$285,475	$332,285
Square footage	1,720	1,879
Bedrooms	3.00	3.19
Distance to coast (meters)	14,639	25,062
Credit score	741	733
AAL non-flood weather losses[2]	0.14%	0.20%

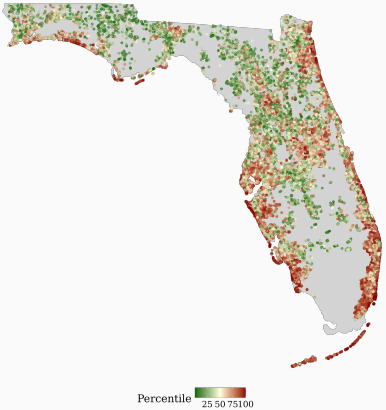
[1] 2023 dollars

[2] Average annual loss (AAL) is expressed as a percent of insurable value

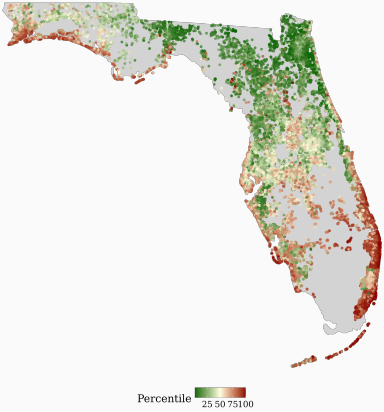
Methods and Empirical Challenges

Key Empirical Challenge

Home prices (2023 dollars)



Expected annual non-flood weather losses



Key Empirical Challenge

Geographic features create confounding when measuring impact of risk on price

- Need flexible controls for location and property characteristics
- For example, coastal proximity increases both:
  - Hurricane/flood risk (negative effect on price)
  - Amenity values—ocean views, beach access (positive effect on price)

Solution: Semiparametric machine learning with rich controls (double/debiased machine learning from Chernozhukov et al., 2018)

Rich Set of Control Variables

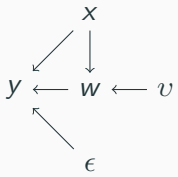
Three Categories:

1. **Transaction features**
   - Sale date
   - Buyer credit score
2. **Property characteristics**
   - Square footage, bedrooms, bathrooms
   - Year built, construction type
   - Amenities: pool, garage, A/C
   - Lot size
3. **Geographic location**
   - Latitude and longitude
   - Distance to coast
   - Distance to nearest major city
   - Nearest major city

Treatment Variables

- **Disaster risk**: Property-level average annual losses (AAL) due to non-flood disasters from CoreLogic
- **Insurance premium rate:** Orthogonalized from AAL; the components of premiums *not* driven by disaster risk
- **Hurricane events:** Time since most recent named hurricane

Identification Strategy



Key Assumption: Conditional on controls X, no unobserved factors affect both risk measures W and prices Y

Model:

$$\log(Y) = g(X) + W'\boxed{\beta} + \epsilon$$
$$W = h(X) + \upsilon$$

where $g(\cdot)$ and $h(\cdot)$ are flexible, unknown functions; ϵ and υ are error terms

Double-Debiased Machine Learning (DD-ML)

Why DD-ML? (Chernozhukov et al., 2018)

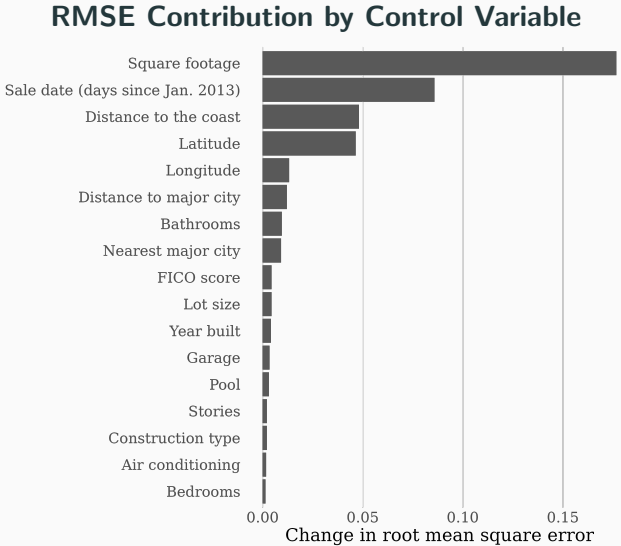
- Flexible functional forms for $g(X)$ and $h(X)$
- No parametric assumptions on control relationships
- Valid inference on treatment effects β
- Addresses high-dimensional confounding

Implementation:

1. Use random forests to estimate $E[Y|X]$ and $E[W|X]$ on training sample
2. Compute residuals on hold-out sample
3. Estimate β from residualized regression
4. Cross-fit across five folds (every data point used in training and validation)

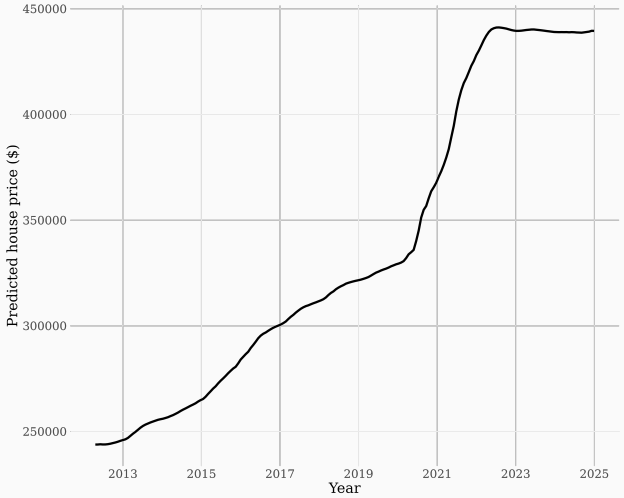
Hyperparameters: Deep trees (min leaf=1), 30% feature sampling with 1,000 trees

Model Validation: Feature Importance for Sale Price

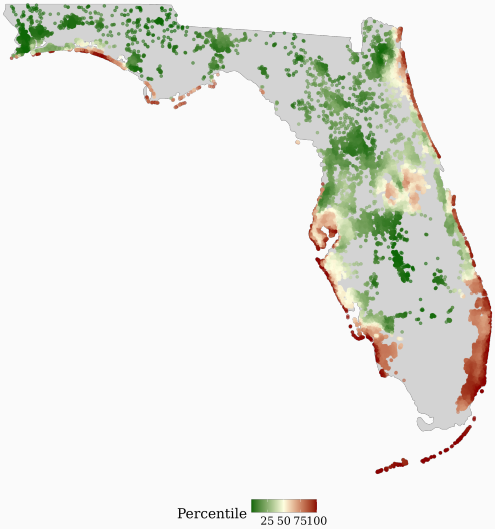


Model Validation: Price Index

Partial dependence plot (PDP) of house price on sale date



Model Validation: Geographic Patterns (Price of Median Home)



Results

Treatment Effects

	(1) AAL	(2) Ins	(3) Hur	(4) AAL+Ins	(5) AAL+Ins+Hur
Log AAL	-0.056^{***}			-0.048^{***}	-0.048^{***}
	(0.001)			(0.001)	(0.001)
Log premium rate		-0.021^{***}		-0.016^{***}	-0.016^{***}
		(0.001)		(0.001)	(0.001)
Hurricane 0-1yr ago			0.005		-0.004
			(0.017)		(0.017)
Hurricane 1-2yr ago			-0.034^{*}		-0.030^{*}
			(0.018)		(0.017)
Hurricane over 2yr ago			-0.035^{**}		-0.029^{*}
			(0.017)		(0.016)

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Conclusions

- Findings
  - The house price elasticity with respect to AAL implies a real discount rate of 2.1 percent, consistent with plausible estimates of the long-run neutral risk-free interest rate (r^*)
  - The elasticity with respect to insurance premiums implies a real discount rate of 31 percent
  - Exposure to recent hurricanes may have a modest negative effect on home prices
- Implications
  - Florida home prices seem to rationally reflect ex ante hurricane risk exposure
  - Insurance premiums have a more modest effect – they may be viewed as non-persistent or only weakly related to property characteristics

Appendix

Data Merge

- Restrict to arms-length single family home sales with a mortgage in Florida from 2012-2024
- CoreLogic and McDash data are merged based on zip code, close date, and origination amount
- HURDAT2 data is merged based on lat/long of home in CoreLogic
- Final sample is 465,203 Florida home sales across 445,654 homes

Model Validation: Structure Features

