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

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Abstract

Using fine-grained data on 465,000 Florida home sales over twelve years and semi-parametric machine learning methods, we examine how home prices respond to weather-related risk factors. After controlling for geography, home characteristics, and transaction features, we find that home prices are negatively related to property-level expected weather losses derived from catastrophe models, insurance premiums, and exposure to recent hurricanes, but with notably different magnitudes. Expected weather losses show the strongest association with prices and are consistent with markets rationally capitalizing anticipated future losses into current property valuations. Insurance premiums have a statistically significant but economically more modest negative effect on home prices, suggesting that housing market participants may view premium differences across properties as more transitory. Recent hurricane exposure has only a marginal effect on house prices, suggesting that hurricane risk is well-understood in Florida so that realized weather events convey little new information about future losses.

*We would like to thank Tess Scharlemann for her help in merging complex datasets and participants in the Consumer Finance Round Robin for helpful comments. **Disclaimer:** The views expressed here are those of the authors and do not reflect the opinions of the Federal Reserve Board of Governors, the Federal Reserve Bank of Philadelphia, or of any other entity of the Federal Reserve System.

1 Introduction

Large losses from recent natural disasters, including wildfires in western states and windstorms and flooding in eastern and southern states, have focused attention on how catastrophe risks can influence local residential real estate markets. Damage to properties and infrastructure may reduce home values in directly affected communities. But changes in risk perceptions may also have longer-lasting and more far-reaching consequences. For example, property insurance coverage is becoming increasingly expensive or unavailable in some high-risk areas, making it difficult for existing home owners to manage risk and for prospective home buyers to obtain financing. This paper examines the relationship between *ex ante* weather risks and residential real estate prices. We focus on Florida, a state with high hurricane risk exposure that has experienced rising insurance premiums and insurer exits in recent years.

The extent to which weather risks are capitalized into home prices has important implications for resource allocation and social welfare. Over the long term, home prices that do not fully reflect future risks may create incentives for over-development in high-risk areas or under-development elsewhere, placing more homes and people in harm's way. Insensitivity to future risks may also lead to greater volatility in home prices, as risk perceptions and prices may then change rapidly as shocks are realized or new information becomes available. Homes are the largest financial asset for most U.S. households and serve as collateral for an estimated $13 trillion in mortgage loans; excess volatility in real estate markets has the potential to adversely affect household and financial institution balance sheets.

Accurately measuring the effects of risk exposure on home prices is challenging for two reasons. First, risk exposure is not easily observable. We measure *ex ante* weather risk exposure using granular data on property-level expected non-flood weather losses from a leading catastrophe risk model. We also consider the effects of insurance premiums, a market-based signal of risk, and exposure to recent named hurricanes, which may influence the salience of relevant risks to investors.

Second, many of the geographic features that give rise to higher catastrophe risk also convey significant positive amenity values to homeowners. In Florida, ocean views and beach access are highly prized, for example. We address this problem by using a rich set of control variables and flexible model specifications to isolate the incremental effects of risk exposure measures on home values holding proxies for amenity values and other home characteristics constant. We analyze fine-grained data on 465,000 home sale transactions in Florida from 2012 to 2024 using semiparametric machine learning models, which allow us to test hypotheses about the effect of risk exposure measures on home prices without imposing strong functional form assumptions on the relationships between treatment, control, and outcome variables.

After controlling for broad macroeconomic conditions, geography, house features, and buyer credit quality, we find that higher projected non-flood weather losses are strongly negatively related to home transaction prices. For a typical home the magnitude of measured effects imply a real discount rate for future expected weather losses of about 1.7 percent, suggesting that investors rationally incorporate expected losses into property valuations. Because expected weather losses are highly correlated with insurance premium rates, it is difficult to say whether these effects are mediated through insurance prices. However, we find a negative but economically less impactful relationship between insurance premiums rates and home prices. In Florida, home buyers appear to be highly sensitive to relative differences in weather risks but are less sensitive to other factors that may influence insurance premiums. Recent hurricane exposure has only a modest negative effect on home values, consistent with the idea that hurricane risk is generally well understood in Florida so that hurricane events provide little new information relative to prior beliefs.

Our findings contribute to a growing literature on the effects of natural catastrophe risk on residential real estate markets.[1] While the broad consensus of this literature is that, after controlling for relevant confounding factors, various measures of catastrophe risk exposure tend to be negatively correlated with house prices, these studies point to a variety of ways in which particular market features and context mediate that relationship.

Heterogeneous preferences and risk perceptions appear to have a strong influence on relationships between risk and equilibrium home prices. For example, Kousky (2010) finds that recent severe flooding causes local house prices to become more sensitive to whether or not a house is located in a designated flood zone, while Gallagher (2014) finds that homeowners are more likely to purchase flood insurance in the weeks following reporting of large-scale floods in local media markets. Bernstein et al. (2019) finds that sensitivity of house prices to projected sea level rise depends on whether homes are owner occupied and on community attitudes toward climate risk.

Several studies have shown that home prices are more sensitive to whether a home is in a designated floodplain than to more granular measures of flood risk and that the magnitudes of such effects are similar to the discounted value of anticipated flood insurance premiums (MacDonald et al., 1987; Harrison et al., 2001; Bin et al., 2008; Ge et al., 2022). These findings suggest that home prices depend primarily on the extent to which flood risk is priced into required insurance coverage. Using a policy instrument, (Eastman et al., 2024)

[1] See Contat et al. (2024) for a review of research on the effects wildfire, flooding, and sea level rise. See Jung and Smith (2022) for a survey of the effects of earthquake risk.

attempt to disentangle the effects of insurance prices and hurricane risk in Florida. Similar to the research on flood risk, they find that insurance premiums have a strong negative effect on Florida home prices, while variables capturing whether a home was recently exposed to a hurricane or is located in a county that is at high risk for hurricanes have little measurable effect.

Our investigation of the effects of non-flood weather risk – primarily hurricane risk – in Florida tells a somewhat different story from previous research. While we do not disentangle the effects of weather risk and insurance costs, we find that real estate investors in Florida appear to be well informed of the risks posed by hurricanes and other severe weather and are sensitive to whether homes are at high risk for such hazards. To be sure, homes nearer to the coast and in the Florida Keys command significant market premiums, reflecting the high amenity values associated with these locations. But similarly situated homes that are more exposed to weather risks, for example because of highly localized differences in topology, sell at a meaningful discount. Most homeowners are required to carry insurance covering non-flood weather hazards and homeowners insurance premiums in Florida are highly correlated with expected weather losses, so it is possible that insurance prices in Florida provide a stronger and clearer signal to homeowners about risk exposure than they do in other contexts. Alternatively, the state's long history of weather losses and the extensive attention paid to such loses by local media and governments may result in an investor pool that is particularly sensitized to these risks.

The rest of our paper is organized as follows. Section 2 describes the data used in our analysis. Section 3 provides an overview of our semiparametric machine learning approach and presents parameter estimates. Section 4 discusses the economic implications of our findings, and Section 5 concludes.

2 Data

At the center of our analysis is granular data on home sales in Florida, where we observe transactions of mortgaged single-family homes between 2012 and 2024. For each such transaction we gathered information on the terms of the sale, property characteristics, premiums and coverage amounts for the primary insurance policy associated with the home's mortgage, and measures of the home's *ex ante* and *ex post* exposure to wind risk. This involved combining information from several different databases among multiple vendors.

2.1 Data sources and variable construction

2.1.1 Property sales and mortgage information

CoreLogic's Owner Transfer dataset provides nationwide transaction-level data on home sales collected from deed transfers recorded by county registries of deeds. These records indicate sale price, sale date and property zip code, among other details of the transactions. CoreLogic's Mortgage Basic dataset provides further information on mortgages associated with sold properties, which we use to link deed transfer data to insurance data. We limit our analysis to arms-length transactions of single-family homes with a mortgage in Florida.

2.1.2 Insurance contract characteristics

ICE/McDash's Property Insurance Module dataset provides insurance contract details associated with home mortgages, based on information collected from the servicing portfolios of some of the largest residential mortgage servicers in the U.S. We observe insurance contract details annually, including monthly premium, coverage amount, and deductible amount.[2] We focus our analysis on primary insurance policies, which usually cover non-flood weather damage and other non-weather sources of damage. For each loan in the ICE/McDash dataset, we observe mortgage origination date, origination amount, and zip code, which we link to a seperate CoreLogic property transaction dataset.[3] The ICE/McDash data cover about two-thirds of the mortgage market and insurance policy information is available for about 70 percent of the mortgages included in the dataset.

The main role of the ICE/McDash dataset is to provide us with information on the price of insurance at the time a property is sold. We create a standardized measure of insurance premiums for our analysis, premium per dollar of coverage, by divding a property's annual insurance premium by its policy's total coverage amount less deductible.[4]

The ICE/McDash Property Insurance Module coverage is limited to mortgaged properties. Property insurance is required by nearly all lenders to obtain a mortgage, so we only observe properties on which insurance is mandatory. We do not capture non-mortgaged properties, such as those purchased with cash or transferred among family members. This may limit the extent to which our analysis can be generalized to the the broader single-family real estate market.

[2]ICE/McDash insurance records are available annually in December from 2013-2022, and the data are provided monthly back to September 2023. For consistency across our time series, we keep only December records in years where monthly data are available.

[3]We thank Tess Scharlemann for sharing her expertise in combining these two datasets.

[4]ICE/McDash also provides information on a borrower's credit score at the origination of the mortgage in a separate dataset. Because credit score is an important determinant of a borrower's insurance premiums, we include credit score as a control in our models (Blonz et al., 2026).

2.1.3 Expected non-flood weather losses

Information on expected non-flood weather losses comes from CoreLogic's Climate Risk dataset, which provides property-level measures of natural disaster risk derived from the vendor's proprietary catastrophe risk models. Non-flood weather perils reflect the weather damages covered by most primary insurance policies and include hurricane wind, severe convective storm, winter storm, wildfire, and earthquake with fire following. We use the average annual loss (AAL) metric in our analysis, which represents the average total loss value of all non-flood weather perils expected in a given year and is expressed as a share of the property's total insurable value.

2.1.4 Realized weather exposure

We identify whether a property has been exposed to hurricane-force winds using hurricane track data from the National Oceanic and Atmospheric Administration's HURDAT2 Atlantic Hurricane Database. This dataset provides location and wind cone information for hurricanes and tropical storms at a six-hour frequency. We first compute polygons showing the area affected the six major hurricanes that hit Florida between 2012 and 2024: Irma, 2017; Michael, 2018; Ian, 2022; Idalia, 2023; Helene, 2024; and Milton, 2024. Using latitude and longitude information, we then record all properties within each polygon.

2.1.5 Property features

We source property-level physical characteristics from the CoreLogic Historical Property Basic dataset. This data is collected from annual property tax assessment records, as reported by the local government entity responsible for levying property taxes (usually the county). We observe square footage, year built, number of bedrooms, number of floors, lot size, and dummy variables indicating the presence of other features like central air conditioning or a swimming pool. Importantly, the data include latitude and longitude for each property, which we use to construct other geographic variables, including distance to the nearest coastline and nearest major city.

2.2 Summary statistics

Our final dataset contains 465,203 transactions of 445,654 single-family homes in Florida between April 2012 and December 2024. Table 1 presents summary statistics for several key variables. The median house price for transactions in our data expressed in real 2023 dollars is $318,687. The median home was built in 1989. Homeowners pay a median of about

Table 1: Data summary statistics.

Variable	Median	Mean	% Missing
Sale amount[1]	\$318,687	\$396,562	0.0
Year built	1989	1986	0.7
Monthly premium[1]	\$154	\$195	0.0
Coverage amount[1]	\$285,475	\$332,285	0.0
Deductible amount[1]	\$2,544	\$2,386	0.0
Premium per dollar of coverage	0.01	0.01	0.0
Building square footage	1,720	1,879	0.0
Number of bedrooms	3.00	3.19	19.4
Number of bathrooms	2.00	2.30	6.3
Distance to nearest coast[2]	14,639	25,062	0.0
Distance to nearest major city[2]	48,310	72,280	0.0
Credit score	741	733	0.0
AAL for non-flood weather perils[3]	0.14%	0.20%	0.0

[1]In 2023 dollars

[2]In meters

[3]Expressed as a percentage of the total insurable value of the property

\$1,850 per year in insurance premiums, or \$154 monthly, and their median coverage limit of \$285,475 lies below the median house price of \$318,687. This makes sense, since insurance policies are typically designed to cover costs home structures and contents, but not the value of land on which a structure is situated. On a per claim basis, the median homeowner is responsible for a deductible of \$2,544. The median credit score at mortgage origination for borrowers in our sample is super prime, at 741. The mean is lower at 733, but still lies in the super prime range.

Although the median values together do not necessarily represent an actual property in our sample, the hypothetical median home in our sample is 1,720 square feet with 3 bedrooms and 2 bathrooms. It is about 9 miles (14,639 meters) from the nearest coastline and about 30 miles (48,310 meters) from the nearest major city among Jacksonville, Miami, Orlando, Tallahassee, and Tampa. Additionally, its average annual loss from non-flood weather events is 0.14% of the total insurable value of the property.

3 Empirical Analysis

Isolating the effects of measured non-flood wind risks on home values is complicated by two important features of the data generating process. First, measured storm risk exposure is but one of a very large number of observable variables that are likely to affect a home's

$$
\begin{tikzcd}
 & x \arrow[dl] \arrow[d] & \\
y & w \arrow[l] & \upsilon \arrow[l] \\
 & \epsilon \arrow[ul] &
\end{tikzcd}
$$

Figure 1: Dependence relationship among study variables.

market value. For most home buyers, building structure features, such as house size and the number of bedrooms, or geographic amenities, such as proximity to jobs and schools, are likely to figure much more prominently than is a property's exposure to storm risk. Second, many of the same variables that affect a home's market value also have a direct influence on its risk exposure. For example, ocean views and beach access are highly valued in Florida, and properties with these amenities command a significant market premium relative to those farther from the coast. At the same time, properties located near the coast or in low-lying areas are at much higher risk for hurricane-induced wind and flood hazards than are those located inland or at higher elevations. Thus, in order to isolate the effects of risk exposure it is critical that we properly control for a large number of observable property characteristics that may influence both home prices and risk exposure.

Let y denote the natural logarithm of a home's observed sale price at a point in time. Let x denote a vector of observable variables associated with the sale transaction. This vector includes variables describing the timing of the sale, physical features of the house structure and land parcel, and the property's geographic location, but does not include direct measures of the property's risk exposure. Let w denote a much smaller vector of observed risk exposure measures for the property. Finally let ϵ and υ denote unobserved variables that affect y and w respectively, but are independent of one another. The directed acyclic graph in Figure 1 illustrates the assumed causal relationship among these variables. x is a vector of confounding variables that affects both w and y. The goal of this paper is to measure the direct effect of w on y. Our identification strategy rests on the assumption that, conditional on x, there are no unobserved factors that influence both y and w. In other words, to accept our results the reader must be convinced that x captures all variables that are likely to simultaneously affect both a home's market value and its risk exposure. Our identification strategy should be robust to the omission of variables that affect either a home's market value or its risk exposure, but not both.

We are agnostic about the functional form of the expectation of y and w conditional on x. However we assume that w enters the conditional expectation function of y linearly. Our empirical model can thus be described by the following system of equations.

$$y = g(x) + w'\beta + \epsilon$$

and

$$w = h(x) + v$$

where $\mathbb{E}[\epsilon|x, w] = 0$ and $\mathbb{E}[v|x] = 0$. The vector β contains the risk sensitivity parameters we seek to estimate.

Modern nonparametric approaches to predicting house prices use machine learning algorithms such as random forests, boosted trees, or neural networks that impose only mild assumptions on the relationship between y and x. These highly flexible methodologies have more accurate out-of-sample forecasts than parametric approaches but do not readily lend themselves to statistical inference, which is the primary focus of this paper. The semiparametric double-debiased machine learning (DD-ML) approach of Chernozhukov et al. (2018) allows for estimation and inference about β without requiring strong restrictions on $g(x)$ and $h(x)$. Machine learning models are applied to a subsample of the data to estimate conditional expectation functions for y and w given x and simple empirical moment conditions are then imposed on the remaining data to produce a consistent and asymptotically normal estimator for β.[5]

We control for three broad types of confounding variables: (i) transaction features including the date of the sale and the credit score of the homeowner, (ii) property features such as the house size, number of bedrooms and bathrooms, construction type, and vintage, and (iii) property location information including geodetic coordinates, distance from the coast, and distance to the nearest major city. To identify optimal hyperparameters for the random forest models used in the DD-ML estimators, we first trained a random forest regression model of log house prices on the full vector of confounding variables using five-fold cross validation on an 80 percent training sample of about 370,000 home sale transactions. The remaining 90,000 observations in our dataset were withheld and used to evaluate model performance after hyperperameters were selected. Based on this analysis we determined that "deep" trees were needed to best capture the complex nonlinear relationships between control variables – particularly those describing geography – and house prices, while over-fitting could be mitigated by using a relatively small number of control variables in each tree.[6] Once

[5]In typical applications, including this one, efficiency is improved by repeating this process across multiple folds of the data set and then averaging across estimated parameter values. This cross-fitting approach, which is very similar to the cross-validation procedures commonly used in training machine learning models, allows one to use the full dataset in estimating the parameters of interest.

[6]All of the random forest models presented in this analysis use a minimum leaf size of one observation,

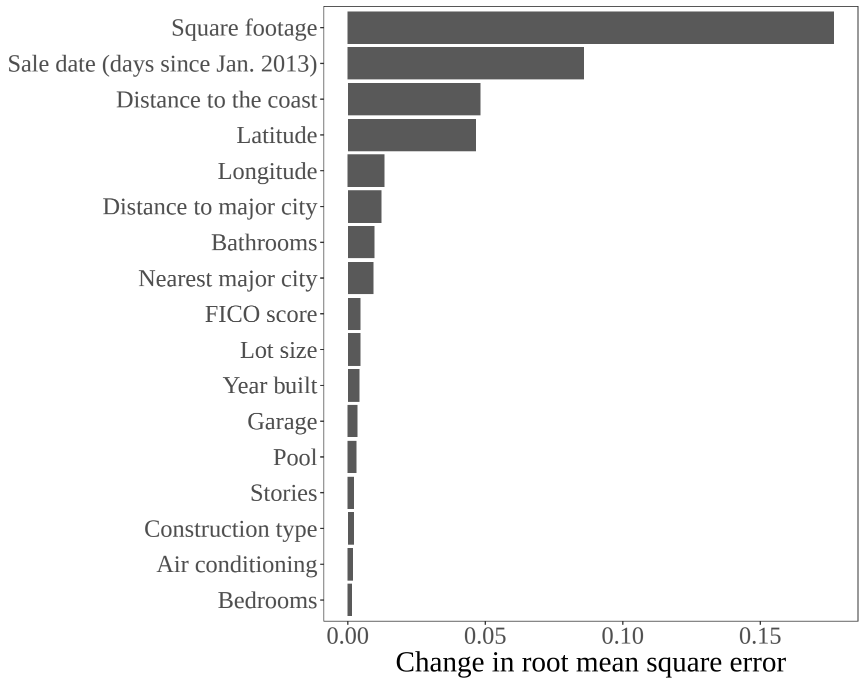


Figure 2: Root mean squared error feature contribution for house price control variables.

hyperparameters were selected, a final model was estimated using the full training sample.

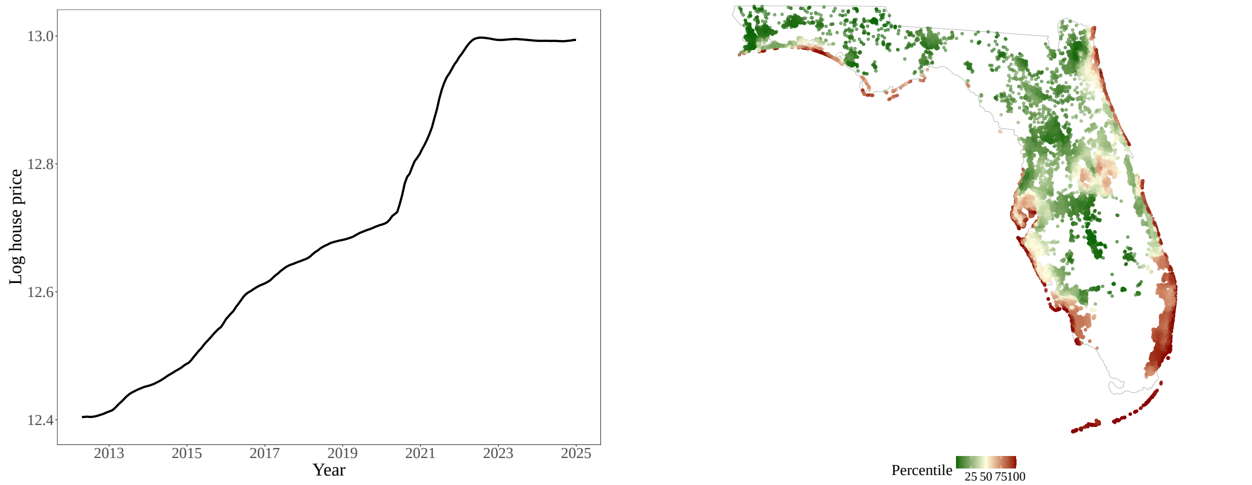
Model diagnostics show that the DD-ML approach provides sensible predictions. First, Figure 2 shows how excluding each of the control variables affects the mean squared error of out-of-sample house price predictions. By far the most important control variable is house size, followed by the sale date and most of the variables that describe a home's geographic location. Aside from house size, other structure features such as the number of bedrooms and bathrooms are relatively less important.

Second, temporal and geographic variations are sensible. Figure 3a shows a partial dependence plot (PDP) of log house price on sale date. This graph can be interpreted as a quality-adjusted real house price index. It shows a similar pattern to those of widely used indexes published by Zillow and CoreLogic, with steady growth before 2019, a sharper acceleration during the COVID pandemic, and a levelling off thereafter. Figure 3b shows how the predicted log price for a house with median structure features varies with geography.[7] Consistent with other research we find that houses located near the coast are more expensive than those located inland, houses near major urban centers are more expensive than those

a thirty percent sample of feature variables per tree, and 1000 random trees. Models were estimated using Python's Scikit-Learn machine learning library.

[7]The prototypical house used in this plot was 1,723 square feet, had 3 bedrooms and 2 bathrooms, and was built between 1990 and 2009. It was a single-story structure of unspecified construction type with central air conditioning, and a finished garage.

in rural areas, and houses in the south of the state are more expensive than those in the north.



(a) Partial dependency plot of log house price on sale date.

(b) Relative predicted price of a house with median characteristics by location.

Figure 3: House price variations by time and location

Finally, Figures 4 and 5 show PDPs for selected house structure features. As one would expect, larger homes are more expensive than smaller ones, newer homes are preferred to older ones, and additional bathrooms or bedrooms command a price premium.

For each version of the DD-ML model conditional expectation functions for log house price and the risk variables given control variables were estimated using random forest regressions fit to an 80 percent sample of the data, then the risk variable coefficients were computed by solving estimated moment conditions for the remaining 20 percent of the data. This process was repeated for five folds of the data and estimated values were averaged across iterations.

We examine the effects of house prices on projected annual weather losses, insurance premiums, and hurricane events. Our main treatment variable is the natural logarithm of the projected average annual loss (AAL) rate on a property from non-flood weather hazards produces by a third-party vendor's catastrophe risk model. This measure of *ex ante* risk exposure is computed at the individual property level using the vendor's proprietary engineering and statistical loss forecasting models, which account for local topological and hydrological features, site characteristics, and structure features. The vendor's 2024 non-flood risk model is used; AAL estimates do not vary over time. The insurance premium rate per dollar of coverage is measured as the annual dollars paid on a home's primary insurance policy shortly after it was sold divided by the difference between the maximum coverage

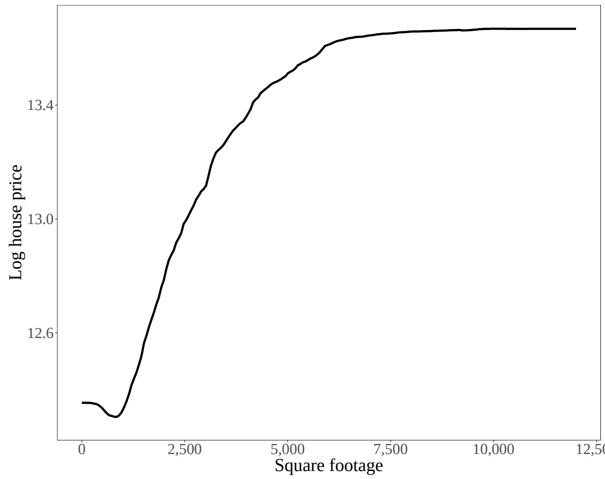


Figure 4: Partial dependency plot of log house price on structure size.

amount for the policy and any deductible associated with the policy. As one would expect, insurance premium rates are highly correlated with AAL (see Figure 6) so it is not possible to determine whether the effects of AAL on home values are mediated through insurance premiums. Exposure to a hurricane is described using dummy variables that identify whether a home had recently been in the path of the hurricane force wind cone associated with a named hurricane at the time it was sold.

Coefficients for versions of the model with various combinations of risk exposure measures are reported in Table 2. The log predicted AAL rate and log annual property insurance premium rate both negatively affect house prices. The regressions suggests that homes that were recently affected by a named hurricane sell at a modest discount. We discuss our interpretation of these results in the next section.

4 Results and Discussion

Our most general model suggests that, after controlling for macroeconomic conditions, property characteristics, and geographic amenities, equilibrium home prices are sensitive to *ex ante* non-flood weather risk and home insurance premiums. *Ex post* exposure to hurricanes has a modest and only marginally statistically significant effect on home prices. Broadly, these findings are consistent with an asset pricing view of home valuations in which, *ceteris paribus*, with higher future expected losses or holding costs are valued less richly. However, as discussed below, the story is more nuanced.

The coefficients on log average annual weather loss rate and log insurance premium rates can be interpreted as elasticities, so our analysis suggest that a ten percent increase in

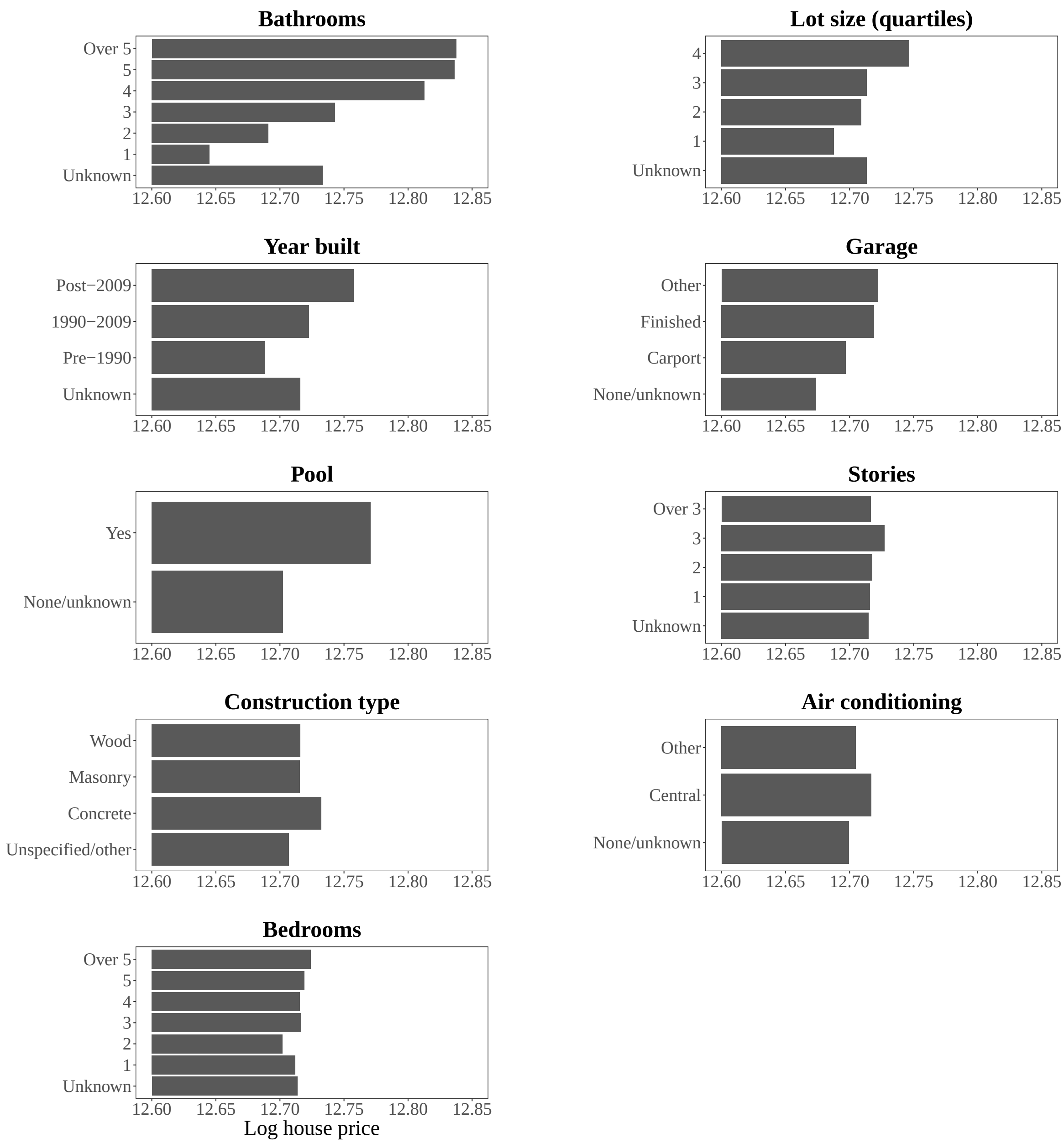


Figure 5: Partial dependency plots of log house price on selected house features.

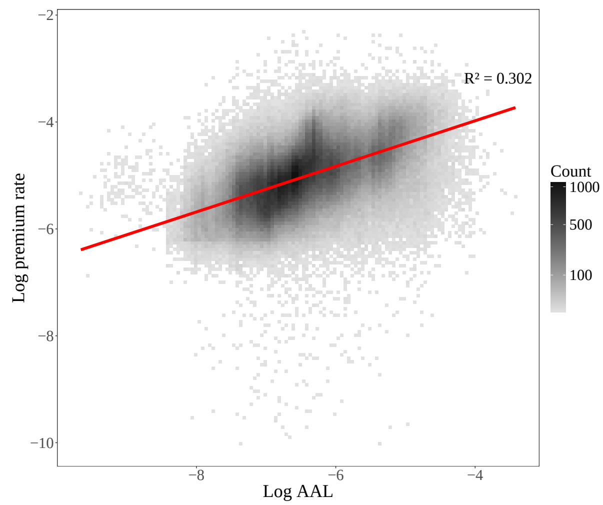


Figure 6: Relationship between non-flood weather average annual loss and effective insurance premium rate.

Table 2: Double-debiased machine learning model treatment variable parameter estimates.

	(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)

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

weather AAL would reduce a home's market value by about one-half of one percent, while a ten percent increase in insurance premiums would reduce a home's value by about one-seventh of a percent. One way to check the economic plausibility of these estimates is to ask whether they imply reasonable discount rates.

Higher future weather losses imply a lower future benefit stream from owning a home, and the change in the present value of future benefits should equal the change in the home value. Consider a \$300,000 property with a structure replacement cost of \$150,000. A plausible average annual weather loss rate on the structure might be two-tenths of a percent, or \$300 per year. If AAL were to increase 10 percent to \$330 per year, our model predicts that the home value would fall by about \$1,440, all else equal, implying a discount rate on future wind losses of about 2.1 percent.[8] This is well within the range of typical estimates of long-run risk-free interest rates. Our estimates of the elasticity of home prices with respect to expected wind losses thus appears to be consistent with the rational capitalization of expected future weather losses into home values.

We can use a similar calculation to determine the implied discount rate for a change in insurance premiums not associated with AAL. Suppose the structure replacement cost on our \$300,000 home is fully insured at an initial premium of \$1,500 per year. According to our model a \$150 increase in the insurance premium that is expected to last in perpetuity would reduce the home's market value by about \$480. This implies a remarkably high discount rate on future insurance premiums of 31 percent. In other words, our estimated elasticities suggest that while higher insurance premiums are correlated with lower home prices, home prices are far less sensitive to insurance premiums than would be consistent with a plausible asset pricing framework.

Why is the implied discount rate for insurance premiums so high? A few factors may be at play. One possibility is that home buyers do not expect differences in premium rates to be persistent. Housing characteristics and expected wind losses also affect premiums. Since we control for those, the remaining variation in premiums may be due to idiosyncratic factors that are not specific to the property (e.g., insurance company, homeowner's claim history). Additionally, regulators face substantial pressure to limit rate increases in high-risk areas, and transitory factors, like changes in global reinsurance costs, may lead to fluctuations in relative premiums across markets over time.[9]

[8] More generally, let L denote expected weather losses in dollars, let Y denote the initial home value, and let β_{AAL} denote the elasticity of home prices with respect to weather losses. The implied real discount rate for a permanent change in L is

$$\delta_{\text{AAL}} = -\frac{L}{Y \cdot \beta_{\mathbf{AAL}}}.$$

[9] Keys and Mulder (2024) find evidence that reinsurance shocks are passed through to home prices in

We find that recent exposure to a hurricane has only a modest and marginally statistically significant negative effect on home prices. This is consistent with the view that investors are forward looking. Hurricane risk in Florida is well appreciated by homeowners and investors, so, conditional on available information, new weather events are unlikely to convey much new information on future risk exposures and hence should not to have a lasting effect on equilibrium prices. To the extent that hurricane strikes may temporarily affect prices, this likely reflects transitory dislocations in supply and demand conditions in storm-ravaged markets. While we only look out a few years after each hurricane event, we expect that these transitory effects should dissipate over time as has been observed with flood events and earthquakes.

5 Conclusion

We find that underlying weather risk is well-capitalized into Florida house prices, while variation in insurance premiums stemming from features not tied to the property or underlying risk have a much smaller impact. Given that Florida is the second-largest housing market after California, our findings are reassuring, as they show prices reflect underlying risks. At the same time, we advise caution in generalizing these results nationwide. In Florida, hurricanes are a familiar risk to home buyers and state policymakers have worked hard to improve communication about risk, increase disclosure of risks during property transactions, and enhance resilience through strict building codes. As a result, it may be particularly easy for Florida housing market participants to incorporate risk into pricing. For markets with risks that may be rarer and more destructive or less severe but more frequent, it is possible that house prices may be less sensitive to expected future losses.

highly exposed areas.

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