Hutchins Center Working Paper #114

September 2026

Pricing Climate Risk:

Hurricane Models and Home Insurance Over the Last Two Decades

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Abstract

To what extent do rising homeowners insurance premiums reflect growing climate risk? We examine hurricane risk in Florida and how insurers price it. Insurers rely on proprietary, third-party catastrophe models that estimate property-level expected losses. Using data from these models, we describe estimated hurricane risk across the state and how it evolved from 2006 to 2023. Expected losses per property from hurricanes increased by 50%. Turning to insurance prices, we collect the premium rate regulatory filing data for insurers representing 70% of the total market. Leveraging discrete updates to hurricane models, we estimate that a $1 increase in expected losses increases hurricane premiums by $3.90. Overall, hurricane premiums increased by more than 200% during our period of study. We consider potential mechanisms and find that the large load above expected loss appears to reflect 1) reliance in the insurance market on local, limitedly diversified insurers, paired with 2) the time-varying cost of reinsurance.

Acknowledgment: The authors thank the Hutchins Center on Fiscal and Monetary Policy at Brookings Institution for supporting this research and Karen Clark, Fran Moore, and Adam Solomon for helpful comments. They also thank professionals at the Florida Office of Insurance Regulation and Citizens Property Insurance Corporation for their assistance and feedback.

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https://www.brookings.edu/articles/pricing-climate-risk-hurricane-models-and-home-insurance-over-the-last-two-decades

1 Introduction

Homeowners insurance prices have grown rapidly. From 2017 to 2024, real premiums for homeowners insurance grew by 28% nationally and even more in disaster-prone areas (Keys and Mulder, 2024). Insurers and journalists cite increasing climate risk as the culprit. The New York Times (2024) describes "how the climate crisis became an insurance crisis." Christian Mumenthaler, as the head of Swiss Re Group, one of the largest insurers in the world, stated, "Insurance premium is sort of a feedback to society about climate change...this is the bill of what we have collectively done to the planet" (CNBC, 2023). However, escalating disaster risk is one contender in a set of potential explanations (e.g., inflation in the cost of home repairs, rising litigation costs). Untangling the drivers of insurance costs has become a critical policy question. Rapid premium growth is affecting home values (Keys and Mulder, 2024), mortgage approvals (Matic, 2024), and the affordability of insurance (Ge et al., 2025), leading to mounting pressure on policymakers to intervene. Yet if premium growth reflects changing disaster risk, policies that lower insurance bills may inadvertently distort adaptation incentives. To what extent do rising home insurance premiums reflect growing climate risk?

Quantifying the contribution of disaster risk to insurance prices has been difficult. Property-level risk estimates are closely protected trade secrets between insurers and risk modeling firms. Moreover, homeowners insurance bundles a set of coverages, making it difficult to isolate the contribution of a particular climate risk such as hurricane or wildfire.

We overcome these challenges by assembling granular regulatory data on modeled hurricane risk and insurance premiums in the state of Florida. These efforts yield a first-of-its-kind panel dataset of expected hurricane costs from a full suite of models along with insurer-specific premiums over a nearly 20-year period. Hurricanes are the costliest disasters in the U.S.: nine of the 10 largest disasters by damages were hurricanes (Insurance Information Institute, 2025). And hurricane risks are increasing (IPCC, 2021).[1] Florida is the most hurricane-exposed U.S. state. It is also the third-most populous and has the highest homeowners insurance premiums (Insurance Information Institute, 2022).

To estimate hurricane risk, the insurance industry relies on proprietary, third-party catastrophe (CAT) models, which provide property-level estimates of expected annual losses from hurricanes. In Florida, insurers who want to adjust their premium rates in response to changing hurricane risk must file a justification with the state regulator using one or more hurricane models from a set that has been approved for use by a state oversight commission. For this commission's review process, hurricane model vendors must report annualized expected losses on specific reference properties in every Florida zip code. We use these reports to construct a panel of hurricane expected losses from 2006 to 2023 that includes all (7) major hurricane model vendors.

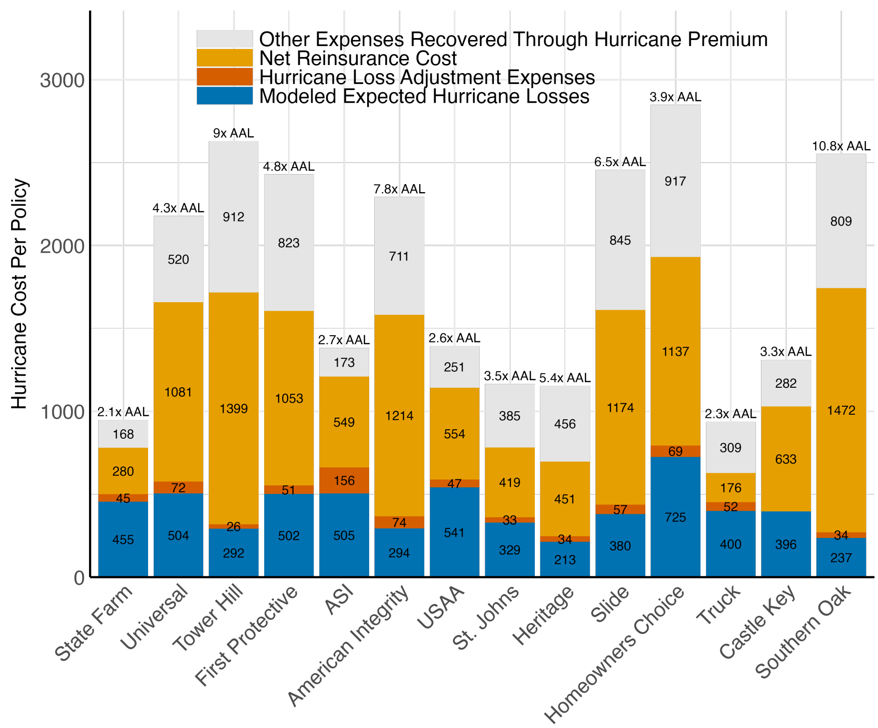
We pair these risk estimates with insurer pricing data. We hand-collect rate filings for homeowners premiums for 16 large insurers, which represent almost 70% of total current market share. These filings separately report the hurricane and non-hurricane portions of premiums, which aids in disentangling variation in hurricane risk from other time-varying factors such as inflation.

We find that homeowners pay hurricane premiums that are much larger than their expected hurricane losses. Figure 1 reports Florida-specific, insurer-level data on hurricane-related expense items that we col-

[1] It is likely that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades (IPCC, 2021, Chapter 11.7.1).

lected from annual insurance rate filings. It includes the largest private insurers in Florida and reports data from their most recent filing with the state insurance regulator (all filings are between 2021 and 2024). The blue bars show expected hurricane losses. Red bars show expected loss adjustment expenses for hurricane claims. The large orange region is the insurer's *net cost of reinsurance*: the difference between premiums paid to reinsurers and the expected loss transferred. This is the load above expected loss that the insurer pays to transfer tail loss risk to global financial markets. Strikingly, for most insurers these net costs of risk transfer exceed total expected losses. Finally, the gray bars reflect the additional expenses that insurers allocate to hurricane premiums, such as overhead, commissions paid to agents, and an expected profit margin for their own investors.

Figure 1: Hurricane-Related Costs for Florida Homeowners Insurers



Notes: The figure describes insurers' reported average costs per hurricane policy for the largest private insurers in Florida. Data are from Florida Office of Insurance Regulation Standardized Rate Indications Workbook, reflecting each insurer's most recent rate filing during 2021–2024. "Net Reinsurance Cost" is the difference between premiums paid to reinsurers and the expected losses transferred to the reinsurer. "Other Expenses Recovered through Hurricane Premiums" reflect additional costs such as agent commissions.

The evidence in Figure 1 suggests an important role for frictional costs of tail risk transfer in hurricane insurance pricing. However, these insurer-level averages have limitations. The composition of customers varies across insurers and within insurers over time as firms adjust their business strategies. Moreover, these averages cannot tell us how reinsurance loads are shared across customers. If net reinsurance costs are allocated in proportion to expected losses, this would lead premiums to substantially exceed expected losses on the margin, with important implications for the risk mitigation incentives perceived by households. In contrast, socializing these costs across customers in a lump sum fashion, as has been argued to occur in related markets (e.g. Oh et al., 2026), would yield quite different incentives.

To make empirical progress on these issues, we turn to the new ZIP code-level data that we have assembled on insurer premiums and modeled expected losses. We focus on a standardized reference home that closely matches the modal home in Florida during our period of study. This reference home is made of masonry, was built prior to the 2001 Florida Building Code (FBC), and has a replacement cost value of $150,000. For reference, pooling across both the state and the entire period of study, the average expected loss from hurricanes for this type of home was $493 and average hurricane premium was $1,862, about 3.8 times the expected loss.

We first examine modeled hurricane risk and then turn to how growth in expected loss influences premiums. While several hurricane models are approved in Florida, most insurers use the same one or two (AIR and RMS) in their rate filings. We find that prices are best explained by the average of AIR and RMS alone, which is consistent with insurers' regulatory filings, our conversations with them, and industry reports. For example, NASDAQ (2019) describes the CAT model industry as "essentially in a duopoly." We focus primarily on these two models while exploring the less widely used models in auxiliary analyses.

We find that modeled expected losses increased by 50% in the median zip code from 2006 to 2023. Much of this increase has occurred since 2017, which was a year marked by three severe hurricanes (Harvey, Irma, and Maria). We also find that while the models generally agree on the ranking of zip code risks, there is meaningful disagreement about the level of risk, especially in the highest risk and lowest risk areas. For example in Key West, which has the highest risk zip code in the state, the property-level expected loss estimates are over three times larger for AIR than RMS. Finally, while risk has grown across most of the state over the last twenty years, the cross-sectional variation in risk is much larger than the intertemporal variation.

We next examine how these risk estimates have shaped insurance prices in the state. Our preferred specifications leverage discrete changes in CAT model estimates of the expected loss in each zip code. CAT models update on regular intervals governed by the state's model review cycle, which is every two years for most of our time series. Focusing on the major model updates that followed the 2017 hurricane season, we measure how within-zip-code changes in modeled risk affect insurance prices. This design compares how the same property is priced by the same insurer in the same zip code before versus after the model update. The design is further strengthened by the unusually well-suited data, which separately report hurricane and non-hurricane premiums and explicitly hold constant customer-specific factors (e.g., credit scores, deductible choices) that also affect pricing and may be correlated with hurricane risk. We find that a $1 increase in modeled expected losses increases premiums by $3.90.

Our findings are qualitatively similar when estimating the pass-through of expected losses to premiums using all the years in the sample. For the full study period, we estimate that a $1 increase in modeled expected loss increased premiums by about $3.43 on average. This pass-through has grown over time: a $1 increase in expected loss increased premiums by $2.42 in 2008–2013, by $3.41 in 2014–2019, and by $4.17 in 2020–2025 (the latter being consistent with the zip code fixed effects design that leverages the model update following the 2017 hurricane season).

What explains the large and growing pass-through of expected hurricane losses? We find evidence suggesting that the large premium loads reflect the costs of managing tail risks. The potential of extremely large loss events limits the ability of even the largest insurers to diversify the risk. CAT models estimate the loss exceedance probability for a portfolio, illustrating the magnitude of potential losses. Insurers provide a portfolio of insured properties to a CAT model, which returns an estimate of the annual aggregate distribution of potential losses. Insurers and their regulators and ratings agencies use this distribution to determine the amount of capital an insurer needs, commonly focusing on a standard that insurers should organize sufficient capital to survive in 99% of the states of the world. An example of the 99th percentile loss scenario in our setting is a severe hurricane hitting a large city such as Miami. Using data from effectively all insured residential properties in the state, the models indicate that insurers would need to hold capital that equals about 15 times the portfolio's expected loss to survive the 99th percentile loss, which was approximately $90 billion in insured residential property losses in 2023. These large capital needs reflect the spatially correlated nature of hurricane losses.

We find suggestive support for two channels through which the difficulty of diversifying hurricane risk affects insurance premiums. The first is reinsurance costs. While the global portfolios of reinsurers allow them to better diversify Florida hurricane risk than local insurers, potential hurricane losses remain large relative to reinsurers' risk bearing capabilities. For example in 2021, Swiss Re reported that most reinsurers were "at capacity" for taking on U.S. hurricane risk (Artemis, 2021). The capital of the entire reinsurance industry was $570 billion as of 2023 (Guy Carpenter, 2026). Thus, in Florida alone, a 1-in-100 year hurricane loss of $90 billion would equal over 15% of industry capital. We show that hurricane premiums in Florida co-move with global reinsurance prices: declining as the reinsurance market "softened" from 2013 to 2017, rising rapidly after 2018, then declining slightly in 2025.

A second factor contributing to the large premium load is likely the Florida insurance market structure. National insurance groups such as State Farm and Allstate ration their participation in the market, primarily operating in low hurricane risk areas. Using subsidiaries, these national insurers sell around two-thirds of the policies in the lowest hurricane risk decile of the state but only a quarter of the policies in the highest risk decile. High risk areas instead rely on either Citizens (the state-run-insurer-of-last-resort) or insurers that operate almost solely in Florida. These Florida domestic insurers have limited capacity to diversify hurricane risk, which increases the cost of holding the risk and amplifies the pass-through of reinsurance costs to consumers. From 2020 to 2025, they charged an additional $5.06 in hurricane premiums for every $1 increase in expected losses, whereas diversified national insurers charged an additional $3.98 for every $1 increase in expected losses.

We also test and reject other candidate explanations for observed changes in pricing. The CAT models show that the shape of the exceedance curve is relatively constant across years, implying that modeled annual loss risk has not become more heavy-tailed during our sample period. Similarly, aggregate data on litigation costs, which would likely mostly influence the non-hurricane portion of premiums, do not support that channel as a major explanatory factor. We also compare our premium data, collected from rate filings, to county-level premiums on transacted insurance policies, which Keys and Mulder (2024) collect from mortgage escrow data from 2014 to 2024. We find that these datasets are similar in both the level and evolution of home insurance premiums during this time.

Finally, we present a new index of homeowners insurance prices that summarizes market-wide trends in pricing over time and across types of properties. This index draws on similar standardized insurance price data for other reference homes to calculate a weighted average insurance premium measure reflecting the full population of Florida homes. The resulting total premiums closely correspond to average premiums from transaction data. The index shows that recent premium increases have been driven by hurricane premiums as opposed to other peril premiums.

We contribute to a literature documenting the growing price of property insurance and its implications.

The insurance price run-up has caused substantial disruption and distress to household budgets (Sastry et al., 2024), mortgage markets (Ge et al., 2025), and property values (Keys and Mulder, 2024). Using mortgage escrow data, Keys and Mulder (2024) isolate property insurance premiums and document that U.S. homeowners insurance premiums have grown by an average of 28% since 2017. They find that much of this premium increase can be explained by the rising cost of reinsurance. They measure reinsurance exposure based on the within state correlation of historic losses from natural disasters. Boomhower et al. (2024) measure the pricing of wildfire risk by homeowners insurers in California using insurer rate filings and property-level expected losses from a leading wildfire catastrophe model. They show substantial variation both in the information that insurers use to estimate risk and in the prices they charge.[2] We add to this literature by studying modeled risk and insurer-specific prices over a generation, from the post-Katrina era to today. A growing concern is that severe climate risks may make living in certain places unsustainable. Florida is on the short list. We find that, according to the most-trusted industry models, hurricane risk has grown materially, by around 50%, in the last 20 years, but explains only a portion of the over 200% increase in insurance prices during this time.

We also add to a literature examining how price signals through insurance, credit, and property markets may steer climate adaptation. Research on flood insurance demand suggests that many households may miss risk-based signals in their insurance premiums: even when insurance is priced below expected losses, many households fail to insure against flood risks (Wagner, 2022) or drop their coverage when prices increase (Collier et al., 2023). Households appear to respond more directly to insurance price effects on mortgage and residential property markets, shaping where they live. Insurance premium increases reduce property values (Keys and Mulder, 2024; Ge et al., 2022), and declines in insurance availability in California have led to an increase in cash buyers for wildfire exposed areas (Bass and Fogarty, 2025). We add to this literature by documenting that, in addition to the cost of covering the expected loss, hurricane premiums also pass substantial frictional costs of insuring hurricane risk to consumers, affecting the carrying costs of homeownership.

Finally, we contribute to a literature on the challenges of insuring catastrophes and public policies to facilitate these markets (e.g., Born and Viscusi, 2006; Born and Klimaszewski-Blettner, 2013; Kunreuther and Michel-Kerjan, 2011; Oh et al., 2026; Blonz et al., 2026). Through surveys and aggregate data, prior research concludes that the premiums on catastrophe insurance may notably exceed expected loss due to the "cost of capital" (i.e., the need for insurers and reinsurers to dedicate large sums of equity capital to address potential tail risks events, Kunreuther and Michel-Kerjan, 2011). Using a database of reinsurance contracts from 1970 to 1994, Froot and O'Connell (1999) report that reinsurance premiums can be up to seven times larger than the expected value of the contract. We quantify homeowners insurance contract loads using a novel, granular dataset on premiums and expected losses over the last two decades, showing how these reinsurance loads are passed through to primary insurance policies. Our results add empirical support to public policy proposals focused on reducing the social cost of managing tail risks. Examples include reforms that might increase the participation of national insurers in high risk areas (e.g., Bohn and Hall, 1997; Abramson et al., 2025). Other potential interventions consider reducing the cost of reinsurance such as through tax reforms (Baxley and Katz, 2017) or by government reinsurance programs that expand

[2] In addition to these earlier papers, Heitfield (2025), which was developed concurrently with our study, uses recent data from hurricane models in Florida to study the relationship between aggregate average premiums and disagreement in expected loss estimates across models. Our paper focuses on a different set of questions, leverages insurer-specific price data, and examines many years of longitudinal data on prices and modeled losses.

reinsurance supply (e.g., King, 2008; Solomon, 2025; Collier et al., 2025). Interventions that alleviate the frictional costs of tail risks can potentially improve insurance affordability without distorting the socially valuable linkage between property-level risk and insurance premiums.

2 Setting and Data

This section describes the setting, including background on hurricane models and an overview of the homeowners insurance market in Florida, and the data used in our analyses.

2.1 Setting

2.1.1 Background: Hurricane CAT Models

Catastrophes, whether naturally occurring or resulting from human actions, are unique in their ability to severely and immediately jeopardize insurer solvency. Events like hurricanes, earthquakes, tornadoes, and terrorism are rare and highly destructive. The rarity of events makes it exceedingly difficult to estimate current risk using only historical loss data. This critical deficiency has compelled catastrophe modelers to develop stochastic simulation techniques to capture and quantify risks, thereby enabling insurers to better assess and mitigate their catastrophe exposures.

A catastrophe model leverages data and knowledge from physics, meteorology, engineering, statistics, and actuarial sciences to estimate the likelihood and severity of losses from extreme events. In doing so, these models provide answers to crucial questions such as: What is the probability of a catastrophe affecting a specific property? How much physical damage can be expected? And critically, how much insurance and capital are necessary to cover the risk?

The catastrophe model is a system of algorithms that incorporate the fundamental physical characteristics of the modeled peril, whether it be hurricanes, severe thunderstorms, or floods. Thousands of these mathematical "events," which represent potential future natural or manmade catastrophes, are then combined with detailed information about insured properties and their surroundings, including replacement value, construction type, occupancy class, soil conditions, and elevation. Collectively, this information is distilled into the three key factors to estimate the ultimate level of damage and loss: the event magnitude, the local intensity of the event at the site, and the vulnerability of the specific structure. By simulating the impact of thousands of possible events across a portfolio, the model output delivers a range of potential losses, each associated with a probability of occurrence (see Risk Management Solutions, 2008, for an overview of CAT models).

The first two proprietary hurricane models were developed by Applied Insurance Research Worldwide (AIR), established in 1987, and Risk Management Solutions (RMS), established in 1988. These models gained traction following Hurricane Andrew in 1992 because they provided more accurate estimates of insured losses from the storm than the current insurance industry estimates, which tended to rely on historical loss data. Today, while around seven proprietary hurricane models exist, insurers and reinsurers almost exclusively rely on AIR (now owned by Verisk) and RMS (now owned by Moody's, NASDAQ, 2019; Bermuda Monetary Authority, 2025).[3] NASDAQ (2019) explores the reasons for and implications of this effective

[3] Bermuda is a global hub for reinsurance against natural catastrophes, and the Bermuda Monetary Authority conducts an annual survey of reinsurers regarding their licensing and use of catastrophe models.

duopoly. A key motivation for insurers to use these two models is aligning revenues and expenses: if an insurer's reinsurance is priced using AIR, setting premiums using AIR facilitates pass-through of reinsurance costs. Similarly, insurers' solvency risk assessments from insurance regulators and credit rating agencies rely on portfolio loss estimates from these catastrophe models, further incentivizing an insurer to adopt and consistently use AIR or RMS in its operations.[4] One implication of the model duopoly is the potential for modeling errors to lead to systemic mispricing in the insurance industry.

2.1.2 Background: Florida Homeowners Insurance Market

Prior to Hurricane Andrew in 1992, the insurance industry in Florida, like many U.S. markets, relied mostly on limited historical data and in-house models for pricing catastrophic risk. Underwriting decisions and reinsurance purchasing were often based on simpler calculations, intuition, or regional practices. This approach ultimately led to an insufficient accumulation of capital to withstand a major, high-severity event like Andrew. The hurricane was the main contributor to eight insurer insolvencies and exposed weaknesses and volatility in the state's property insurance market (McChristian, 2012).

Since Andrew, the population in the state has surged from approximately 13.5 million to over 23.3 million Floridians. As of 2023, there are 5,874,831 single-family homes in the state (Florida Office of Insurance Regulation, 2024a). Approximately 98 percent of the population resides in coastal counties with significant hurricane risk (Insurance Information Institute, 2020). The financial exposure has coincided with increased hazard activity. While 25 major hurricanes made landfall in Florida over the last century, around 40 percent of those occurred within the last 25 years. Thus, the state faces both escalating insured values and higher frequency of extreme events.

Notably, Florida building regulations have evolved significantly since Hurricane Andrew. The Florida Building Code was introduced in 2001 and was aimed to streamline and centralize the prior patchwork system of local building codes that were deemed inconsistent, deficient, and not uniformly enforced. The building code is updated every three years to incorporate new technologies, stricter wind load requirements, and energy efficiency.

An additional post-Andrew reform was creation of the Florida Hurricane Catastrophe Fund (FHCF), a public reinsurer. Florida requires insurers to purchase FHCF coverage, which occupies a middle layer of reinsurance for most insurers. That is, insurers typically buy reinsurance coverage for both below and above the layer of protection received from this fund, suggesting that insurers would choose to cover the layer addressed by the fund if it did not exist. The detailed impacts of the FHCF are ripe for future research. With respect to this study, the main implication of the FHCF is that it may reduce the overall cost of reinsurance in a specific layer of risk. Beyond that possible cost reduction, the FHCF does not change forces guiding the insurance market in Florida, which are similar to those in other disaster prone states.[5]

Finally, like many states, Florida has a state-managed residual plan, Citizens Property Insurance Corporation, that is intended to serve as an insurer of last resort. While the plan was not originally designed to be

[4] The prospect that model vendors might strategically underestimate or overestimate the risk is interesting. However, given the broad set of constituents with varying interests that rely on the output of these models — insurers, reinsurers, brokers, ratings agencies, regulators, etc. — vendors' incentives seem to align with providing unbiased estimates of the risk.

[5] All residential property insurance companies with more than $10 million in aggregate sums insured are required to participate in the fund (Florida Department of State, 2010). The fund reports using actuarial standards to price its coverage but offers it at a price that is likely below what a private reinsurer would offer because it "does not include a profit factor or risk load in its rates and since it is exempt from federal taxes" (State Board of Administration of Florida, 2024, p. 4). See State Board of Administration of Florida (2024) for additional information on the fund.

price-competitive with private insurers, rising private market premiums along with legislative limits on the growth rate of Citizens premiums have led Citizens to become one of the state's largest insurers.[6]

2.1.3 Rate Filings, Hurricane Premiums, and CAT Model Justification

Florida homeowners insurers are required to submit detailed pricing formulas to the Florida Office of Insurance Regulation (OIR) upon market entry and whenever these prices change. Filing submissions must generally include actuarial support and justification for how various factors, such as building code adherence, are used in premium calculations. These filings allow the regulator to determine that rates are not excessive or inadequate. Because hurricanes are low probability but high consequence events, an insurer's last 10–20 years of realized claims is an inadequate basis for establishing premiums. The state began integrating catastrophe model output as a primary risk assessment tool into rate filing requirements in the late 1990s (FCHLPM, FCHLPM). Insurers could use common catastrophe model output values, such as the average annual losses for specific zip codes, to justify changing rates across the state. Insurers were initially required to submit the catastrophe model output from one approved vendor. In 2006, the state established its own independent Florida Public Hurricane Loss Model to serve as a baseline for evaluating private insurer rate filings (Florida International University, Florida International University). In 2023, state law was modified to allow property insurers to use an average of two or more approved models in their rate filings. Insurers that use a "blended model" approach must apply the same combination of models across the entire state (Florida Senate, 2023).

Insurers can and do file to revise their premium rates in response to any of a variety of their input costs changing. Only rate filings citing increasing hurricane risk require hurricane model output as a justification. For example, insurers file for rate increases in response to rising reinsurance costs, which they document with their reinsurance contracts.[7] Similarly, an insurer whose costs of settling claims have grown over time might use documentation of these costs as justification in a rate filing.

2.1.4 Florida CAT Model Commission

The Florida Commission on Hurricane Loss Projection Methodology, which we call the "CAT model commission" hereafter, was established by the Florida Legislature in 1995 in the wake of Hurricane Andrew, which revealed a need for more reliable and standardized methods to assess hurricane risk and projected losses (Brannon, 2013). The intent of the legislation was to create an independent panel of experts to evaluate the accuracy and reliability of computer simulation models for the State of Florida, with the goal of improving the accuracy of insurers' estimates of potential hurricane losses. The commission's oversight would also ensure that residential property insurance rates were neither excessive nor inadequate, providing stability for both consumers and insurance companies.

The primary function of the CAT model commission is to adopt a set of standards that must be met by catastrophe modelers. This involved the initial development and regular revision (e.g., every odd-numbered

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6 For example, in 2007 House Bill 1A rolled back Citizens' insurance rates to 2006 levels and froze them until July 2009. After this three-year rate freeze, subsequent increases have been capped at 10% per policy per year. More recently, between 2018 and 2020, the state also froze rates in the high-risk county Monroe, including areas such as the Florida Keys. In 2020, Citizens did not file actuarial rate changes, as directed by the Board of Governors, due to the COVID-19 pandemic. Starting in 2022, Citizen's rate increase caps rise by 1 percentage point each year until reaching 15 percent in 2026 (rather than the original 10 percent) (Citizens, 2024).

7 Reinsurance costs are measured net of expected losses in insurers' worksheets. Our Figure 1 illustrates this breakout.

year for hurricane loss projections) of rigorous technical standards across various domains, including meteorological, engineering (vulnerability), and actuarial components of hurricane loss models. Catastrophe model vendors, along with the Florida Public Hurricane Loss Model (hereafter the "Public Model"), undergo rigorous evaluation by the commission which includes on-site visits by the technical team and commission review of responses to each hurricane standard.

2.2 Data

We merge several sources of information to produce the first granular dataset of insurer-level premiums and modeled hurricane losses for any U.S. state. Sections 2.2.1 – 2.2.3 describe the input data. Section 2.2.4 documents the construction of the final analysis dataset and accompanying validity checks.

2.2.1 Hurricane Loss Projections

Our CAT model data are from reports to the CAT model commission by the model developers. The commission requires each vendor to report estimated property-level expected losses from hurricane winds for a set of standardized homes: a masonry home, a wood frame home, and a mobile home. These standardized homes were built in 1989. The vendor places each home at the population-weighted centroid of each Florida zip code and reports the expected loss.

Model vendors' measure of expected losses is the "average annual loss" (AAL), which is an estimate of the yearly expected damages per dollar of a home's replacement cost. The model estimates describe expected damages from hurricane winds, which insurers cover through homeowners insurance. The model estimates exclude flood damages from hurricanes because homeowners insurance does not cover flooding. Vendors model wind damages as a share of the structure's value and then (linearly) scale expected damages based on the replacement cost value provided by the insurer for the property.

The commission also requires vendors to report portfolio measures of risk. Given that a hurricane can affect many policyholders concurrently, portfolio measures are useful for assessing whether an insurer is likely to have sufficient capital to cover its potential obligations. We use the hurricane model vendors' reported exceedance probability curves for the population of properties insured in the FHCF. While the vendors also report on a notional portfolio, the exceedance curves for the fund are useful because they describe the aggregate risk for effectively all insured residential properties in the state.

As of 2025, vendor reports are publicly available from the CAT model commission for review years 2011–2023. We augment these data with reports for 2006–2011 provided by the commission's staff. To assess the completeness of the reported zips, we also draw on U.S. Census Bureau data for population estimates in zip code tabulation areas (ZCTAs) in 2010 and 2020. Additional information on how these data are constructed is in Appendix 1.1.

2.2.2 Insurance Prices

We observe insurers' prices through their approved rate filings to the insurance regulator. We hand-collect rate filings for insurers' homeowners (HO-3) programs for 2008–2025. These data establish the exact price that each insurer would charge a given home as a function of location, contract features, and structure and occupant characteristics. To facilitate industry analysis, the regulator requires each firm to report premiums for a consistent set of six "notional" policies. The notional policies hold constant contract features (e.g., deductibles) and occupant characteristics (e.g., claims history, credit score) at levels typical for Florida homeowners, while varying reconstruction cost ($150,000 or $300,000) and building characteristics for a masonry structure (built in 2005; built in 1990 without wind mitigation retrofits; and built in 1990 with maximum wind mitigation credit).[8] In each case, the data report separate territory-level hurricane and non-hurricane premiums, which together constitute the total homeowners premium. Full details of the notional contract features are in Appendix 1.2.

Insurers report these notional contract prices for each of their geographic rating territories. Each insurer is free to define its own rating territories, and territory definitions are included in rate filings. The insurer prices all homes within a rating territory identically conditional on coverage, construction features, and occupancy. Lastly, rate filings also identify the catastrophe model used to justify the hurricane premium.[9]

Table 1 lists all collected insurers, ordered by their 2024 homeowners market share, measured in number of policies (with the corresponding 2010 market share shown in parentheses). The insurers in our data represent 68% of homeowners policies in Florida as of 2024. The market is highly atomized: few private insurers have market shares above 5%, and the largest has only 10%, while the state-run insurer-of-last-resort Citizens has a market share of 15%. The table also reports the catastrophe model(s) used for ratemaking. Most insurers report using a single model, 10 of which report using AIR alone and 4 of which report using RMS alone. State Farm and Citizens use multiple models. While not shown in this table, we observe which model insurers use in their rate filings across the time series. Appendix Table 3 shows the share of insurers using each model over time. Insurers very rarely switch models, and if they do, they only switch once (e.g., from RMS to AIR). This behavior is consistent with the conclusion from NASDAQ (2019) that model switching costs are likely large since models influence premium rates, reinsurance costs, and capital requirements. While insurers report a specific model to the regulator for setting premiums and for regulatory capital assessments, it remains possible that insurers unofficially rely on several models to guide their decisions; we look for evidence of insurers informally blending models when we examine the relationship between model estimates and premiums 4. Appendix 1.2 includes additional information on the hurricane premium data.

2.2.3 Insured Properties Data

We additionally use a dataset from the FHCF that describes the universe of insured residential properties in Florida. We have these property-level data for 2007, 2012, 2017, 2023, and 2025. The data are useful for understanding wind risk mitigation and other characteristics of the building stock at a granular level. We also use them to construct sample weights in Section 6 that reflect the number of homes in various vintage categories in each zip code.

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[8] The policy follows the standard homeowners insurance logic, expressing coverage amounts relative to dwelling coverage (Coverage A). Coverage B (other structures) is set to 10% of A, Coverage C (personal property) to 50% of A, and Coverage D (loss of use) to 20% of A. All policy characteristics are specified by Florida OIR's data-reporting requirements and remain constant throughout our observation period.

[9] As an example, the insurer Universal P&C submitted a filing on 16 May 2022 for the HO-3 policy form, under log file number 22-013720, for a rate level increase with a statewide average impact of 17.3%; the specific increases varied by territory. Universal P&C divides Florida into 101 rating territories, each of which contains 8–9 zip codes on average. The filing became effective on 1 June 2022 for new business and on 4 November 2022 for renewals. To support the proposed hurricane rate increase, Universal relied on the version of RMS's hurricane model that had been approved under the 2019 hurricane standards.

Table 1: Florida Insurers in the Dataset

Insurer	Share 2024	(Share 2010)	Model vendor(s) 2024
Citizens	15%	(10%)	AIR, CL, RMS, FPM
State Farm	10%	(16%)	AIR, CL, RMS
Universal P&C	6%	(6%)	RMS
Tower Hill	6%	(-)	AIR
Slide	5%	(-)	AIR
First Protective	5%	(1%)	RMS
American Integrity	4%	(1%)	AIR
Florida Peninsula	3%	(2%)	AIR
ASI Preferred	3%	(1%)	AIR
Heritage	2%	(-)	AIR
Southern Oak	2%	(1%)	AIR
Truck Insurance	2%	(-)	RMS
American Strategic	2%	(2%)	AIR
Homeowners Choice	2%	(2%)	RMS
Castle Key Insurance	1%	(3%)	AIR
St. John's	-	(4%)	AIR
Total	68%	(49%)	

Notes: This table lists the insurers in our sample, which we construct using insurers' rate filings from 2008 to 2025. The Share columns report the insurer's market share, measured in number of policies, as of 2024 and 2010, respectively. The model vendor column indicates the model(s) the insurer reported using in its most recent filing.

Table 2 describes the population of insured homes in Florida. Each panel reports the share of homes across vintage and construction categories in the indicated year. "Pre-Florida Building Code" refers to homes built prior to 2002, when Florida conducted a major revision to its building codes. The CAT model commission requires vendors to report separate expected losses for pre-code properties built from masonry and frame. The table shows that this is the modal type of home across the period of study. For example, 53% of homes in 2017 were masonry, pre-code homes (with frame pre-code homes making up another 15%). Appendix Table 5 describes the median insured value for properties in the FHCF data, which was around $225,500 for a masonry pre-code, no-mitigation property in 2017. This roughly corresponds to the standardized price data reported by insurers, which divide properties into the categories shown in the rows of this table and report prices for a masonry home in each category with coverage limits of $150,000 and $300,000.

2.2.4 Insurer-Zip-Year Panel

This section describes how we merge the foregoing data sources into a harmonized annual panel of zip-code-by-insurer premiums and predicted hurricane losses.[10] There are small differences in the lists of zip codes reported by each insurer and each catastrophe modeler. We focus on a balanced set of 882 zip codes that are present in every insurer rate filing and the catastrophe model data across years. These zip codes include 97% of the 2020 Florida population.

The panel is unbalanced on insurers. Early-year data are missing for firms that entered during the study period. The last several years are missing for three firms that recently began claiming exemption from public disclosure of their rates under trade-secret provisions: American Integrity stopped reporting publicly in

[10] In years where an insurer files multiple rate change, we use the final rate filing in that year. In a small number of cases where insurers do not file rates in a given year, we use the prior-year rates as these are still active.

Table 2: Florida Insured Housing Stock by Construction Type and Vintage

	Masonry	Frame	Other/Unknown
2007			
Pre-Florida Building Code	0.62	0.16	0.05
Post-Florida Building Code	0.13	0.03	0.01
2012			
Pre-Florida Building Code	0.57	0.15	0.05
Post-Florida Building Code	0.17	0.05	0.02
2017			
Pre-Florida Building Code	0.53	0.15	0.04
Post-Florida Building Code	0.20	0.06	0.02
2023			
Pre-Florida Building Code	0.44	0.13	0.04
Post-Florida Building Code	0.27	0.10	0.03
2025			
Pre-Florida Building Code	0.41	0.12	0.04
Post-Florida Building Code	0.29	0.10	0.03

Notes: Table summarizes snapshots of the stock of insured Florida homes in indicated years (2007, 2012, 2017, 2023, 2025). Panels report the share of homes by construction materials and vintage in each of these years. "Pre-Florida Building Code" refers to homes built through 2001.

2021, Florida Peninsula in 2022, and Tower Hill in 2024.[11] In auxiliary analyses we compare to results using a balanced panel.

We merge the premium data with the catastrophe model data by zip code and year. We merge premiums filed in a given year ("rate year") to expected loss data from the model vintage ("model year") in use when the rates were filed.[12] In analyses that compare premiums and expected losses, we focus on the premium for a 1990 masonry home with a $150,000 reconstruction cost, since these are the characteristics of the model home represented by the expected loss data.

In general, the standardized homes used to generate the expected loss data and the insurance premium data are quite similar. Both assume a masonry home built in 1989 or 1990 with $150,000 reconstruction cost, identical ancillary coverage limits (e.g., personal property coverage), and standard HO-3 policy terms. There are two salient differences. First, the insurance premium data assume a 2% deductible, while the expected loss data assume zero deductible. This means that the expected loss data assume a higher insurer loss amount than the insurance premium data, which will lead to conservative estimates of the pass-through of expected losses to premiums.

Second, the insurance premium data assume no investment in wind risk mitigation since the time of construction. The expected loss data take account of information on the local level of mitigation retrofits in a given zip code. Thus, naïve comparisons of the insurance premium and expected loss data may be biased given that retrofit takeup is likely to be higher in areas with higher hurricane hazard. We address this discrepancy between the data sources by taking advantage of additional information on the wind mitigation discounts offered by insurers. Since 2007, insurers in Florida have been required to offer standardized discounts based on the shape of the roof, the presence of structure opening protection, and other hurricane-resistant features (State of Florida, 2026). The large majority of insurers implement the default wind mitigation credits promulgated by Florida OIR (Form OIR-B1-1699, "Windstorm Mitigation Discounts; Single

[11] This recent action by these insurers invokes Florida Statute § 688.002, which defines trade secrets.

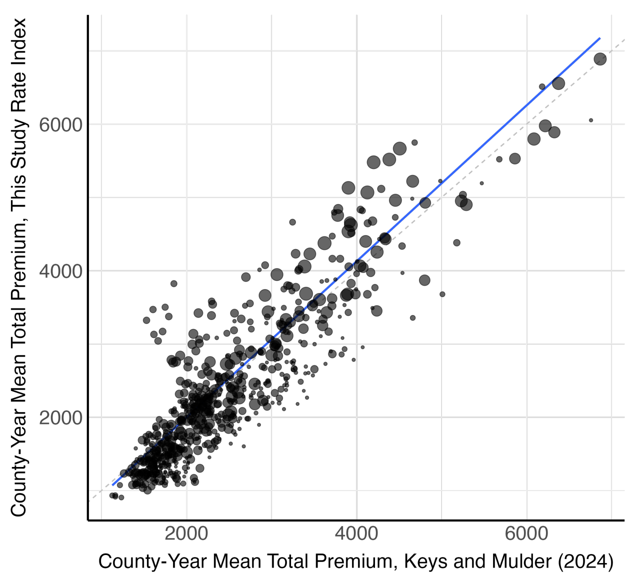
[12] The rate year generally lags the relevant model year by about two years due to the CAT model commission's review cycle. For example, a 2019 rate filing might use a 2017 model.

Family Residences"). We leverage the zip code-level building stock data from FHCF to calculate the share of 1990 masonry homes in every Florida zip code that have a hip roof, structure opening protection, or both. We then adjust the zip code level premium data to reflect the weighted average of wind mitigation discounts that would be received by pre-1994 masonry homes in that zip code. This adjustment to incorporate wind mitigation aligns the assumed mitigation features in the premium data with the expected loss data provided by model vendors.

The resulting panel includes annual premiums and expected hurricane losses for a standardized masonry home for every zip code and insurer from 2008 through 2025. Following convention in insurance rate analysis, our main specifications assume that the notional contract data remove the effects of inflation by holding reconstruction costs constant at $150,000.

Validity Test Using Mortgage Escrow Data. Rate filings describe insurance supply – the price at which an insurer would provide coverage for various properties – but do not reflect actual transactions, which also depend on consumers' purchasing behavior. As a check on the validity of the rate filing data as a measure of insurance prices paid by Florida homeowners, Figure 2 compares our data to revealed premium amounts from mortgage escrow data. The horizontal axis plots average insurance premiums at the county-year level for Florida during 2014–2024 from Keys and Mulder (2024). The vertical axis plots the county-by-year weighted average of premiums in our rate filing data.[13] The slope of the relationship is near one, meaning that the rate filing data are centered on the mortgage escrow data on average. The scatter around the line of best fit is mostly driven by small counties where small sample sizes in the escrow data or the market share data could drive deviations.

Figure 2: Rate Filing Data vs. Mortgage Escrow Data



Notes: Vertical axis is county-average insurance price in the rate filing data, weighted to reflect county-level insurer market shares and county-level building stock. Horizontal axis is county average premium from Keys and Mulder (2024). Every marker represents a single county-year between 2014 and 2024. The marker size varies based on the county number of insurance policies. The solid line is the best linear fit and the dashed line has a slope of 1.

[13] The weights reflect insurers' county-level market shares and the county-level share of homes in each reference home type category, as described in detail in Section 6.

3 Modeled Hurricane Risk

Before proceeding to econometric estimation in later sections, we first present new descriptive evidence on the evolution of modeled hurricane risk from this unusually detailed dataset. Insurers rely on these risk estimates to underwrite and price hurricane coverage. Proprietary catastrophe model projections are typically closely held between insurers and model vendors. The CAT model commission data reveal rarely-seen information about the variation in predicted hurricane losses over space, through time, and across model vendors.

We first examine current modeled risk across zip codes for the widely-adopted AIR model and then compare these estimates to those of the other CAT models. Second, we describe how the zip-level loss predictions from each model have evolved since the beginning of our data in 2006. Finally, we describe the estimated distribution of total annual losses from hurricanes for the state as a whole.

We focus on the four model vendors that have consistently sought certification from the CAT model commission in each review cycle. These are AIR, RMS, CoreLogic, and Florida's Public Model ("Public"). Three more models have selectively sought certification across years: Applied Research Associates, Karen Clark & Company, and Impact Forecasting. We include them in a time series showing model averages over time below (Appendix Figure 1).

3.1 Modeled Risk by Zip Code

We begin with current (2023) estimates of the risk from AIR, which created the first proprietary model and remains one of the most commonly used models by insurers. The top row of Panel (A) of Table 3 show the distribution of average annual losses (AALs) across the state according to AIR. The numbers reflect the expected loss per $100,000 of a home's replacement cost. The median AAL is $319. Thus, in the median-risk zip code, a home with replacement cost of approximately $200,000 (around the median for the state) would face annual expected loss from hurricanes of $638. The distribution is highly skewed: the 10th percentile zip code is a quarter of the median and the 90th percentile zip code is 3.2 times larger than the median.

Figure 3 maps the estimated risk, illustrating that expected losses are higher in the southern part of the state and greatest along the coastlines. The areas with the highest risk are zip codes in the southeastern counties of Palm Beach, Broward, and Miami-Dade, and the Florida Keys. The highest risk zip code is in Key West where the AAL is $2,571.

Risk estimates can vary substantially across models. Panel (A) of Table 3 reports the distribution of AALs for four models in 2023. The models differ in both the level and geographic variation in risk. For example, RMS estimates higher median risk but less variation than AIR. For the median zip code, RMS estimates an AAL of $387, about 20% larger than AIR's estimate, but the standard deviation of the RMS model is about half that of AIR ($209 versus $412). Disagreement across models is not exclusive to AIR and RMS. Comparing any two models in Panel (A) of Table 3 reveals notable differences in the level and/or variation in estimated risk. As another example, the median AAL for RMS is almost double that of CoreLogic.

While the models differ in their numeric estimates of the risk, they tend to agree on the ordering of locations. The Spearman rank correlation between AIR and RMS is 0.91, and is above 0.90 in each case when comparing the four models in Table 3.

Panel (B) of Figure 3 maps the ratio of AIR to RMS zip-level AALs so that values above one indicate a larger risk estimate from AIR while values below one indicate larger estimates for RMS. The figure shows that AIR's estimates are larger along the coasts, but RMS's estimates are larger almost everywhere else.[14] The differences are greatest in Key West where the AALs from AIR are 3.7 times larger than those of RMS. Based on our conversations with insurance industry experts using these models, the differences in modeled risk in southern Florida likely relates specifically to differing assumptions between model vendors regarding building code enforcement.

Panel C of Table 3 shows how the distribution of AALs has grown from the beginning to end of our period of study. We divide the 2023 AAL (Panel A) by the 2006 AAL (Panel B) for each model and zip code. The table shows that AALs grew by a median of 52% according to AIR and 59% according to RMS. The zip codes with the largest changes saw increases of 200% or more, while a small share of zip codes actually saw decreases in predicted losses.

Finally, Appendix Figure 1 shows how modeled expected losses evolved for all seven of the models during the time series. The figure shows the average AAL for each model for each year in which the vendor reported to the CAT model commission. Expected losses from AIR and RMS remain relatively flat for most of the time series and then grew substantially by 2019. This growth closely follows the devastating hurricane season of 2017 during which Hurricanes Harvey, Irma, and Maria created a combined total of $340 billion in losses (NOAA Office for Coastal Management, 2025). For the other five models, expected losses increase during

[14] As described above, the models rank locations by risk similarly: like AIR, RMS views the coasts as riskier than inland locations. The pattern in Panel (B) emerges because the AIR model has more variation in expected losses than the RMS model, resulting in both lower lows and higher highs for the AIR model.

Table 3: Hurricane Models' Expected Loss Summary Statistics

Panel (A): 2023

Model	Mean	SD	P01	P10	P50	P90	P99
AIR	460	412	55	87	319	1029	1916
RMS	425	209	100	170	387	689	1032
CoreLogic	332	329	40	64	204	746	1574
Public	339	180	75	105	308	535	926

Panel (B): 2006

Model	Mean	SD	P01	P10	P50	P90	P99
AIR	332	369	44	71	185	789	1734
RMS	344	311	32	62	250	710	1507
CoreLogic	271	310	13	22	135	682	1328
Public	316	175	41	69	294	550	755

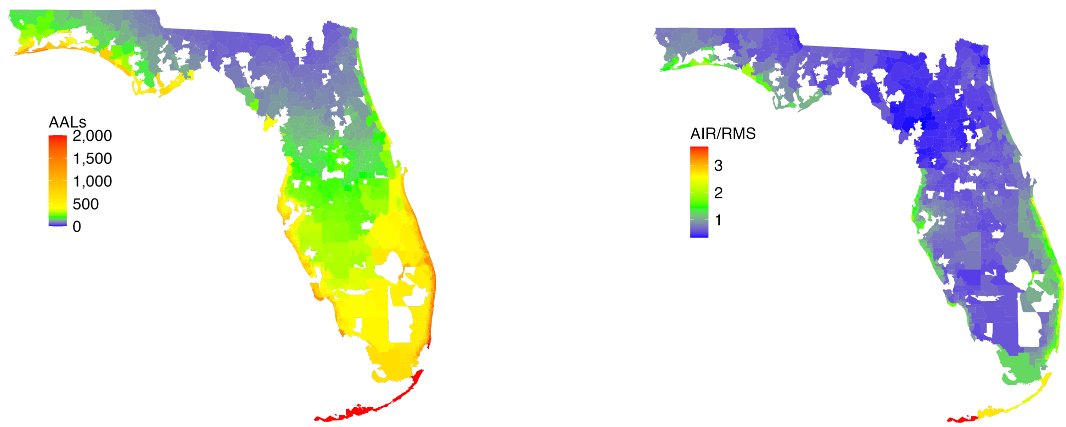
Panel (C): AAL Ratio

Model	Mean	SD	P01	P10	P50	P90	P99
AIR	1.60	0.53	0.64	0.98	1.52	2.32	3.02
RMS	1.90	1.01	0.54	0.86	1.59	3.45	4.30
CoreLogic	1.89	0.93	0.69	0.89	1.61	3.14	4.35
Public	1.16	0.30	0.78	0.87	1.07	1.56	2.14

Notes: Average annual losses (AALs) are the expected loss per $100,000 of a home's replacement cost. Estimates for a representative masonry exterior home built in 1989. "Public" refers to the hurricane model that is funded by the state. Panel (C) divides the 2023 AALs (see Panel (A)) by the 2006 AALs (see Panel (B)) for each zip code.

Figure 3: Modeled Expected Losses Across Zip Codes, 2023

Panel A: AIR **Panel B: AIR vs. RMS**



Notes: Panel (A) shows AIR's 2023 modeled average annual losses (AALs), which are the expected loss per $100,000 of a home's replacement cost. Estimates for a representative masonry exterior home built in 1989. The map shows the expected loss at the centroid of each zip code. Panel (B) divides the AALs from AIR by those of RMS for 2023.

the time series, but the timing, magnitude and persistence of the increase varies.

3.2 Statewide Aggregate Risk

The models' estimated exceedance probability curves are also useful for understanding the correlated nature of hurricane risk. Exceedance curves describe the cumulative loss distribution of a given portfolio of properties.[15] Insurers, regulators, and rating agencies use these curves to assess insurer solvency risks. For example, U.S. state regulators often want insurers to organize enough funding (through reserves, reinsurance, and equity capital) such that the annual chance of claims obligations exceeding this funding is less than 1% (NAIC, 2025).[16] Exceedance curves provide an estimate of the total loss corresponding to a given quantile (e.g., 0.01).

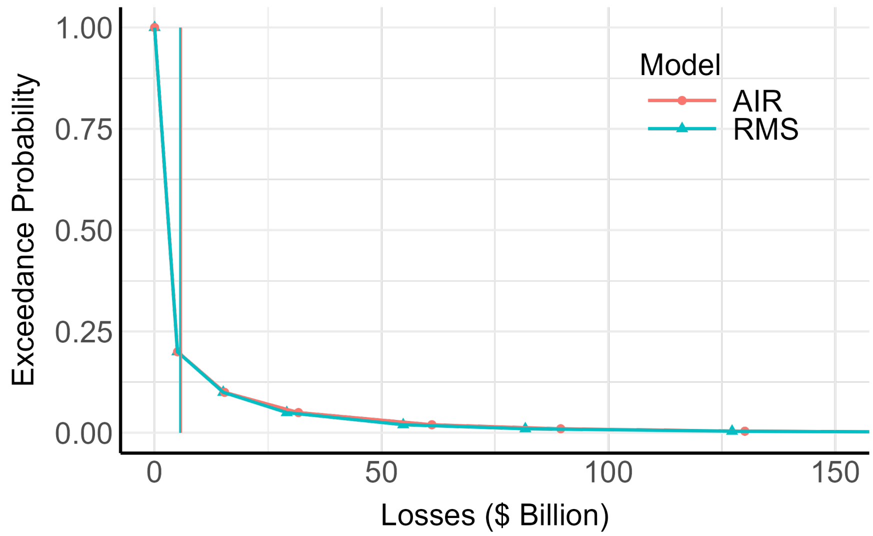
The CAT model commission asks model vendors to report exceedance curves for two portfolios. The first is a portfolio of effectively all properties in Florida (from the FHCF, see Section 2.2.3). We focus on this portfolio. The second is a notional portfolio, which includes a masonry home, a wood framed home, and mobile home, at the centroid of every zip code in the state.

Figure 4 provides the exceedance curves for AIR and RMS in 2023 for effectively all insured properties in the state. The vertical lines (which overlay each other) show the portfolio-level expected losses for each model, which are $5.87 billion for AIR and $5.59 billion for RMS. The right-most dots on the curves reflect the 0.40% exceedance probability and indicate portfolio losses of $130.1 billion for AIR and $127.3 billion for RMS. The corresponding values for the 1% exceedance probability are $89.5 billion for AIR and $81.7 billion for RMS. We have capped the figure for readability, but model vendors report estimates up to a 1 in

[15] Specifically, we refer to the aggregate exceedance probability (AEP) curve, which estimates the probability that the total loss in a year exceeds a given loss level. Given losses $X_1, X_2, \ldots, X_N$, the exceedance curve is defined as: $AEP(x) = \mathbb{P}(X_1 + X_2 + \cdots + X_N > x) = 1 - \mathbb{P}(X_1 + X_2 + \cdots + X_N \leq x)$. An exceedance probability curve is therefore simply the complement of the cumulative distribution function.

[16] Other jurisdictions, such as the European Union – where the largest reinsurers in the world are located – employ a more stringent standard of 0.5% (Gatzert and Wesker, 2012; Chaplin and Adams, 2024).

Figure 4: Exceedance Probability Curves, 2023



Notes: The figure shows exceedance probability curves for AIR and RMS in 2023. The modeled portfolios include effectively all residential properties in Florida. Losses are in billions of dollars. The vertical lines provide the portfolio-level expected loss, which was $5.87 billion for AIR and $5.59 billion for RMS in 2023. From left to right, the points on the curves mark the 100%, 20%, 10%, 5%, 2%, 1%, and 0.4% exceedance probabilities.

10,000 exceedance probability.

We draw attention to two aspects of Figure 4. First, the correlated nature of hurricane losses is large: insurers need to organize funding to cover around 15 times the expected loss (e.g., $89.5B / $5.87B) to meet standard solvency regulation requirements. As a result, insurers in Florida rely heavily on reinsurance. Second, while the property-level estimates from AIR and RMS can differ significantly (as described above), their portfolio estimates are similar. These vendors estimate portfolio expected losses and 1% exceedance probability losses that are within 5-9% of each other. We will return to exceedance probabilities when discussing mechanisms for our primary results in Section 5.

4 Pricing Hurricane Risk

This section examines the prices charged by insurers to cover hurricane risk. Section 4.1 describes the distribution of prices, including across the state and over time. Section 4.2 lays out the empirical strategy for measuring the price of hurricane risk and Section 4.3 presents the results.

4.1 Pricing Descriptives

Table 4 describes the data. The first panel shows hurricane premiums for 1990 masonry homes, accounting for average wind mitigation discounts in each zip code as described in Section 2.2.4. This is the main measure of hurricane premiums used throughout this section. The mean hurricane premium is $1,862, which is nearly 4 times the average expected loss. Because of the dominance of the AIR and RMS models, we use the mean of the AALs from those two models as our main expected loss variable. We also consider the AAL from the model(s) used by each insurer to justify their rates and the mean AAL across all models.

Using any of these risk measures, premiums are on average at least 3.5 times the expected loss for these homes.

The remaining three panels show hurricane and non-hurricane premiums for the three notional home types in the OIR data. Hurricane premiums for post-code and fully mitigated pre-code homes are smaller than hurricane premiums for completely unmitigated homes by about two-thirds. Non-hurricane premiums vary less across notional structures, but are also somewhat lower for post-code and fully mitigated homes.

Figure 5 shows the geographic variation in hurricane premiums in 2024. The highest hurricane premiums are for vulnerable pre-code construction in Southeast Florida. Total premiums for these homes can exceed $15,000 per year, almost all of which is the hurricane premium. Premiums also vary with structure vulnerability. Hurricane premiums for a 2005 (post-code) home in the highest-hazard areas are roughly one-third of those for a 1990 (pre-code) home, holding constant coverage levels and occupant characteristics.

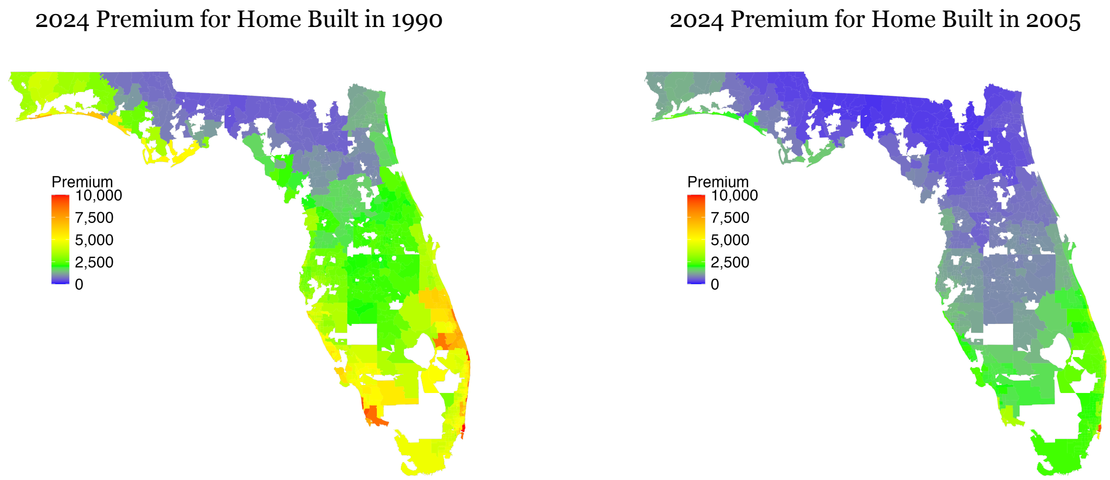
Figure 6 provides graphical evidence on the relationship between premiums and predicted hurricane losses at the zip code level. Panel (A) considers hurricane premiums. Each marker represents the market share-weighted average of insurer's premiums for a pre-code masonry home in a given zip code and time period. The horizontal axis shows the property AAL. The figure shows a linear trend line for each time period. The intercepts are near zero in all years, implying that homes facing negligible hurricane risk pay negligible hurricane premiums. The approximate slope of the premium-risk relationship was about 2 during 2008–2013 and was just below 4 during 2020–2025. Panel (B) shows that non-hurricane premiums are much less correlated with predicted hurricane losses.

Table 4: Prices and Expected Hurricane Losses For Notional Insurance Contracts

	Mean	SD	p5	p50	p95
1990 Masonry Home, Local Average Wind Mitigation					
Hurricane Premium	1,862	1,910	260	1,235	5,410
Hurricane Expected Loss (RMS, AIR)	493	373	97	385	1,250
Hurricane Expected Loss (Model Used by Insurer)	490	420	89	358	1,344
Hurricane Expected Loss (All Models)	504	396	77	371	1,297
1990 Masonry Home, No Wind Mitigation					
Hurricane Premium	2,208	2,499	267	1,362	6,693
Non-Hurricane Premium	1,655	1,482	638	1,257	3,846
1990 Masonry Home, Maximum Wind Mitigation					
Hurricane Premium	713	751	82	458	2,125
Non-Hurricane Premium	1,190	752	455	998	2,633
2005 Masonry Home					
Hurricane Premium	771	796	114	535	2,145
Non-Hurricane Premium	1,122	793	405	888	2,657

Notes: Dataset contains 223,428 zip-insurer-year observations. Statistics are calculated across zip codes, insurers, and years without weighting on population (in this table only). Premiums are annual premiums for the notional homeowners insurance contracts described in Section 2.2.2. Expected losses are average annual losses from the indicated set of models. "RMS, AIR" is the mean of those two models; Model Used by Insurer is the model(s) indicated by the insurer in the rate filing; and All Models is the mean of all approved models.

Figure 5: Average Hurricane Premiums in 2024



Notes: Figure shows zip code-level market share-weighted average hurricane premiums across all insurers in 2024. Left column shows premiums for 1990 masonry home with local average amount of wind mitigation; right column shows 2005 masonry home. Scale is top-coded at $10,000.

4.2 Empirical Design

This section describes how we use observed variation in insurance premiums and catastrophe model estimates of expected losses to measure insurer-specific pricing of hurricane risk. The standardized premium and expected loss data compiled in this study are unusually well-suited for this task. Premium data reported from mortgage escrow accounts (e.g., ICE-McDash, Blonz et al., 2026; Keys and Mulder, 2024; Sastry et al., 2024) reflect substantial unobserved heterogeneity across customers in coverage features (e.g., liability risk coverage), structure characteristics (e.g., roof shape), and occupant characteristics (e.g., claims history). To the extent that these unobserved determinants of premiums correlate with hurricane risk, they may introduce substantial omitted variables bias in an OLS regression of premiums on expected hurricane loss.

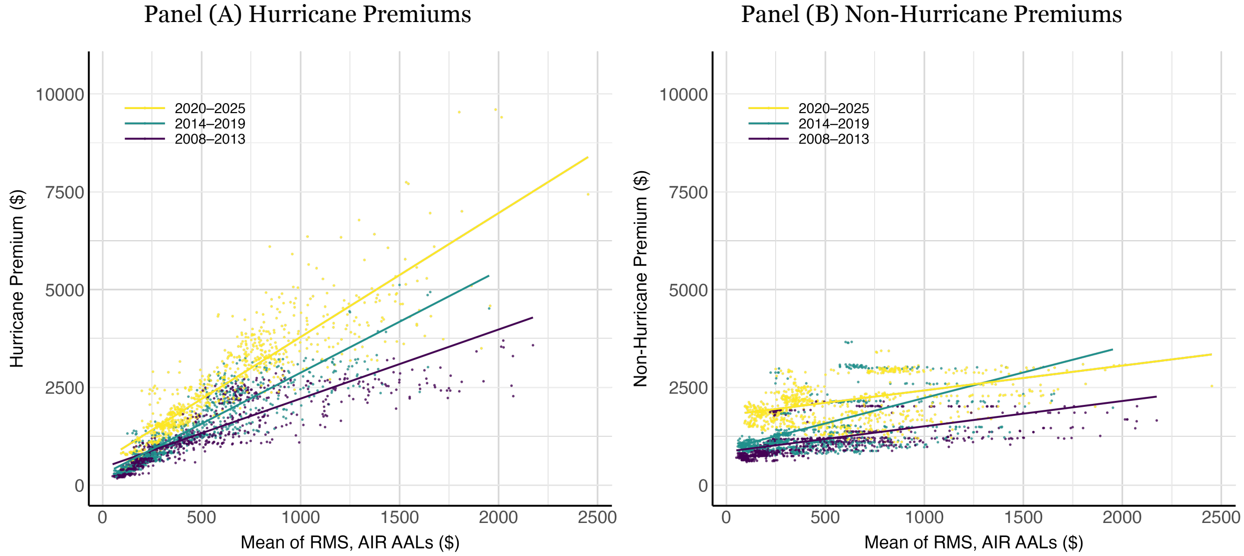
In contrast, we observe premiums and expected losses for a consistent contract that explicitly holds constant all of these features. In addition, we observe premiums disaggregated into hurricane risk and all other factors, which further helps to limit confounding in our analyses. We address any remaining concerns about identification through an extension of our main specification that leverages natural experiment-style variation in modeled hurricane losses due to a major update to the catastrophe models in the 2019 model review cycle following Hurricanes Harvey, Irma and Maria.

Our main specification leverages variation over space and across time in predicted hurricane losses:

$$y_{i(j)t} = \beta \text{AAL}_{i(j)t} + \gamma_{jt} + \epsilon_{i(j)t}. \tag{1}$$

where $y_{i(j)t}$ is premium for insurer j in that insurer's territory i and year t. Following Boomhower et al. (2024), we estimate this regression on territory-level data to most accurately capture insurers' pricing decisions. In a pre-processing step, we aggregate premiums and AALs to weighted territory-level means for each insurer, weighting by zip code population times county-level insurer market share. The insurer-by-year fixed effects γ_{jt} in Equation 1 allow the intercepts to vary for every insurer in every year. The coefficient

Figure 6: Premiums vs. Hurricane Risk by Time Period



Notes: Data are an unbalanced insurer-by-zip-by-year panel of premiums for a standardized masonry home. Horizontal axis shows the simple mean of RMS and AIR modeled average annual hurricane losses for the standardized home. Plot shows weighted average premium by zip code, where weights are the product of county-level insurer market share and zip code population.

of interest β measures the average relationship between premiums and predicted hurricane losses across insurers and years. We weight every insurer-by-territory observation in this regression by the total implied customers that it represents (that is, the sum of the weights from the aggregation step that goes from zips to territories). Thus, the final weighted regression reflects the distribution of population and insurer market shares across the state.[17]

While our standardized premium and expected loss data hold constant many important factors, it is still possible that estimates of β from Equation 1 may suffer from omitted variables bias if the spatial variation in hurricane risk correlates with non-hurricane risk factors (e.g., crime risk). To address any remaining concerns about omitted variables, we explore an additional empirical design that leverages variation in modeled hurricane risk from catastrophe model updates, allowing us to examine the effects of a change in modeled risk on premiums within a given location. We focus on the major changes in the AIR and RMS AALs in the 2019 model update cycle (Appendix Figure 1). These updated models began to be used for pricing in 2022 or 2023, depending on the insurer. We limit the dataset to 2021 and 2023 premiums and run the following regression:

$$y_{i(j)t} = \beta \text{AAL}_{i(j)t} + \gamma_{jt} + \psi_{i(j)} + \epsilon_{i(j)t}. \tag{2}$$

Including firm-by-territory fixed effects $\psi_{i(j)}$ means that estimates of β are now identified only by within-territory changes in predicted hurricane losses due to the CAT model update (as opposed to comparisons across rating territories). There was substantial variation in these territory-specific changes. The average increase was about \$230, while the 10th and 90th percentiles were \$80 and \$400. By leveraging within-territory changes in modeled expected losses, this approach shuts down any cross-sectional omitted vari-

[17] Three insurers in the sample revised their territories during our period of study, moving from territories covering a rather broad geography to pricing by zip code or finer (Appendix Table 4). We account for the contemporary territory when estimating Equation 1. No insurer changed their territory definitions during the more limited time period that we focus on when estimating Equation 2. While aggregating AALs to the territory level most accurately captures pricing responses (Boomhower et al., 2024), estimating Equation (1) at the zip code level yields qualitatively similar results with the expected attenuation.

ables bias and nets out common time varying shocks that affected all territories. We view these updates as generating plausibly exogenous revisions in a property's estimated expected loss based on modeling advances, which the vendors document in their reports (AIR, 2023).

4.3 Regression Results

We begin with results for Equation 2, the natural experiment caused by a major CAT model update that was adopted for pricing starting in 2022/2023. Table 5 shows that a 1-dollar increase in expected hurricane losses in a given location increased hurricane premiums by about $3.9. For a territory with the average risk increase of $230, this regression implies a price increase of about $900. We return to this discussion of overall price changes in Section 6.

Table 5: Price of Hurricane Risk – Pass-through of a Major Model Update

	Hurricane Premium
RMS, AIR AAL	3.90*** (0.393)
Company-Year FE	✓
Company-Territory FE	✓
Observations	8,907
Dep. Var. mean (wtd)	2,283.7
R^2	0.98

Notes: Table shows OLS regression. The dataset is restricted to years 2021 through 2023. Regression includes weights equal to the firm's implied number of customers by territory. Standard errors are clustered by county.

We now expand the design to use all of the variation across years and territories as in Equation 1. Table 6 reports our main results on the overall price of hurricane risk. Column (1) omits the company-by-year fixed effects. Consistent with the graphical evidence in Figure 6, the estimated constant term is small (6.7% of the mean hurricane premium), implying that hurricane premiums are minimal in areas without substantial hurricane risk. Column (2) adds the company-by-year fixed effects and finds that the slope of hurricane premium with respect to hurricane AAL is about 3.43 across insurers and years, a slightly smaller average effect than in Table 5. Column (3) shows that this difference is explained by the time period of analysis; the slope of price with respect to risk has increased over time. The estimated slope during the 2020–2025 period is 4.17, which closely matches the natural experiment result using 2021 through 2023 data. Column (4) shows that the results are robust to restricting to a balanced panel of firms and years.

Our primary specification uses the mean of the AIR and RMS models. While effectively all insurers report using either AIR or RMS in their regulatory rate filings, meaningful disagreements among the models could motivate several strategies among insurers, including setting prices based on an ensemble of models (e.g., taking the mean or median) or increasing premiums to account for ambiguity in locations where models disagree (e.g., Kunreuther et al., 1995; Heitfield, 2025).[18]

Table 7 shows the relationship between prices and alternative model outputs. Column (2) uses the mean of all models (specifically, the mean of all CAT models that were approved for use in each year in the data). This regression has a nearly-identical R^2 and a slightly attenuated slope relative to the benchmark specification in Column (1). Such attenuation is consistent with the hypothesis that insurers primarily use AIR and

[18] Each insurer must show that their final hurricane rates can be supported by a single model within an acceptable margin of error, but nothing prevents them from using multiple models internally to develop these rates. Insurer prices may also indirectly reflect the CAT models used by reinsurers to price reinsurance treaties.

Table 6: Average Price of Hurricane Risk

	Hurricane Premium			
	(1)	(2)	(3)	(4)
Constant	131.2* (73.4)			
RMS, AIR AAL	3.21*** (0.176)	3.43*** (0.087)		
RMS, AIR AAL × 2008-2013			2.42*** (0.148)	2.78*** (0.158)
RMS, AIR AAL × 2014-2019			3.41*** (0.057)	3.15*** (0.056)
RMS, AIR AAL × 2020-2025			4.17*** (0.154)	3.65*** (0.144)
Company-Year FE		✓	✓	✓
Panel	Unbalanced	Unbalanced	Unbalanced	Balanced
Observations	67,859	67,859	67,859	42,988
Dep. Var. mean (wtd)	1,955.8	1,955.8	1,955.8	1,855.9
R^2	0.43	0.77	0.79	0.79

Notes: Table shows OLS regressions. All regressions include weights equal to the firm's implied number of customers by territory. Standard errors are clustered by county.

RMS, such that regression on the all-model mean is attenuated by noise from the other estimates. Column (3) takes the AAL from the CAT model that each insurer uses to formally justify their rates in each rate filing year. Again, the R^2 is extremely similar and the coefficient is attenuated with respect to Column (1). This pattern of results is consistent with insurers putting the largest weight on AIR and RMS, perhaps to the point of ignoring other models. It is also consistent with conventional wisdom discussed earlier about a risk modeling "duopoly" and the homogeneity among insurers in model choice in Table 1.

Table 7: Average Price of Hurricane Risk, Additional Specifications

	Hurricane Premium		
	(1)	(2)	(3)
RMS, AIR AAL	3.43*** (0.087)		
All-Model Mean AAL		3.00*** (0.086)	
AAL from Firm's Reported Vendor			3.17*** (0.078)
Company-Year FE	✓	✓	✓
Observations	67,859	67,859	67,859
Dep. Var. mean (wtd)	1,955.8	1,955.8	1,955.8
R^2	0.77	0.77	0.77

Notes: Table shows OLS regressions. "RMS, AIR AAL" is the mean of the RMS and AIR territory-level hurricane AALs. All-Model Mean AAL is the mean of territory-level AALs from all approved CAT models. Firm's Reported Vendor is the model vendor used to justify hurricane factors in the annual OIR rate filing. All regressions include weights equal to the firm's implied number of customers by territory. Standard errors are clustered by county.

5 Mechanisms & Extensions

Why do consumers pay so much in premiums relative to expected hurricane losses? We explore this question further in this section. Premiums loads may largely reflect the cost of holding tail risk.

To ground ideas on the costs of tail risks, consider the exceedance curves in Figure 4. These curves describe modeled hurricane loss probabilities for the portfolio of effectively all homes in Florida. The exceedance curve reflects the full geographic diversification potential in the state but also portfolio concentrations in population centers (e.g., Miami, Tampa, Jacksonville, etc.). As a reminder, this distribution has an expected loss of \$5.9 billion and a 1% probability loss exceedance (often used as a solvency target) of \$89.5

billion. Suppose that a single insurer held this portfolio. A back-of-the-envelope calculation suggests that maintaining $83.6 billion in equity above the expected loss would cost the insurer around $8.36 billion a year: equity investors in property and casualty insurance expect a return on equity of about 10% according to industry benchmarks (e.g., see Kunreuther and Michel-Kerjan, 2011; Swiss Re Institute, 2024). Thus, capital costs could be roughly 1.4 times the portfolio expected loss.

While illustrating tail risk concepts, this stylized example is unrealistic for at least two reasons. First, insurers can use reinsurance instead of holding such large equity reserves. Second, insurers operating in Florida are typically less diversified, specializing geographically and in certain market segments, than the stylized statewide portfolio described above. Below, we discuss reinsurance and then the Florida insurance market structure, which relies on insurers who operate almost exclusively in the state to provide insurance in the most hurricane prone areas. These mechanisms interact: state insurers are less diversified than national insurers so rely more heavily on reinsurance.

5.1 Reinsurance

Reinsurance might affect hurricane insurance premiums in Florida through two distinct channels. The first possibility is that climate change has led to larger storms that affect more properties at once. If so, growing risk would not only increase property-level expected losses, but thicken the tail of the loss distribution, requiring insurers to expand their reinsurance coverage.

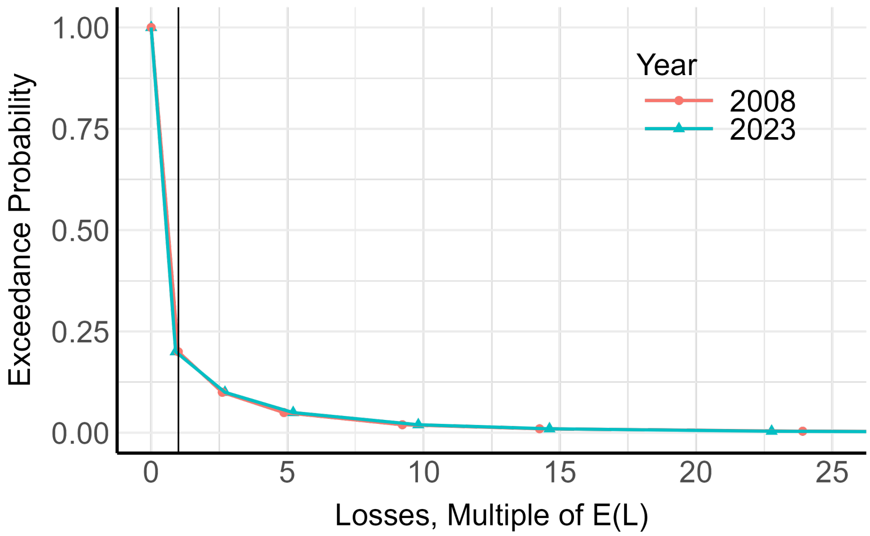
To explore this possibility, we return to the models' exceedance probability curves. Figure 7 compares the exceedance curve estimated by RMS in 2008 to that in 2023 for the portfolio of effectively all insured properties in Florida.[19] To facilitate comparisons over time, we report losses as multiples of the expected loss in each year (i.e., the 2023 curve is divided by the mean value in 2023). The black vertical line intercepts the horizontal axis at 1, showing the expected loss relative to other points on the curve. The figure shows that, after demeaning the 2008 and 2023 curves, they are effectively identical, indicating that the estimated tail risk has not changed. We provide additional exceedance curves in Appendix 2. Those include a similar figure for AIR and statistics on the notional portfolio, which includes three houses (a masonry home, a wood home, and a mobile home) for each zip code in the state. An attractive feature of this notional portfolio is that it holds the set of properties fixed over time. These additional curves similarly support the conclusion that the dramatic rise in premiums is not due to changes in the modeled tail risk.

A second channel through which reinsurance might contribute to the rise in insurance premiums is through changes in reinsurance costs over the reinsurance pricing cycle. Reinsurance prices are volatile, often increasing after large loss events that deplete reinsurers' equity capital (Froot and O'Connell, 1999). Figure 8 tracks insurers' expected hurricane costs per policy from their rate filings, using the same portfolio-level data as in Figure 1, but extending the time series. These expected costs are for the insurer's portfolio of insured homes in Florida. We focus first on the leftmost panel, which aggregates all the insurers in our sample. The blue bars describe the average modeled expected hurricane losses. In contrast to the CAT model data used in Sections 3 and 4, which estimate the risk for a pre-code masonry home, the expected hurricane losses here reflects an average across all the types of homes in an insurer's Florida portfolio.

The striking feature of Figure 8 is how insurers' net reinsurance costs vary across the reinsurance cycle. Reinsurance prices were high following Hurricane Katrina in 2005, declined in the early 2010s, and

[19] 2008 is the earliest available exceedance probability curve data.

Figure 7: RMS Exceedance Curves, 2008 vs. 2023



Notes: The figure reports the exceedance curve as multiples of the expected loss. From left to right, the points on the curves mark the 100%, 20%, 10%, 5%, 2%, 1%, and 0.40% exceedance probabilities. It shows that losses at the 1st percentile of the distribution are about 15 times the expected loss in both 2008 and 2023.

then rose again from 2018 to 2024. The pattern follows aggregate measures of reinsurance prices such as Guy Carpenter's Rate-on-Line (ROL) Index for U.S. property and casualty risks (Guy Carpenter, 2024, see Appendix Figure 3).

As we describe above when discussing Figure 1, the aggregate measures in the barplot can mask compositional changes in the portfolios of these large insurers. For example, while we document a 50% increase in expected losses for pre-code masonry homes using data from the CAT models in Section 3, no clear pattern is visible in the blue bars of the leftmost panel, which may reflect the largest private insurers shifting toward lower risk areas or insuring mitigated homes.

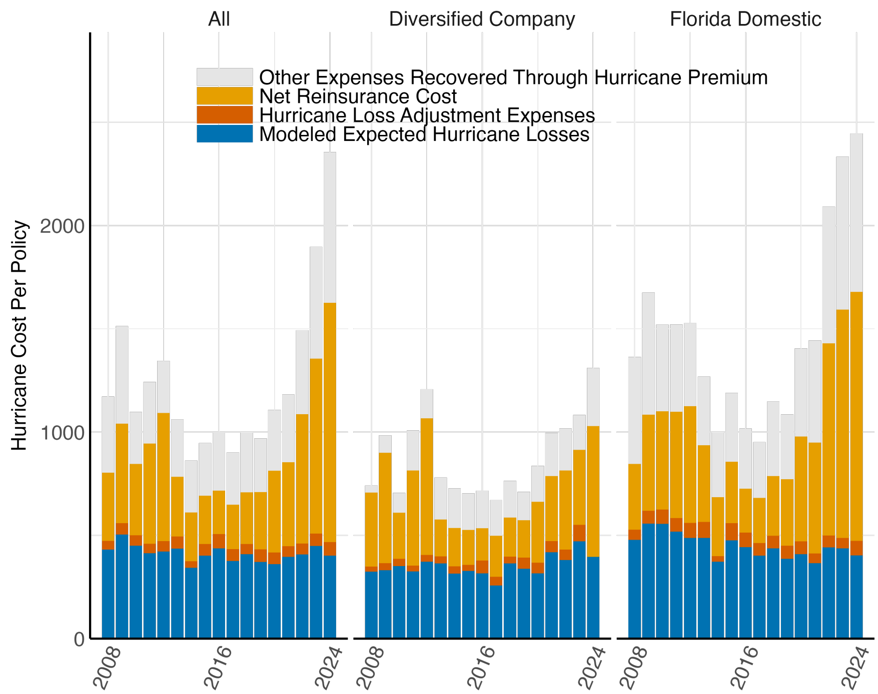
To address these compositional concerns, we return to our zip-code level dataset describing expected hurricane losses and insurance prices for the modal Florida home (pre-code, masonry) that we used in the price analysis in Section 4. We interact the home's AAL (mean of RMS and AIR) with the reinsurance ROL index. While AALs vary across zip codes and time, ROL is a global measure and only varies with time.[20]

Table 8 reports the results. The first column, which includes only insurer fixed effects, shows that the base level of ROL does not have a statistically significant effect on hurricane premiums. The point estimate is small: a 10% increase in reinsurance prices changes hurricane premiums in a zip code with zero hurricane AAL by about $13. The interaction term, however, is positive and statistically significant, indicating that reinsurance price changes increase premiums more in higher risk territories. The second column includes year fixed effects, which absorb arbitrary annual trends in ROL and average hurricane premiums. The interaction term remains positive and significant.

Insurance linked securities (ILS) are financial products that act as substitutes for traditional reinsurance

[20] ROL measures the price of reinsurance per dollar of coverage relative to a base year (2000 in this case). Guy Carpenter reports ROL as a percentage; we divide the value by 100. Thus, an ROL of 1.10 indicates a 10% increase relative to reinsurance prices in 2000.

Figure 8: Hurricane-Related Costs for Florida Homeowners Insurers Over Time



Notes: Data are from Florida Office of Insurance Regulation Standardized Rate Indications Workbook. The figure allocates insurer's expenses per policy from 2008 to 2024. "Net Reinsurance Cost" is the difference between premiums paid to reinsurers and the expected losses transferred to the reinsurer. "Other Expenses Recovered through Hurricane Premiums" reflect variable expense factors applied by the insurer per dollar of hurricane premium. The leftmost panel includes all private insurers in our data. The other two panels subset the "All" insurers panel into two mutually exclusive types of insurers. The middle panel, "Diversified Company," includes insurers that operate in several states or are part of a multi-state insurance group (e.g., State Farm Florida is a subsidiary of State Farm). The rightmost panel, "Florida Domestic," includes insurers who operate almost exclusively in Florida.

and are playing an increasing role in insurers' reinsurance arrangements (Polacek, 2018). Instead of being backed by a reinsurer, capital market investors (e.g., hedge funds, investment banks) bear the risk of loss for ILS. Catastrophe bonds are the most common form of ILS.[21] The contracts loads for catastrophe bonds are around 4-to-1 (Artemis, 2026) – insurers pay roughly four times the expected loss to cover tail risk exposure through a catastrophe bond – so is similar to the premium loads that we estimate in the primary insurance market. The growth of the catastrophe bond market suggests that these loads are at least as attractive as those offered by traditional reinsurers to cover similar risks. The reinsurance expenses in Figures 1 and 8 reflect a combination of traditional reinsurance and ILS costs.

5.2 Market Structure

Another contributing factor is that Florida's insurance market relies on state-level insurers, especially in areas most prone to hurricane risk. Prior to the severe hurricanes of 2004 and 2005 (e.g., Charley, Katrina, Rita, and Wilma), national insurers covered a larger share of the market (Citizens, 2025). Following those events, national insurers took steps to limit their exposure. National insurers began selling insurance

[21] Catastrophe bonds are special purpose investment vehicles structured like corporate bonds in that the investor receives a stream of coupon payments for holding the risk, but if a catastrophe occurs, the investor may lose their principal (and future coupons), which would then flow to the issuing insurer to cover insured losses. Braun and Kousky (2021) provide a primer.

Table 8: Passthrough of Reinsurance Prices to Hurricane Premiums

	Hurricane Premium	
	(1)	(2)
RMS, AIR AAL	3.22*** (0.086)	3.29*** (0.086)
RMS, AIR AAL × Rate-on-Line Index / 100	0.917*** (0.132)	0.803*** (0.123)
Rate-on-Line Index / 100	-125.1 (131.0)	
Company FE	✓	✓
Year FE		✓
Observations	67,859	67,859
Dependent variable mean (wtd)	2,141.0	2,141.0
R^2	0.68	0.70

Notes: Table shows OLS regressions. "RMS, AIR AAL" is the mean of the RMS and AIR territory-level hurricane AALs. Rate-on-Line Index is the Guy Carpenter U.S. Property Reinsurance Rate-on-Line index. All regressions include weights equal to the firm's implied number of customers by territory. Standard errors are clustered by county.

through subsidiaries, insulating the parent company. For example, State Farm now offers coverage through "State Farm of Florida" and Allstate sells coverage through its subsidiary "Castle Key." This transition seems to reflect national insurers' concerns about tail risks. For example, in the event of a severe hurricane that leads to the insolvency of several insurers, the surviving insurers may need to help fund the claims of the failed insurers via the state's insurance guaranty fund (Abramson et al., 2025). Subsidiaries can still benefit from connection with a parent company, including through access to "affiliated reinsurance" by which an insurer purchases coverage from a reinsurer in the same company group. The contraction of national insurers has been partly filled by "Florida Domestic" insurers who operate almost exclusively in the state (Sastry et al., 2026). These state-level insurers would seem to have less capacity to manage risk through diversification than subsidiaries of national insurance groups.

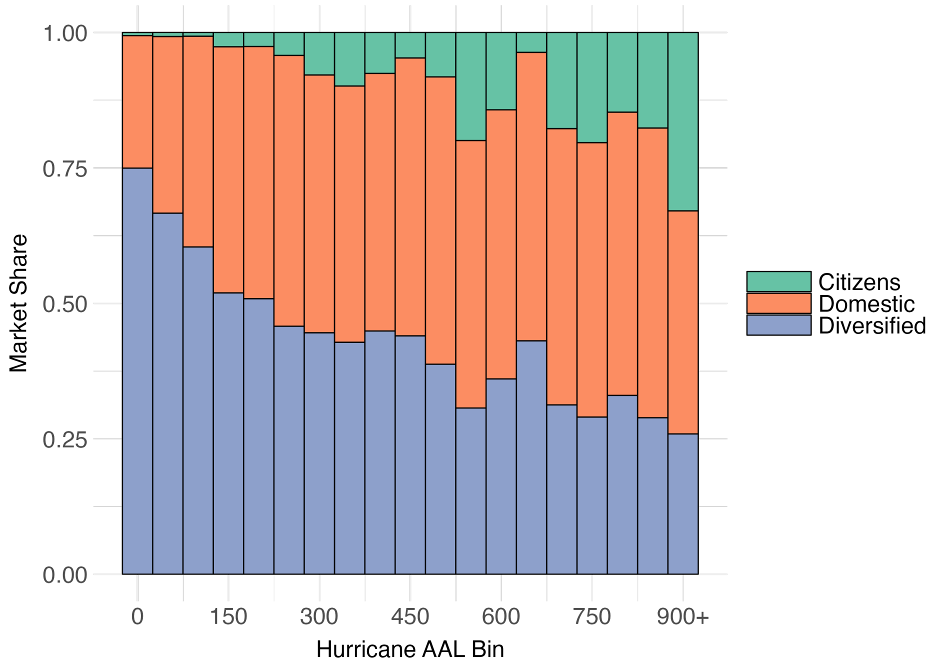
National insurance groups have also limited their exposure by operating in the areas of the state with the lowest hurricane risk. Figure 10 compares hurricane risk and market shares for Florida Domestics, Citizens, and "Diversified Companies," which comprise national insurance groups who are mostly represented by subsidiaries. The horizontal axis reflects binned county-level hurricane AALs.[22] The figure reflects average market shares across our period of study, which have remained remarkably stable. We include all insurers in the state to be comprehensive; however, the figure is similar if we restrict to our regression analysis sample, the insurers for whom we have collected rate filings.

The figure shows that national insurers dominate the lowest risk counties, selling between 60 and 75% of policies in the bottom decile of the hurricane risk distribution. Florida domestics sell all the remaining policies in these low risk areas, suggesting that homeowners can access insurance there without Citizens, the state-run insurer-of-last-resort. As hurricane risk grows, the Diversified Company participation decreases, and Citizens participation increases, almost monotonically. In the highest risk decile, Diversified Companies cover roughly a quarter of policyholders, Domestics cover half, and Citizens insures the rest.

Returning to the insurer cost data in Figure 8, the middle and rightmost panels in that figure similarly divide insurers into Diversified and Florida Domestic insurers. It illustrates that the costs in excess of expected loss are typically much larger for the Domestics, including for reinsurance. Moreover, these costs are more volatile across the reinsurance cycle.

[22] We use county averages because market share data is only available by county. The market share data reflects all insurers and is not publicly available. The publicly available version excludes some insurers who do not report market shares due to "trade secrets" (Florida Office of Insurance Regulation, 2024b). The county-level averages are weighted by zip-code population.

Figure 9: Insurer Market Share by Hurricane Risk



Notes: Figure reports aggregated market share data for 2008–2024 for firms in our data. Counties are assigned to risk bins based on the population-weighted average of zip code AALs from RMS and AIR.

As noted before, these barplots can mask compositional differences, motivating us to return to regression using the analysis sample.[23] In Table 9, we regress hurricane premiums on AALs for each type of insurer using our analysis sample. We use interaction terms to examine the relationship between AALs and premiums separately during different eras of our data: early (2008-2013), middle (2014-2019), and late (2020-2025). In the last five years, a dollar increase in AAL leads to a $3.98 increase in hurricane premiums by Diversified Companies versus a $5.06 increase by Florida Domestics. The pass-through for Citizens is smaller ($2.89), presumably because it capped rate increases to no more than 15% during this time (Citizens, 2024). The higher prices of Florida Domestics align with the expectation that these insurers have less capacity to diversify than national insurance groups and so they need to rely more heavily on costly reinsurance or capital reserves. Indeed, using the financial statements of all Florida Domestics during our period of study, we find that on average, for every dollar in premium a Florida Domestic insurer receives, it spends $0.58 on reinsurance.

6 Market-wide Price Indices

We now turn from policy-level pricing of hurricane risk to explore market-wide trends in prices. We use the new data to construct an index of homeowners insurance prices that summarizes average premiums over time for homes with varied hurricane vulnerability. We validate the approach by showing that the resulting price index closely corresponds to average premiums from transaction data. We then use the price indices to understand premium trends over a longer historical period than exists in the transaction data, to reveal

[23] As one example of the differences between the types of insurers, Diversified insurers typically insure higher value homes than Florida Domestics.

Table 9: Average Price of Hurricane Risk by Insurer Type

Insurer Type	Florida Domestics (1)	Hurricane Premium Diversified Companies (2)	Citizens (3)
RMS, AIR AAL × 2008-2013	2.32*** (0.078)	3.81*** (0.157)	1.55*** (0.219)
RMS, AIR AAL × 2014-2019	3.92*** (0.106)	2.84*** (0.124)	2.59*** (0.383)
RMS, AIR AAL × 2020-2025	5.06*** (0.148)	3.98*** (0.167)	2.89*** (0.564)
Company-Year FE	✓	✓	✓
Observations	21,887	44,294	1,678
Dependent variable mean (wtd)	2,038.3	2,222.7	1,321.6
R^2	0.83	0.77	0.67

Notes: Table shows OLS regressions. All regressions include weights equal to the firm's implied number of customers by territory. Standard errors are clustered by county.

the relative contributions of hurricane vs. non-hurricane risks, and to show the extent to which prices vary with investments in structure-level risk mitigation.

6.1 Constructing the Price Index

Our data include zip-level premiums for 16 insurers for different types of masonry homes in 882 zip codes. The premium index for each year is a weighted average of these prices. Each zip-year-insurer-home type observation receives weight

$$w_{jzst} = \frac{1}{N_t} n_{zst} q_{jc(z)t},$$

where n_{zst} denotes the number of homes in zip code z of structure type s in year t, $q_{jc(z)t}$ is the market share for insurer j in county c in year t, and $N_t = \sum_z \sum_s n_{zst}$ denotes the total number of Florida homes in year t. Intuitively, these weights represent the share of Florida homeowners in each of the cells in the data. We draw on auxiliary data on the local building stock and insurer market shares to calculate weights that reflect market outcomes as closely as possible.

We construct n_{zst} using data from the FHCF on the universe of HO-3 policies in Florida in 2007, 2012, 2017, 2023, and 2025. These data include year built and measures of hurricane risk mitigation. We subset the FHCF data to masonry homes (73 – 75% of homes depending on year) and use them to identify the composition of the building stock in each zip code, covering five masonry structure types: pre-code without hip roof or structure opening protection, pre-code with both, precode with hip roof only, precode with structure opening protection only, and post-code (built 2002 or later).[24] We calculate prices for the various pre-code home types by applying the insurance regulator's default wind mitigation credits (OIR-B1-1699) to the reported no-mitigation insurance premiums.

To construct $q_{jc(z)t}$, we use auxiliary data on annual county-level insurer shares of total HO-3 policies. This implicitly assumes that market shares are constant across zip codes within counties.

We apply these sample weights to calculate annual index values for hurricane premiums p_h according to

$$\sum_j \sum_z \sum_s w_{jzst} p_h,$$

[24] For each year t in the premium data, we use FHCF data from the nearest of the reported years (2007, 2012, 2017, 2023, and 2025).

and analogously for non-hurricane premiums p_{nh}. The annual index value can be interpreted as the average annual premium across insurers for a masonry home in year t, holding constant reconstruction cost and other contract features.

6.2 Hurricane & Non-Hurricane Premiums Over Time

Figure 10 shows the resulting annual average premiums. The blue line indicates total premiums, which are the sum of hurricane and non-hurricane premiums. From 2008 to 2019, prices increased gradually by about $100 per year. This growth accelerated to about $400 per year during 2020–2024. The average total premium reached $4,800 dollars per year in 2024.

The dashed gray line in Figure 10 shows annual average insurance premiums for Florida from transaction data for the subset of years that are available. These prices are inferred from mortgage escrow accounts by Keys and Mulder (2024). Our weighted average of standardized contract prices closely corresponds to observed transaction prices in all years. This is a reassuring validity test on the usefulness of the premium index. It implies that the standardized contract prices we use do indeed reflect contract choices for typical Florida homeowners (reconstruction cost, deductibles, etc.), and that our price index is therefore a useful measure of changes over time in Florida insurance premiums.

The orange and purple lines in Figure 10 show hurricane and non-hurricane premiums over time. Until about 2020, each risk type accounted for about half of the total premium. In more recent years, hurricane premiums have increased rapidly from about $1,400 in 2019 to about $2,500 in 2025. The hurricane premium increase is responsible for almost all of the acceleration in total premiums over this period. Hurricane premiums declined slightly in 2025, falling by about $100 on average. This decline is consistent with measures from industry reports, which tend to highlight the softening reinsurance cycle (e.g., Intercontinental Exchange, 2026; Guy Carpenter, 2026).

While the figure shows a state-level, aggregate price index across home types and vintages, we can also subset the index to describe specific homes and locations. For example, much of our analyses focuses on the modal home in the state, a pre-code masonry house, for which we have modeled expected loss data. Hurricane premiums grew by about 200% for this home during our period of study, from 2008 to 2025.

7 Discussion and Conclusion

To what extent do rising home insurance premiums reflect growing climate risk? We offer new evidence on this question by linking the proprietary hurricane catastrophe models that insurers use to price risk with the hurricane premiums they charge. Hurricanes are the costliest disasters in the U.S. (NOAA, 2024) and their risk is growing according to climate science (IPCC, 2021). Using 17 years of data from Florida, the most hurricane-prone state in the U.S., we find that property-level expected losses from hurricanes have increased by an median of around 50% according to the leading CAT models. We examine how these estimates of growing risk are passed on to consumers. Using our preferred estimation strategy, which leverages discrete changes in hurricane model estimates within a zip code, we find that a $1 increase in property-level expected loss increases homeowners premiums by an average of $3.90. This large price gradient seems to reflect the high cost of managing tail risk, the potential that insurers and reinsurers would need to fund billions of dollars in repairs from a single event. Much of the Florida insurance market is dominated by

Figure 10: Florida Home Insurance Price Index, 2008–2025

Notes: Solid lines show annual index values. Dashed line shows annual average premiums paid for Florida from mortgage escrow data compiled by Keys and Mulder (2024).

small insurers who cannot diversify hurricane risk and instead rely heavily on reinsurance. Ultimately, the premiums that homeowners pay are substantially larger than their expected losses: across our period of study, an average Floridian owning a home with the most common construction features paid over $1,800 in hurricane premiums, roughly four times their expected hurricane loss.

Home insurance prices have ebbed and flowed over time, often increasing after a severe event such as Hurricane Andrew (Kunreuther and Michel-Kerjan, 2011). Those increases led to calls for insurance and reinsurance market reforms (e.g., U.S. House of Representatives, 1995; Congressional Budget Office, 2002; King, 2008). Insurance premiums might increase following a catastrophe for two reasons: new events could influence insurers' estimates of the risk and/or industry losses erode the equity capital required to insure catastrophes (e.g., Froot and O'Connell, 1999; Cummins and Lewis, 2003). Disentangling these mechanisms is empirically challenging but important for effective public policy design. Relative to previous periods, the recent run-up in insurance prices has been dramatic and raised questions regarding whether climate change has fundamentally altered home insurance markets (e.g., New York Times, 2024).

Our analyses offer detailed and long-running measures of the hurricane premium-to-risk relationship in Florida, one of the most disaster-exposed U.S. states, but do not examine how premium-to-risk loads vary in other locations or for other types of disasters. The insurance industry describes hurricanes and earthquakes as "primary" perils because of their extreme tail risks. Private reinsurers report that they are "at capacity" for these perils in the U.S. (Artemis, 2021) due to existing portfolio concentrations. Severe tail risks and portfolio concentrations add to the cost of insuring against Florida hurricanes. As a result, we expect that premium loads in other settings are often smaller than the loads of around 4-to-1 that we measure in Florida.

Many parts of the U.S. are exposed to "secondary perils" including wildfires and severe thunderstorm risks (e.g., hail, tornadoes). These risks are growing (Verisk, 2025). For example, CoreLogic (recently rebranded "Cotality") is a leading catastrophe model vendor for severe thunderstorm risk and reports "a paradigm shift in extreme weather risk: a single hailstorm can now generate catastrophic financial losses similar to a major hurricane" (Cotality, 2026). Looking forward, the challenges of managing tail risks may become increasingly relevant for other perils.

Our findings offer new insights to this longstanding dialogue regarding public policy interventions in catastrophe insurance markets. By using two decades of data from the hurricane models on which insurers rely, we isolate property-level hurricane risk, quantifying both how risk and the add-on costs of insurers taking this risk contribute to homeowners' premiums. This new evidence provides empirical insights for policy proposals focused on reducing these add-on costs. One set of potential policy interventions focus on Florida and similar states and entail revising rules that limit the participation of the largest U.S. insurers in high risk areas. For example, the financing structure of state insurance guaranty funds can penalize well-capitalized insurers who are more likely to survive severe disasters (Abramson et al., 2025). Another line of policy proposals focuses on expanding the supply of reinsurance. One area of consideration is the tax treatment of reinsurance (Baxley and Katz, 2017). Government reinsurance programs is another, which has been standard policy for terrorism risk, especially since the September 11, 2001 attacks, including in the U.S., the U.K., Germany, and many other countries (Webel, 2022). Recently, the Australian government established a public reinsurer for cyclones, which has expanded the supply and reduced the cost of reinsurance there (Solomon, 2025). Similar proposals exist for a U.S. government reinsurer (e.g., Collier et al., 2025; Dixon et al., 2025). Whether these proposals would meaningfully affect the premiums that homeowners pay is an unresolved but important question given the continued growth of hurricanes and other severe climate risks.

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1 Construction of the Dataset

1.1 Hurricane AALs by Zip Code

During the model review process, each catastrophe model vendor is required to report predicted average annual hurricane losses in each Florida zip code for a standardized frame, masonry and mobile home. These data are reported on the Actuarial Hurricane Standard Form A-1. As of 2025, these forms are publicly available from the commission for model review years 2011–2023. We augment these data with reports for 2006–2011 provided by the commission's staff. To assess the completeness of the reported zips, we also draw on U.S. Census data for population estimates in zip code tabulation areas (ZCTAs) in 2010 and 2020.

A common set of 903 zip codes are included by every model vendor in every year. Appendix Table 1 shows that this balanced sample of zip codes includes 98.1% or 97.5% of Florida's total population depending on whether we compare it to 2010 or 2020 ZCTA population data. Nearly all (901 of 903) zip codes have corresponding ZCTA entries.

Appendix Table 1: Population in Balanced Zip Sample

ZCTA Year	Population in Balanced Zips	Population in all Florida ZCTAs	Share in Balanced Zips	Zips with no ZCTA
2010	18,448,904	18,801,226	0.9813	2
2020	21,005,746	21,538,103	0.9753	2

Notes: Includes 903 zip codes that are included in every model review year (2006–2023) by every vendor with a submission.

The full list of zip codes reported by each model vendor varies, for example, due to differences in the treatment of non-standard areas like unpopulated areas. For completeness, Appendix Table 2 reports the number of zip codes included in Form A-1 for each model vendor and model review year. It also includes the total population represented by those zip codes based on 2020 ZCTA populations, and the number of zip codes on the vendor's Form A-1 that do not have a matching ZCTA.

Appendix Table 2: Summary of Unbalanced Zip Codes

	AIR	RMS	CoreLogic	Public	ARA	KCC	Impact
Number of Zips							
2006	1,479	1,479	1,479	1,456	1,479	-	-
2007	1,479	1,479	1,479	1,456	1,479	-	-
2008	1,479	1,479	1,479	1,453	1,479	-	-
2009	1,479	1,479	1,441	1,453	1,479	-	-
2011	949	1,620	1,476	1,480	933	-	-
2013	945	1,620	1,477	1,477	934	-	-
2015	950	1,622	1,494	1,478	935	-	-
2017	956	1,623	1,495	1,477	935	1,514	-
2019	964	1,623	1,495	1,475	935	1,514	1,472
2021	982	1,623	1,495	1,468	1,006	1,475	1,465
Population							
2006	21,092,032	21,092,032	21,092,032	21,092,032	21,092,032	-	-
2007	21,092,032	21,092,032	21,092,032	21,092,032	21,092,032	-	-
2008	21,092,032	21,092,032	21,092,032	21,092,032	21,092,032	-	-
2009	21,092,032	21,092,032	21,092,032	21,092,032	21,092,032	-	-
2011	21,471,678	21,538,103	21,538,103	21,538,103	21,455,943	-	-
2013	21,470,576	21,538,103	21,538,103	21,538,103	21,485,085	-	-
2015	21,502,902	21,538,103	21,538,103	21,538,103	21,485,085	-	-
2017	21,508,262	21,538,103	21,538,103	21,538,103	21,485,085	21,538,103	-
2019	21,519,560	21,538,103	21,538,103	21,538,103	21,485,085	21,538,103	21,538,103
2021	21,525,794	21,538,103	21,538,103	21,536,064	21,526,139	21,536,064	21,536,064
Zips without ZCTA							
2006	486	486	486	463	486	-	-
2007	486	486	486	463	486	-	-
2008	486	486	486	460	486	-	-
2009	486	486	448	460	486	-	-
2011	14	607	463	467	3	-	-
2013	12	607	464	464	3	-	-
2015	12	609	481	465	4	-	-
2017	12	610	482	464	4	501	-
2019	13	610	482	462	4	501	459
2021	15	610	482	457	30	464	454

Notes: Statistics for zip codes included on Form A-1 by a given model vendor in a given model review year. The second and third panels are based on 2020 ZCTAs. Public is the Florida public model. ARA is Applied Research Associates. KCC is Karen Clark and Company. Impact is Impact Forecasting.

1.2 Insurance Prices

1.2.1 Notional policy terms

Insurers are required to report territory-level premiums for a consistent set of six "notional" insurance contracts, which hold constant structure and occupant characteristics and reconstruction cost. They are constructed by varying "reconstruction cost" and "description of structure" in the following description of the home and policyholder:

> "Masonry structure insured for replacement cost at **[RECONSTRUCTION COST]** with a 2% Hurricane Deductible and a $500 deductible for all other Section I perils combined; Other structures insured at 10% of the amount of insurance on the structure; Contents insured for replacement cost at 50% of the amount of insurance on the structure; Loss of Use insured at 20% of the amount of insurance on the structure; $100,000 Liability coverage; $1,000 Medical expense; Ordinance or law coverage provided at 25% of the amount of insurance on the structure; I.S.O. Protection Class 4; I.S.O. HO-3 Policy Type. The rates should be annual rates for new business for a 40 year old insured with no claims in the past 3 years and a neutral credit score. **[DESCRIPTION OF STRUCTURE]**. Sinkhole coverage is included with a $500 deductible. Screened enclosure and mold coverage are excluded. (If screened enclosure or mold coverage cannot be excluded, it should be noted under Risk Difference that the coverage is included and the associated limit provided.) The only recoupment that should be included in the rate is the Florida Hurricane Catastrophe Fund reimbursement premium recoupment, if applicable."

The relevant combinations of [COVERAGE A AMOUNT] and [RECONSTRUCTION COST] are as follows:

Coverage A Amount	Description of Structure
$150,000	The structure was built in 1990 and does not have a hip roof.
$150,000	The structure was built in 1990 and does not have a hip roof. Include the maximum possible windstorm loss mitigation credit for this risk.
$150,000	The structure was built in 2005 and does not have a hip roof.
$300,000	The structure was built in 1990 and does not have a hip roof.
$300,000	The structure was built in 1990 and does not have a hip roof. Include the maximum possible windstorm loss mitigation credit for this risk.
$300,000	The structure was built in 2005 and does not have a hip roof.

As with the catastrophe model data, there are small differences in the lists of zip codes reported by each insurer in their rate filings. We restrict the dataset to a consistent set of 882 zip codes that are present in every rate filing and in the catastrophe model AAL data. These zip codes represent 97.0% of Florida population based on 2020 ZCTA data.

1.2.2 Catastrophe Model Usage Over Time

Table 3 documents catastrophe model usage over time. RMS and AIR are dominant in all periods.

Appendix Table 3: Models Used in OIR Rate Filings

	2008–2013	2014–2019	2020–2025
AIR (Verisk)	15	14	15
RMS (Moody's)	9	7	7
CoreLogic	1	2	2
Florida Public Model	4	1	1
Applied Research Associates	1	0	0
Karen Clark and Company	0	0	0
Impact Forecasting	0	0	0

Notes: Table reports counts of unique insurers using each model in one or more rate filings during the period. Insurers may use multiple models so count of models is larger than count of firms.

1.2.3 Rating Territories

Table 4 lists the number of distinct rating territories spanned by the 882 zip codes in our study for each insurer.

Appendix Table 4: Territories by Insurer and Year

Company	2023	2011
ASI	882	81
AmericanStrategic	882	81
State Farm	882	69
Truck	882	NA
Southern Oak	310	310
Heritage Voluntary	272	NA
Tower Hill	122	NA
Citizens	99	99
First Protective	99	99
Florida Peninsula Takeout	99	99
Florida Peninsula Voluntary	99	99
Heritage Takeout	99	NA
Homeowners Choice	99	99
Slide	99	NA
Universal	99	99
Castle Key Ins	50	50
AmericanIntegrity Takeout	NA	99
AmericanIntegrity Voluntary	NA	81
St. Johns	NA	99

Notes: Table reports counts of unique rating territories used by the 16 insurers in 2023 and 2011.

1.3 FHCF Insured Properties Data

Appendix Table 5: Median Insured Value by Construction and Vintage

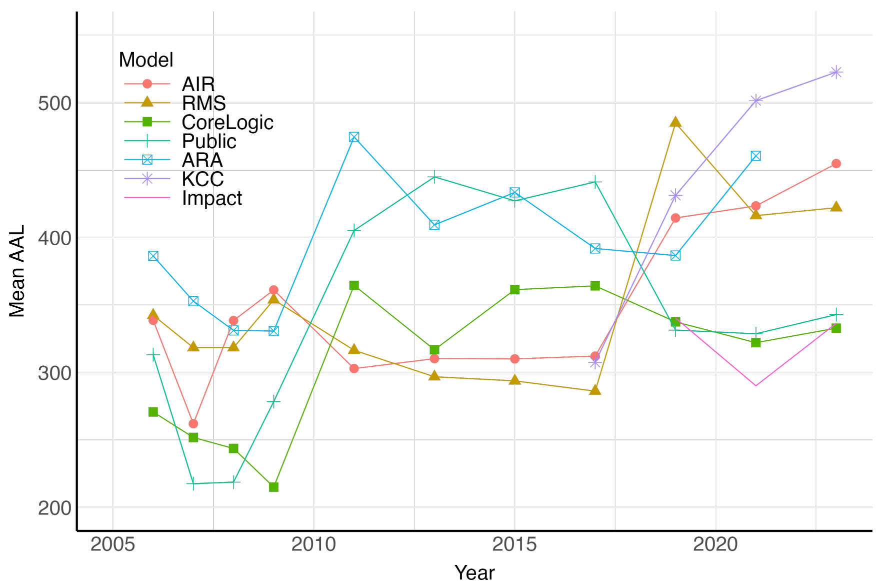
	Masonry	Frame	Other/Unknown
2007			
Pre-Florida Building Code	192,818	177,181	195,949
Post-Florida Building Code	259,032	236,645	249,800
2012			
Pre-Florida Building Code	212,939	202,650	233,000
Post-Florida Building Code	270,200	248,177	277,750
2017			
Pre-Florida Building Code	225,480	212,900	248,055
Post-Florida Building Code	281,191	266,700	287,200
2023			
Pre-Florida Building Code	317,456	306,400	350,658
Post-Florida Building Code	390,475	377,063	414,820
2025			
Pre-Florida Building Code	337,155	320,404	371,500
Post-Florida Building Code	426,933	419,062	445,000

Notes: Table summarizes FHCF data on the population of insured homes as of various years. "Pre-Florida Building Code" refers to homes built through 2001. Table reports the median coverage limit on the structure (Coverage A) for each of these home types over time.

2 Hurricane Models, Additional Material

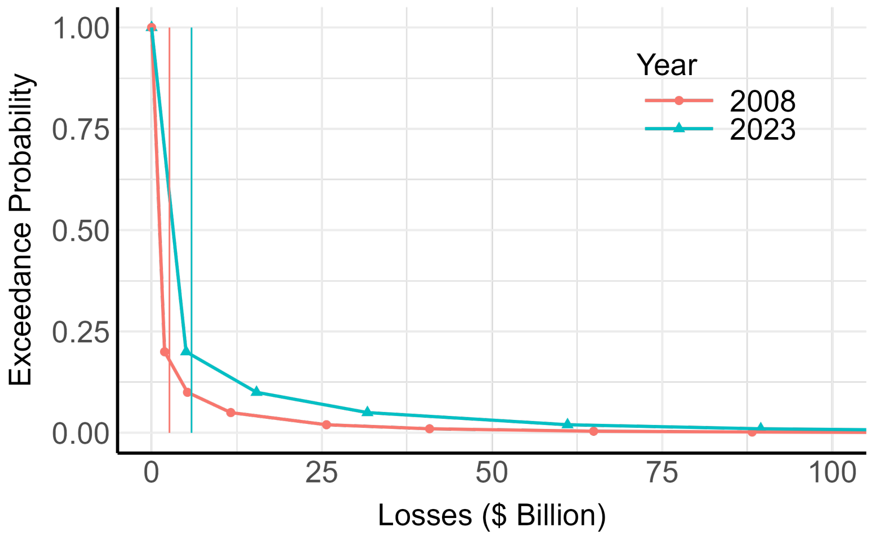
Appendix Figure 1 shows how expected losses have evolved for all seven of the models over the time series. The figure shows the average AAL for each model for each year in which the vendor reported to the CAT model commission since 2006. Early in our time series, the commission met annually, but switched to biannually after 2009. Expected losses from AIR and RMS remain relatively flat for most of the time series and then grew substantially by 2019. This growth closely follows the devastating hurricane season of 2017 during which Hurricanes Harvey, Irma, and Maria created a combined total of $340 billion in losses (NOAA Office for Coastal Management, 2025). For the other five models, expected losses increase during the time series, but the timing, magnitude and persistence of the increase varies. The model from Karen Clark & Company (KCC) enters the data in 2017 and mirrors this increase through the end of the time series. The other notable increase in average AALs occurs in 2011 for several models, including CoreLogic, Applied Research Associates (ARA), and Florida's public model. These changes reflect model revisions based on data from the 2004 and 2005 hurricane seasons. For example, ARA revised its approach to modeling wind speeds (Vickery et al., 2009).

Appendix Figure 1: Mean AAL Over Time

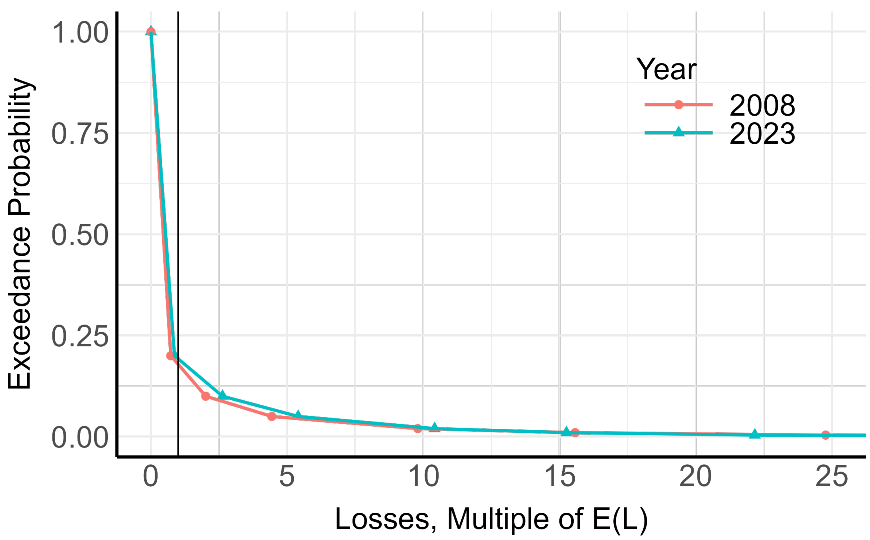


Notes: This figure shows the mean AAL for each model vendor from 2006 to 2023. The values reflect the AALs for a pre-code, masonry home at the center of every zip code in the state. AALs are per $100,000 of a home's replacement cost.

Appendix Figure 2: Exceedance Curves for AIR



Exceedance Curve in Billions of Dollars of Losses



Exceedance Curve in Multiples of Expected Loss

Notes: The figures are exceedance probability curves for model vendor AIR in years 2008 and 2023. The modeled portfolios include effectively all residential properties in Florida. The upper panel describes losses in billions of dollars. The vertical lines provide the portfolio-level expected loss, which was $2.62 billion in 2008 and $5.87 billion in 2023. The lower panel reports the exceedance curve as multiples of the expected loss. It shows that losses at the 1st percentile of the distribution are 15 times the expected loss in both 2008 and 2023.

Appendix Table 6: Exceedance Curves by Model Vendor and Year

Panel (A): Florida Portfolio

	AIR			RMS		
Probability	2008	2011	2023	2008	2011	2023
1.0000	0.00	0.00	0.00	0.00	0.00	0.00
0.2000	0.73	0.83	0.86	1.00	0.82	0.90
0.1000	2.01	2.30	2.63	2.61	2.73	2.71
0.0500	4.44	4.58	5.40	4.87	5.46	5.21
0.0200	9.80	9.39	10.41	9.22	10.17	9.81
0.0100	15.57	14.09	15.25	14.26	14.70	14.62
0.0040	24.77	21.61	22.17	23.92	22.37	22.78
0.0020	33.65	27.82	27.92	32.57	30.04	30.33
0.0010	42.78	34.94	34.85	41.55	39.64	39.51
0.0005	51.21	41.60	41.71	50.45	51.05	50.86
0.0002	58.67	51.24	53.37	62.06	68.09	69.09
0.0001	65.38	61.46	65.53	70.68	81.86	84.71

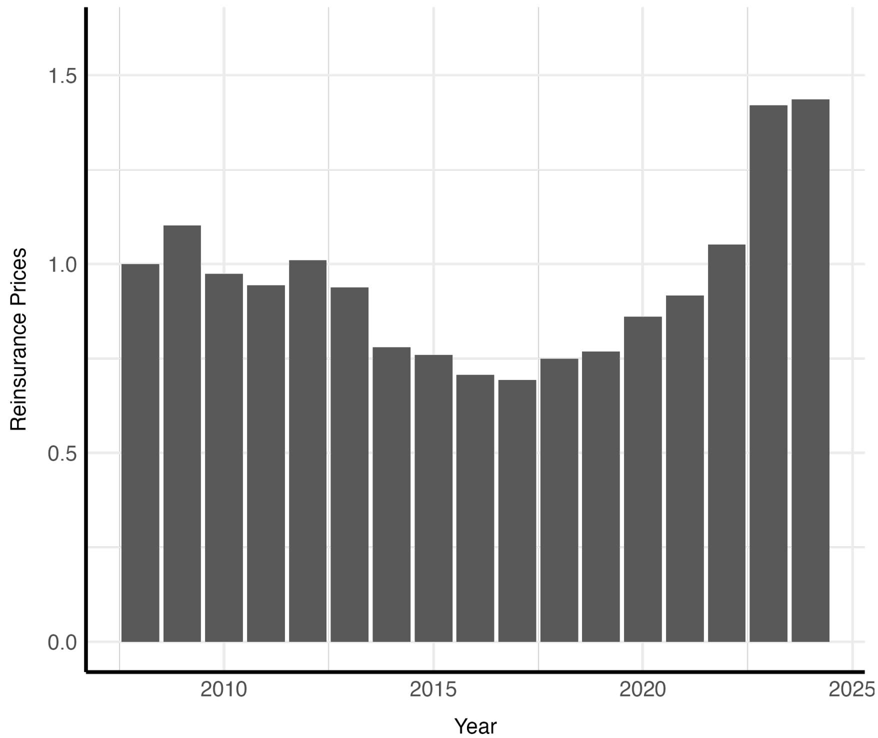
Panel (B): Notional Portfolio

	AIR			RMS		
Probability	2008	2011	2023	2008	2011	2023
1.0000	–	0.00	0.00	–	0.00	0.00
0.2000	–	0.91	1.07	–	1.09	1.17
0.1000	–	2.40	2.96	–	3.00	2.97
0.0500	–	4.55	5.59	–	5.41	5.26
0.0200	–	9.03	9.81	–	9.32	9.10
0.0100	–	12.76	13.23	–	12.84	12.75
0.0040	–	19.71	18.10	–	18.39	18.49
0.0020	–	25.09	21.43	–	23.56	23.62
0.0010	–	30.82	24.45	–	29.84	29.75
0.0005	–	35.55	27.68	–	37.28	37.03
0.0002	–	43.54	35.33	–	48.19	48.25
0.0001	–	55.36	39.83	–	57.05	57.74

Notes: Values are in multiples of the model's expected loss. Exceedance curves for the notional portfolio were not reported prior to 2011.

3 Additional Figures and Tables

Appendix Figure 3: Rate on Line for U.S. Property and Casualty Reinsurance



Notes: The figure shows the evolution of reinsurance prices based on Guy Carpenter's Rate on Line Index for U.S. Property and Casualty Risks (Guy Carpenter, 2024). The price is measured as reinsurance premiums per dollar of reinsurance coverage and is normalized to the 2008 price in this figure.

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