# 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 property losses from hurricanes increased by 50%. Turning to insurance prices, we collect the premium rate filing data for insurers representing 70% of the total market. Insurers wanting to adjust their hurricane premium rates must file a request with the state regulator and justify the change with hurricane model output. Leveraging discrete updates to hurricane models, we estimate that a $1 increase in expected losses increases hurricane premiums by $5.82. 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 rising cost of reinsurance.

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# 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 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 disentangle 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 the hurricane component of their premium rates 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.

[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).

We pair these risk estimates with insurer pricing data. We hand-collect rate filings for homeowners premiums for 16 large insurers, which represent 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 insurer-level data on hurricane-related expense items that we collected from annual insurance rate filings. Panel (A) shows current rates for the state's largest insurers. 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 Florida insurers these net costs of risk transfer exceed total expected losses. Finally, most insurers recover a variety of operating costs, such as commissions paid to agents, as a percentage of hurricane premium. While these expenses would exist even in the absence of hurricane risk, incorporating them into hurricane premiums on the margin amplifies the risk price signal perceived by insurance customers. Panel (B) of Figure 1 shows a time series of hurricane-related expenses for a single large insurer. Expected hurricane losses, which are derived from the catastrophe models we study, are relatively stable across years from 2009 – 2024. In contrast, net costs of reinsurance vary substantially over time. The reinsurance costs in Panel B co-move closely with indices of global property reinsurance prices like the Guy Carpenter U.S. Property Reinsurance Rate-on-Line Index.

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., 2022), would yield quite different incentives.

To make empirical progress on these issues, we turn to the new ZIP code-level data 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 not been substantially retrofitted to reduce hurricane vulnerability, and has a replacement cost value of $150,000. In the most recent year of our analysis, the average expected loss from hurricanes for this type of home across the state was $600. The average hurricane premium was $3,700, about six times the expected loss.

To explain this finding, we first discuss 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, e.g., 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 $5.82.

Our findings are qualitatively similar when estimating the pass-through of expected losses to premiums using all of the years in the sample. For the full study period, we estimate that a $1 increase in modeled expected loss increased premiums by about $4.55 on average. This pass-through has grown over time: a $1 increase in expected loss increased premiums by $3.53 in 2008–2013, by $4.15 in 2014–2019, and by $5.35 in 2020–2024 (the latter being consistent with the zip code fixed effects design that leverages the 2021 model update).

What explains the large and growing pass-through of expected hurricane losses? We find suggestive support for two factors, both of which relate to the difficulty of diversifying hurricane risk. The first factor is reinsurance costs. We find that, on average, insurers operating in the highest risk areas spend $0.58 on reinsurance for every $1 in premiums they receive.

The hurricane models illustrate the need for reinsurance in Florida. A key function of CAT models is to estimate the loss exceedance probability for a portfolio. 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. 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. These large capital needs reflect the spatially correlated nature of hurricane losses and the essential role of reinsurance for covering tail risks in this market. We show that hurricane premiums in Florida co-move with global reinsurance prices: declining as the reinsurance market "softened" from 2013 to 2017, and then rising rapidly since 2018.

The second factor explaining the large and growing pass-through of expected losses is 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 2024, they charged an additional $7.13 in hurricane premiums for every $1 increase in expected losses, whereas diversified national insurers charged an additional $5.34 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.

We conclude the discussion of results by presenting 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. We use the index to show that recent premium increases have been driven by hurricane premiums as opposed to other peril premiums; that hurricane premiums have risen much faster than modeled expected losses; and that insurers reward investments in structure vulnerability reduction with substantial

premium discounts.

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. Florida is one of the largest states by population, and has the highest insurance premiums. 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 the 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., 2022; Blonz et al., 2024). 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,

[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.

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 that, on average, a $1 increase in modeled property-level expected losses increases premiums by $4.55. 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 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, by their very nature, rare and highly destructive. The rarity of events makes it exceedingly difficult to accurately project future losses using only historical loss data. This critical deficiency has compelled catastrophe modelers to develop sophisticated stochastic simulation techniques to capture and quantify risks that history alone cannot address, thereby enabling insurers to better anticipate and mitigate the financial impact of future catastrophes.

A catastrophe model leverages data and knowledge from physics, meteorology, engineering, statistics, and actuarial sciences to provide the most comprehensive depiction of the likelihood and severity of losses from extreme events. In doing so, these models provide answers to crucial questions such as: What is the likelihood 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 itself 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 that determine 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).

### 2.1.2 Background: Florida Homeowners Insurance Market

The Florida homeowners insurance market faces significant pressure from a variety of forces, primarily stemming from population growth and development. Prior to Hurricane Andrew in 1992, the insurance industry in Florida, like many U.S. markets, relied mostly on limited historical data and less sophisticated, proprietary models for pricing catastrophic risk. Underwriting decisions and reinsurance purchasing were often based on simpler calculations, intuition, or regional practices rather than rigorous science. 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.

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, according to the Florida Department of Revenue. This growth is highly uneven, with approximately 98 percent concentrated in coastal counties with significant hurricane risk. The financial exposure has coincided with increased hazard activity. While 25 major hurricanes made landfall in Florida over the last century, 44 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. Florida implemented a substantial building code revision in 1995, and 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 in the reinsurance tower for most firms. 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 subsidy, the FHCF does not change forces guiding the insurance market in Florida, which are similar to those in other disaster prone states.[3]

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 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.[4]

### 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 (FLOIR) 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 Florida is a high-risk hurricane zone, an insurer's last 10–20 years of "actual" 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. 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. 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 average across the entire state.

### 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 project losses. 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,

[3] All insurers 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.

[4] 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 (rather than the original 10 percent) (Citizens, 2024).

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 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. Vendors model 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.

Vendor reports are publicly available from the CAT model commission for review years 2011 and later. 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 Florida Office of Insurance Regulation (FLOIR). We hand-collect FLOIR rate filings for insurers' homeowners (HO-3) programs for 2008–2024. 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, FLOIR 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).[5] 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, and occupancy. Lastly, rate filings also identify the catastrophe model used to justify the hurricane premium.

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 lists all collected insurers, ordered by their 2024 homeowners market share (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, which is almost always AIR or RMS.

[5]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 FLOIR's data-reporting requirements and remain constant throughout our observation period.

State Farm and Citizens use multiple models. 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, and 2017. The data are useful for understanding the stock of insured homes. 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.

Table 2 describes the population of insured homes for comparison to the reference home types provided by the hurricane models and insurer rate filings. Each panel reports the share of homes across vintage and construction categories in the indicated year. "Pre-Code" refers to homes built prior to 2001, when Florida conducted a major revision to its building codes. "With Mitigation" refers to pre-code homes that have been substantially retrofitted to reduce hurricane vulnerability (e.g., replacing the roof and windows to modern standards). The CAT model commission requires vendors to report separate expected losses for pre-code, no-mitigation properties built from masonry and frame. The table shows that this is the modal type of home across the period of study. For example, 57% of homes in 2007 were masonry, pre-code no-mitigation homes. Appendix Table 5 describes the median insured value for properties in the FHCF data, which was around $218,000 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.[6] 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. Appendix 1.2 shows that 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 2021, Florida Peninsula in 2022, and Tower Hill in 2024.[7] 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

[6] 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.

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

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.[8] In analyses that compare premiums and expected losses, we focus on the premium for a 1990 masonry home with no wind retrofits and $150,000 reconstruction cost. These characteristics match the characteristics used to generate the expected loss data. Because of the dominance of the AIR and RMS models, our main expected loss variable is the mean of the AALs from those two models. We also consider the mean AAL across all models and the AAL from the model(s) used by each insurer to justify their rates.

The resulting panel includes annual premiums and expected hurricane losses for a standardized masonry home for every zip code and insurer from 2008 through 2024. Following convention in insurance rate analysis, our main specifications assume that the notional contract data remove effects of inflation by holding reconstruction costs constant at $150,000. In robustness tests currently under development, we consider alternative inflation adjustments.

**Validity Test Using Mortgage Escrow Data.** While the standardized homeowners insurance premiums we observe are meant to capture typical customer characteristics, they do not reflect actual transactions. 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.[9] 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.

# 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,

[8] The relevant model year generally lags the rate year by about two years due to the CAT model commission's two-year review cycle.

[9] 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.

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, and CoreLogic (the most widely used private models) 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 (Figure 4).

### 3.1 Current 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. Panel (A) of Figure 3 and 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 median-value home with replacement cost of approximately $200,000 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.

However, 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. Consistent with the description 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. The differences are greatest in Key West where the AALs from AIR are 3.7 times larger than those of RMS.

### 3.2 Changes Over Time in Modeled Risk

We next examine how expected losses have evolved. Figure 4 shows the mean AAL for each model over the time series.[10] While expected losses increased for all models during the time series, the timing, magnitude and persistence of the increase varies. 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). 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).

To complement this figure, we report the distribution of how AALs have grown for each zip code in Panel C of Table 3. 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.

### 3.3 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.[11] Insurers, regulators, and rating agencies use these curves to assess insurer solvency risks. For example, regulators and rating agencies often want insurers to organize enough funding (through reserves, reinsurance, and equity capital) to pay claims in 99% of states of the world (NAIC, 2025). Exceedance curves provide an estimate of the total loss corresponding to a given quantile (e.g., 99%).

The CAT model commission asks model vendors to report exceedance curves for two portfolios.

[10] For the population weighting, we use the zip code population from the 2000 census because it provides a consistent and pre-determined weighting for the time series.

[11] 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 $X_1$, $X_2$, ..., $X_N$, 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.

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 5 provides the exceedance curves for AIR and RMS in 2021 for effectively all insured properties in the state.[12] The vertical lines (which overlay each other) show the portfolio-level expected losses for each model, which are $3.97 billion. The right-most dots on the curves reflect the 1% exceedance probability, which is $58.5 billion for RMS and $61.5 billion for AIR. We have capped the figure for readability, but model vendors report estimates up to a 1 in 10,0000 exceedance probability.

We draw attention to two aspects of Figure 5. First, the correlated nature of hurricane losses is large: insurers need to organize funding to cover around 15 times the expected loss 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 almost identical portfolio expected losses, and their 1% exceedance probability loss estimates are within 5% of each other. We will return to exceedance probabilities when discussing mechanisms for our primary results in Section 5.

**Summary of modeled hurricane risk.** We summarize this section with four stylized facts regarding modeled hurricane risk based on this dataset of granular risk estimates over the last 17 years. First, modeled expected losses have increased by a median of around 50% according to the most commonly used models, AIR and RMS. Much of this increase occurred following the severe hurricane season of 2017. Second, while the various model vendors rank locations by hurricane risk similarly, their point estimates of expected losses can differ widely (e.g., AIR's modeled expected loss in Key West is 3.7 times larger than that of RMS). 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). Insurers might also respond to model differences by specializing, with insurers selecting into various models based on their market segment or their perceptions of the credibility of model assumptions. We return to this theme in Section 4.4. Finally, the statewide aggregate modeled risk, which predicts that a 1-in-100 year event would lead to losses that are approximately 15 times the expected loss, illustrates the fundamental challenge of insuring correlated hurricane risk. Insurers operating in Florida seemingly either need to diversify this risk by pooling it with policies written in other locations, which a national insurer might do, or by purchasing reinsurance and thus transferring the risk to global markets.

[12] Our most recent exceedance probability curve data is from 2021.

# 4 Pricing Hurricane Risk

This section examines the prices charged by insurers to cover hurricane risk. Section 4.1 presents new summary data on insurer-level average hurricane expenses from annual rate filings to the Florida OIR. The remaining sections focus on results from the microdata. Section 4.2 describes the distribution of prices, including across the state and over time. Section 4.3 lays out the empirical strategy for measuring the price of hurricane risk and Sections 4.4 and 4.4 present the results.

## 4.1 Insurer-level Average Hurricane Loads

Figure 1 reports insurer-level data on hurricane-related expense items from annual insurance rate filings. Panel (A) shows current rates for the state's largest insurers. 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 Florida insurers these net costs of risk transfer exceed total expected losses. Finally, most insurers recover a variety of operating costs, such as commissions paid to agents, as a percentage of hurricane premium. While these expenses would exist even in the absence of hurricane risk, incorporating them into hurricane premiums on the margin amplifies the risk price signal perceived by insurance customers. Panel (B) of Figure 1 shows a time series of hurricane-related expenses for a single large insurer. Expected hurricane losses, which are derived from the catastrophe models we study, are relatively stable across years from 2009 – 2024. In contrast, net costs of reinsurance vary substantially over time. The reinsurance costs in Panel B co-move closely with indeces of global property reinsurance prices like the Guy Carpenter U.S. Property Reinsurance Rate-on-Line Index.

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 are limited in several ways. 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.

To make empirical progress on these issues, we turn to the new ZIP code-level data on insurer premiums and modeled expected losses.

## 4.2 Pricing Descriptives

Table 4 describes the panel. The first panel shows pre-code homes without wind retrofits, the dominant structure type in Florida. For this group of homes, the mean hurricane premium of $2,121 accounted for almost 60% of the total premium across the sample period. Expected losses

from hurricanes are about one-fourth of the hurricane premium on average. The remaining two panels show retrofitted pre-code homes and post-code homes. For these less common structure types, hurricane premiums are smaller by about two-thirds. Non-hurricane premiums for these structure types are also somewhat lower, suggesting that older homes are costlier to insure overall for reasons besides hurricane exposure (e.g., aged wiring and other building materials that might increase the risk of a claim).

Figure 6 shows the geographic variation in premiums in 2023. 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. Panel B shows that non-hurricane premiums have a much different geographic pattern, with little relationship to hurricane hazard.

Figure 7 provides graphical evidence on the relationship between premiums and predicted hurricane losses at the zip code level. The top panel considers hurricane premiums. Each marker represents the market share-weighted average of insurer's premiums for a pre-code, no retrofit masonry home in a given zip code and time period. The horizontal axis shows the property AAL. The figure shows a cubic polynomial fit 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 2.5 before 2010 and was above 5 in 2024. The lower panel shows that non-hurricane premiums are much less correlated with predicted hurricane losses.

### 4.3 Empirical Design

This section describes how we use observed variation in insurance premiums and catastrophe model predictions 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 in more typical transaction datasets like ICE-McDash (Blonz et al., 2024; Sastry et al., 2024) or mortgage escrow data (Keys and Mulder, 2024) reflect substantial unobserved heterogeneity across customers in coverage features (e.g., deductibles, coverage limits), structure characteristics (e.g., roof shape), and occupant characteristics (e.g., credit scores, 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:

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

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. Insurer-by-year fixed effects $\gamma_{jt}$ allow the intercepts to vary for every insurer in every year. The coefficient of interest $\beta$ 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.

While our standardized premium and expected loss data hold constant many important factors, it is still possible that estimates of $\beta$ 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 (Figure 4). 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:

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

Including firm-by-territory fixed effects $\psi_{i(j)}$ means that estimates of $\beta$ 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.

### 4.4 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. Column (1) of Table 5 shows that a 1-dollar increase in expected hurricane losses in a given location increased hurricane premiums by about \$5.80. For a territory with the average risk increase of \$230, this regression implies a price increase of \$1,340.

We return to this discussion of overall price changes in Section 6. Column (2) of Table 5 shows that updates to modeled hurricane losses had no measurable effect on non-hurricane premiums.

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 7 that we discuss below, the estimated constant term is close to zero (about 4% 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 4.5 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 2020–2024 period is 5.8, which closely matches the natural experiment result using 2021 and 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. 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 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.[13] 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. From an economic perspective, outsize reliance on only two models is striking given the seeming value of ensemble approaches in the presence of ambiguity.

## 5 Mechanisms & Extensions

What has led to the dramatic increase in the premiums that consumers pay relative to expected loss? We highlight two central mechanisms. The first is reinsurance prices. The second is 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.

[13] While each insurer must show that their final hurricane rates can be supported by a single model within an acceptable margin of error, 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.

### 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 8 compares the exceedance curve estimated by RMS in 2011 to that in 2021 for the portfolio of effectively all insured properties in Florida.[14] To facilitate comparisons over time, we report losses as multiples of the expected loss in each year (i.e., the 2021 curve is divided by the mean value in 2021). 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 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 reinsurance prices. Reinsurance prices ebb and flow, often rising after large loss events that deplete reinsurers' equity capital (Froot and O'Connell, 1999). Figure 9 plots reinsurance prices over time using the rate-on-line for U.S. property catastrophe risks. Rate-on-line is the standard metric for reinsurance prices and is calculated as the premiums paid by insurers to reinsurers per dollar of reinsurance coverage (Guy Carpenter, 2024). For comparison in the figure, we also include average hurricane insurance premiums and average hurricane AALs in Florida. Each series is normalized by its 2008 value. The figure illustrates how hurricane premiums and reinsurance prices co-move with both series declining during the mid-2010s and then rising through the rest of the time series. Part of the increase in reinsurance prices in the 2020s may reflect reinsurers' revised views of the risk based on hurricane model updates since reinsurers also rely on the AIR and RMS models (Moody's, 2024).[15] In summary, while not a causal analysis, the figure illustrates that homeowners insurance premium volatility moves with the reinsurance cycle. The connection between the prices for primary insurance and reinsurance is documented in the literature (e.g., Froot and O'Connell, 1999; Keys and Mulder, 2024); our contribution centers on our ability to contrast this co-movement with the estimates from the risk models that the insurance and reinsurance industry relies on.

[14] 2011 and 2021 are the earliest and latest exceedance probability curve data.

[15] Moody's, which owns RMS, reports that 28 of the largest 30 reinsurers and 10 of the largest 10 reinsurance brokers license their model.

### 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., 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. One step was that national insurers began selling insurance through subsidiaries, insulating the parent company. For example, State Farm began offering coverage through "State Farm of Florida" and Allstate sold 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). The contraction of national insurers has been partly filled by "Florida Domestic" insurers who operate almost exclusively in the state (Sastry et al., 2023). These state-level insurers would seem to have less capacity to diversify their portfolio 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 11 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.[16] 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 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.

Finally, we show that over the last decade, the Florida Domestic insurers charge more per dollar of expected loss. In Table 8, 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 (2020-2024). In the last five years, a dollar increase in AAL leads to a $5.34 increase in hurricane

[16] 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, 2024). The county-level averages are weighted by zip-code population.

premiums by Diversified Companies versus a $7.15 increase by Florida Domestics. 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 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 three different types of masonry home and 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

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

where $n_{zst}$ denotes the number of homes in zip code $z$ of structure type $s$ in year $t$, $q_{jc(z)}$ 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, and 2017. 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 assign these homes to the three masonry structure types in the premium data as follows.[17]

[17] For each year $t$ in the premium data, we use FHCF data from the nearest of the three reported years (2007, 2012, 2017).

| | Applies to FHCF Homes... | |
|---|---|---|
| Standardized Premium Type | Year Built | Structure Opening Protection |
| 1990, no retrofit | $\leq 2001$ | No |
| 1990 with wind retrofit | $\leq 2001$ | Yes |
| 2005 | $\geq 2002$ | Yes or No |

To construct $q_{jc(z)}$, 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

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

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 11 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 11 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 11 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 over $2,900 in 2024. The hurricane premium increase is responsible for almost all of the acceleration in total premiums over this period.

### 6.3 Premiums and Expected Losses by Structure Type

Figure 12 disaggregates the premium indices by the three model home types in the data. Non-hurricane premiums are relatively similar across the three panels. They are slightly smaller for 2005 homes (the "Post-Code" homes), possibly reflecting reduced claims risk from newer plumbing, wiring, and other features. The annual rate of increase in non-hurricane premiums is relatively constant over time and across home types. In contrast, hurricane premiums differ markedly across the three home types. In 2019, the average hurricane premium was \$1,800, \$1,050, and \$650 across the three panels. By 2024 the disparities were even larger, with hurricane premiums at \$3,700, \$2,350, and \$1,450 for the three home types. This disaggregation shows how insurance price increases have been disproportionately borne by owners of the most physically vulnerable homes. It also illustrates the large degree to which insurers differentiate prices with respect to structure-level risk mitigation. These results suggest that a typical owner of a 1990 home could substantially reduce their annual insurance premiums by upgrading wind protections.[18]

Figure 12 also plots average expected losses due to hurricanes for the structure type where these data are available. The jump in expected hurricane losses due to adoption of the updated AIR and RMS models in 2022 is clearly visible. Nevertheless, the main visual takeaway is that the growth of hurricane premiums dwarfs the growth in expected losses.

### 6.4 Citizens vs. Private Insurers

Figure 13 shows average premiums over time for Citizens vs. all other insurers. As discussed in Section 2.1.2, Citizens faces binding statutory limits on the rate of increase in prices, and these limits are apparent in the figure. Overall average premiums for customers on Citizens have increased little during the study period. Recent increases in hurricane premiums have been offset by corresponding decreases in non-hurricane premiums. This contrasts sharply with the growth in private market premiums over the same period.

## 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 scientists (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 average of 50% according to the leading CAT models. We examine how these estimates of growing risk are passed on to consumers and find that a \$1 increase in property-level expected loss increases homeowners premiums by an average of

[18]The figure actually understates the effect of risk mitigation on premiums because of compositional effects: mitigated homes are disproportionately located in high-hazard counties. Appendix Figure 2 disaggregates by both structure type and local hurricane hazard to make this point more cleanly.

$4.50 over the last two decades. 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 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: in 2024, an average Floridian owning a home with the most common construction features would have paid over $3,700 in hurricane premiums, roughly six 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 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 adds empirical support for policy proposals focused on reducing these add-on costs. One set of potential policy interventions focus 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 since the 9-11 attacks, including in the U.S., the U.K., Germany, and many other countries (Webel, 2022). Private reinsurers report that they are "at capacity" for hurricane/cyclone and earthquake risks (CNBC, 2023), and 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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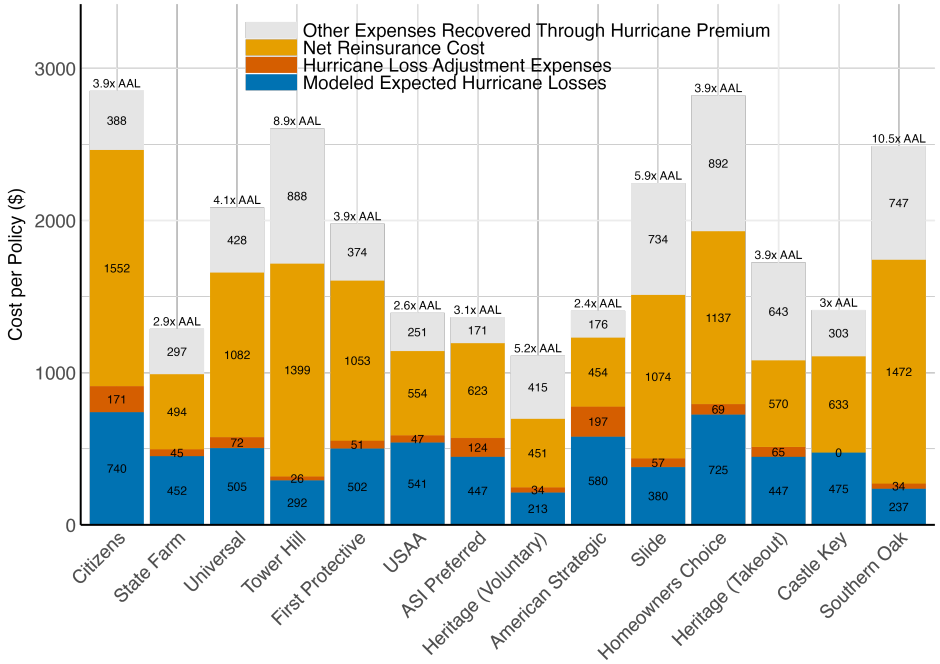
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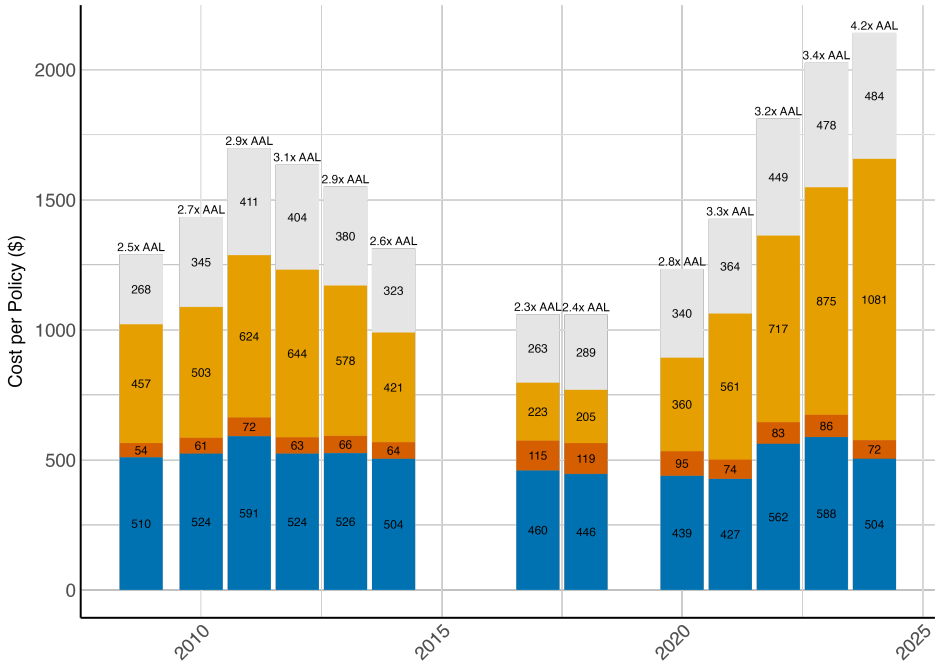
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Figure 1: Hurricane-Related Costs for Florida Homeowners Insurers

Panel (A) Most Recent Rate Filing (2023–2025)

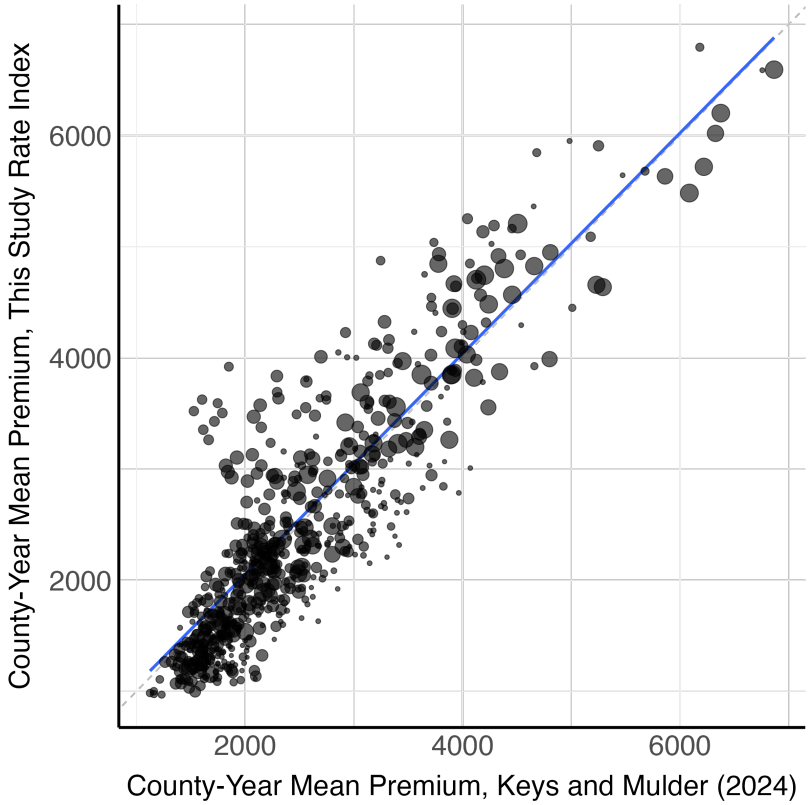



Panel (B) Universal Property & Casualty Over Time




*Notes:* Data are indicated premium components from Florida Office of Insurance Regulation Standardized Rate Indications Workbook. Panel (A) shows the largest insurers in Florida ordered by policies in force at most recent rate filing. Panel (B) shows a single insurer, Universal Property and Casualty, across rate filings from 2009 to present. "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.

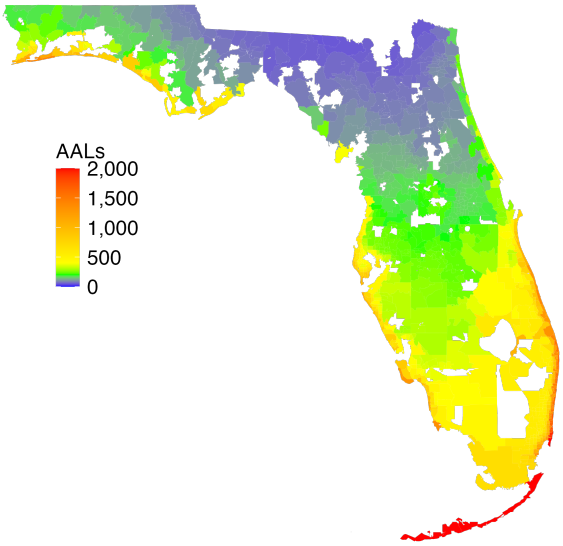
Figure 2: Rate Filing Data vs. Mortgage Escrow Data



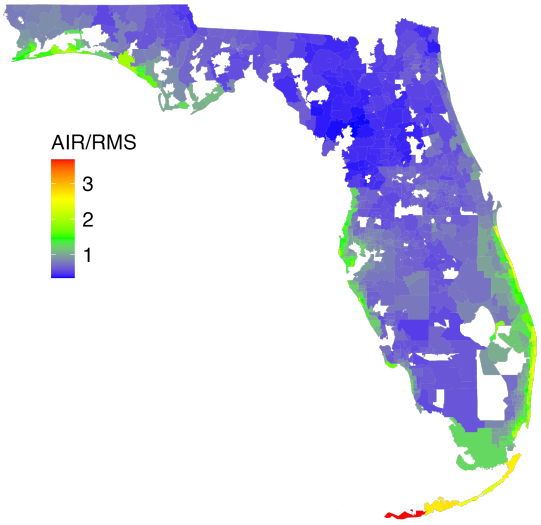

*Notes:* Vertical axis is county-average insurance price in the rate filing data, weighted to reflect county-level insurer market shares and county-level building stock. Horizontal axis is county average premium from Keys and Mulder (2024). Every marker represents a single county-year between 2014 and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

Figure 3: Modeled Expected Losses Across Zip Codes, 2023

**Panel A: AIR**

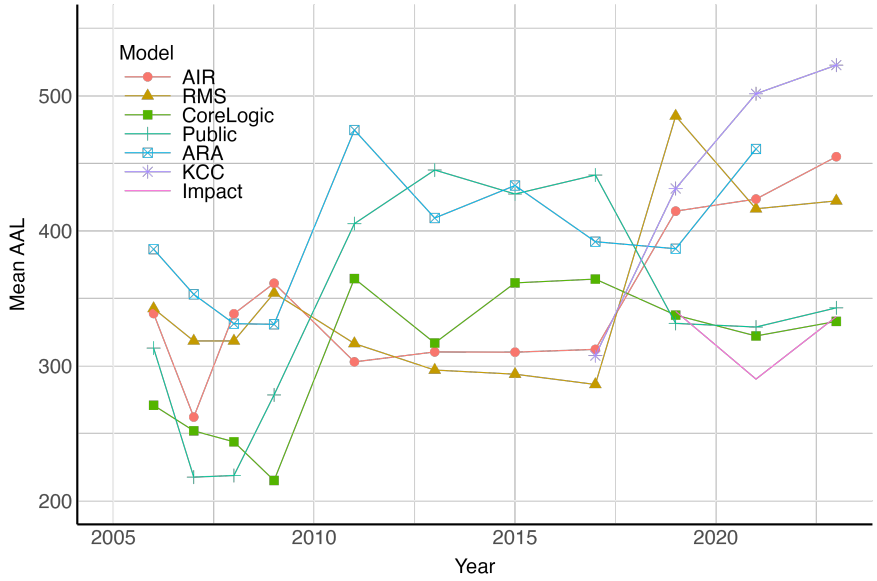



**Panel B: AIR vs. RMS**



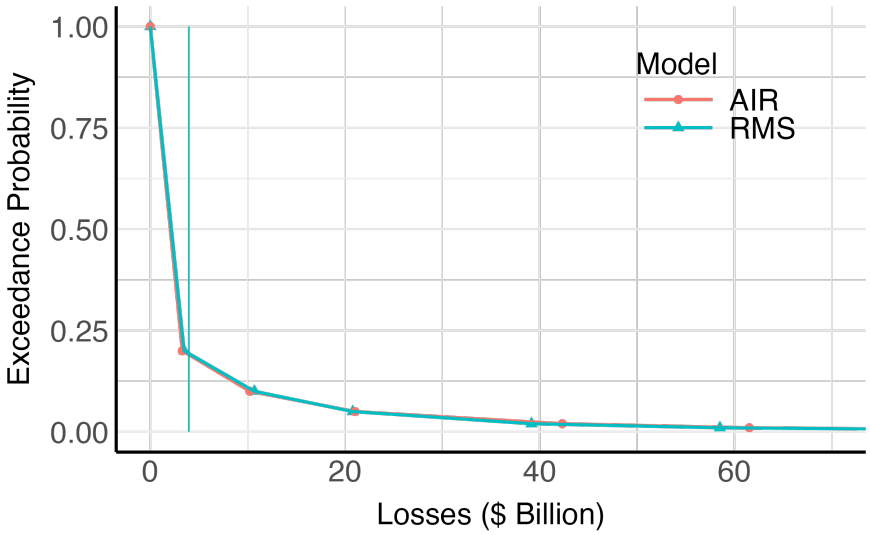

*Notes:* Panel (A): shows AIR's 2023 modeled average annual losses (AALs), which are the expected loss per $100,000 of a home's replacement cost. Estimates for a representative masonry exterior home built in 1989. The map shows the expected loss at the centroid of each zip code. Panel (B) divides the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

Figure 4: 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.

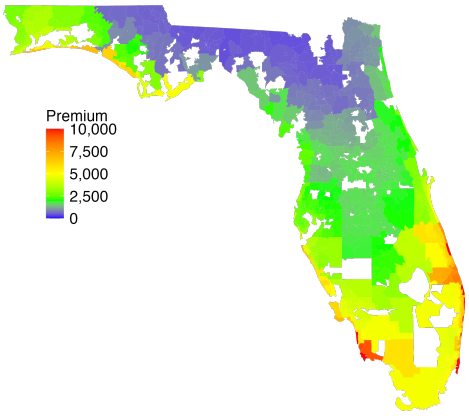
Figure 5: Exceedance Probability Curves, 2021



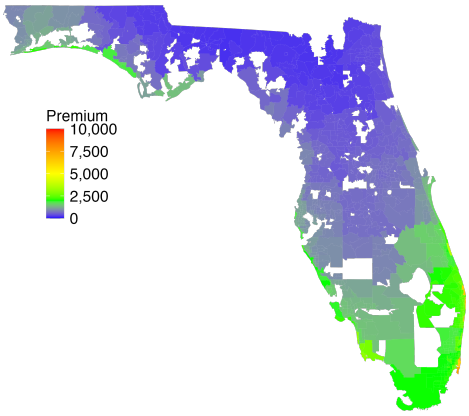

*Notes:* The figure shows are exceedance probability curves for AIR and RMS in 2021. The modeled portfolios include effectively all residential properties in Florida. Losses are in billions of dollars. The vertical lines provide the portfolio-level expected loss, which was $3.97 billion for both models in 2021. The right-most dots on the curves reflect the 1% exceedance probability.

Figure 6: Average Hurricane and Non-Hurricane Premiums in 2023

**Panel A: Hurricane Premium**

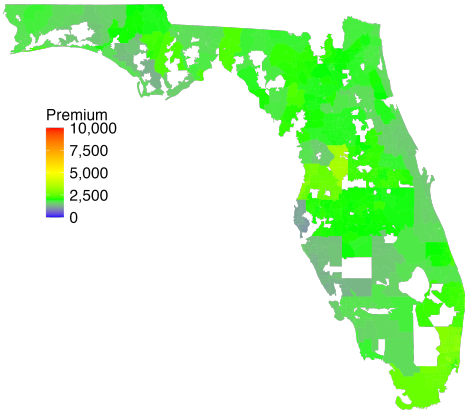



Home Built in 1990

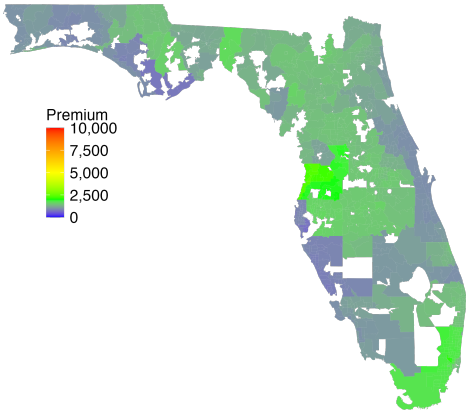



Home Built in 2005

**Panel B: Non-Hurricane Premium**




Home Built in 1990

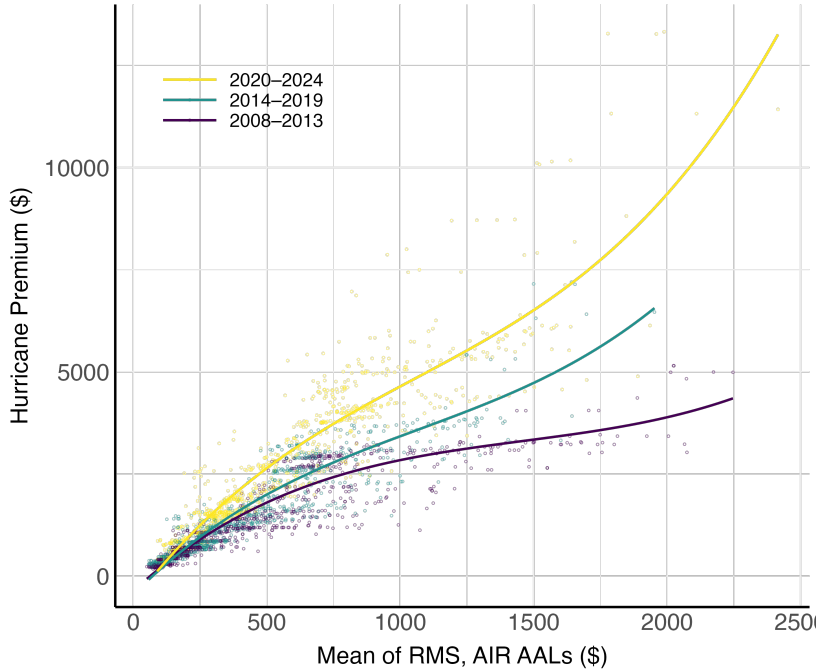



Home Built in 2005

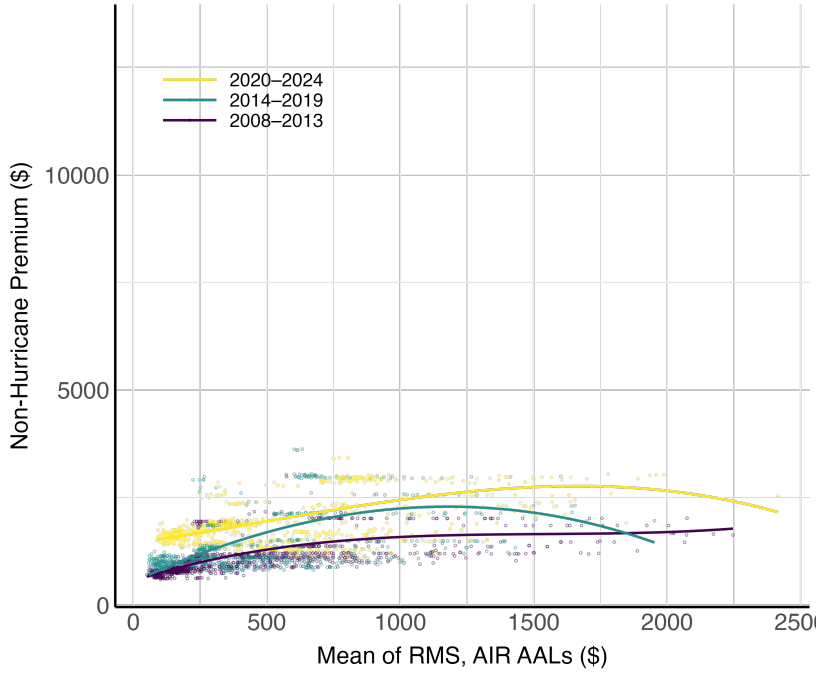
*Notes:* Figure shows zip code-level market share-weighted average premiums across all insurers in 2023. Left column shows premiums for reference 1990 home without wind retrofits; bottom row shows reference 2005 home. Scale is top-coded at $10,000.

Figure 7: Hurricane and Non-Hurricane Premium vs. AAL by Year

Panel (A) Hurricane Premiums

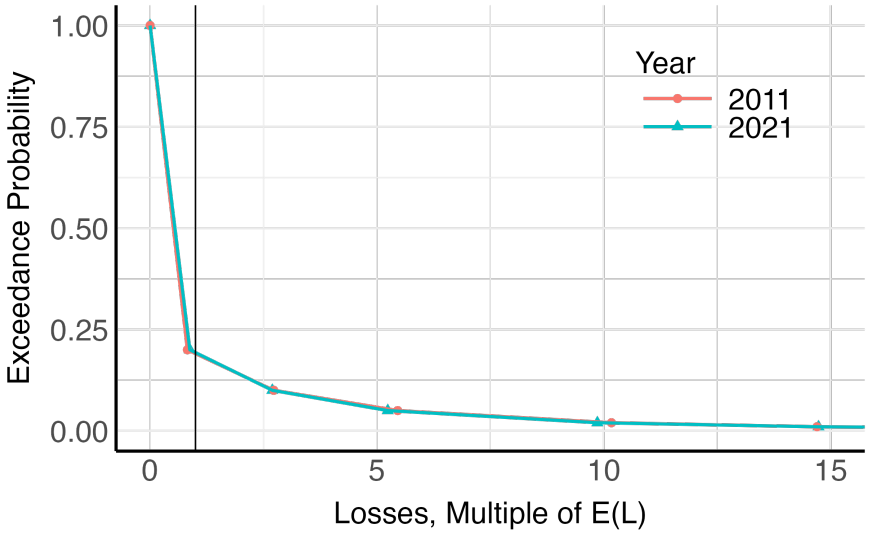



Panel (B) Non-Hurricane Premiums



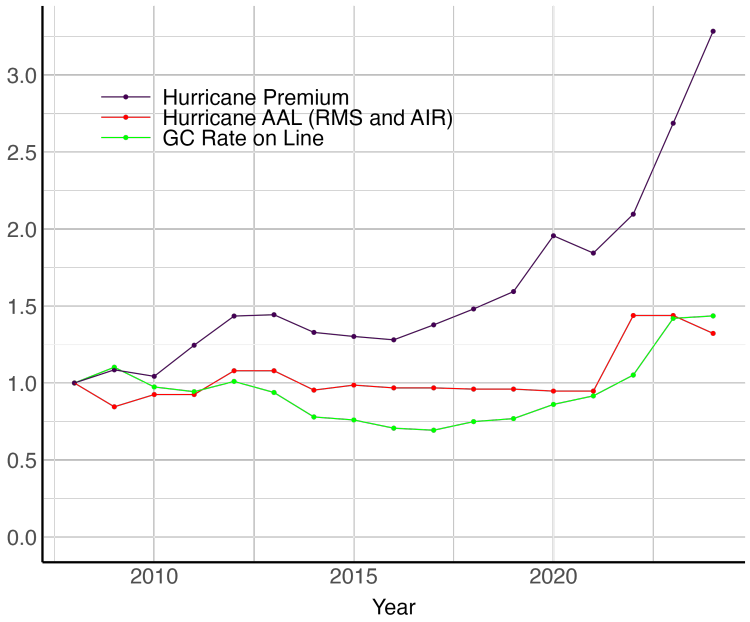

*Notes:* Data are an unbalanced insurer-by-zip-by-year panel of premiums for a standardized masonry home. Horizontal axis shows the simple mean of RMS and AIR modeled average annual hurricane losses for the standardized home. Plot shows weighted average premium by zip code, where weights are the product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

Figure 8: RMS Exceedance Curves, 2011 vs. 2021



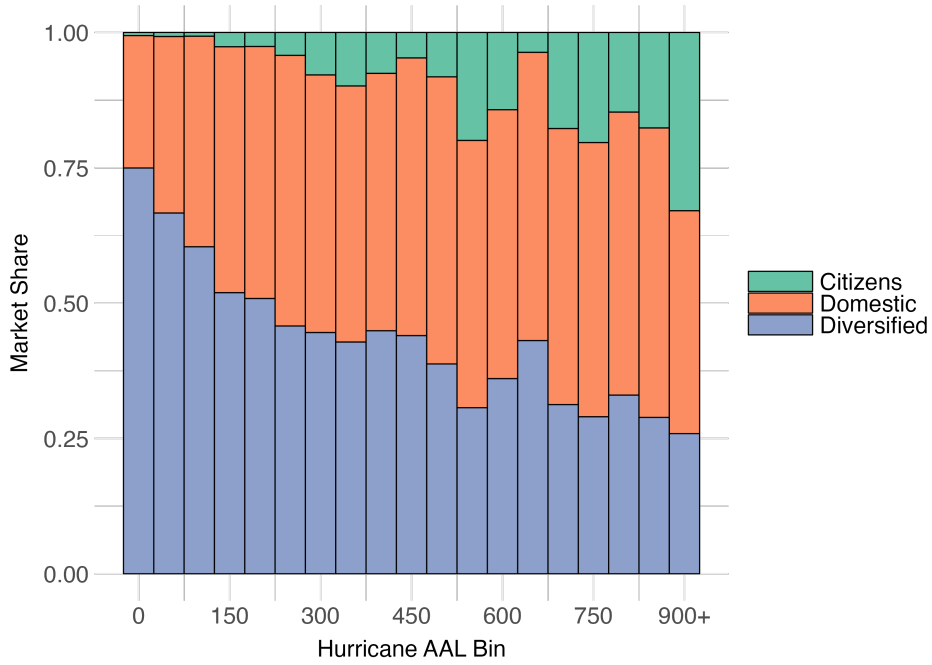

*Notes:* The figure reports the exceedance curve as multiples of the expected loss. It shows that losses at the 1st percentile of the distribution are 15 times the expected loss in both 2011 and 2021.

Figure 9: Hurricane Premiums, Expected Losses, and Reinsurance Prices



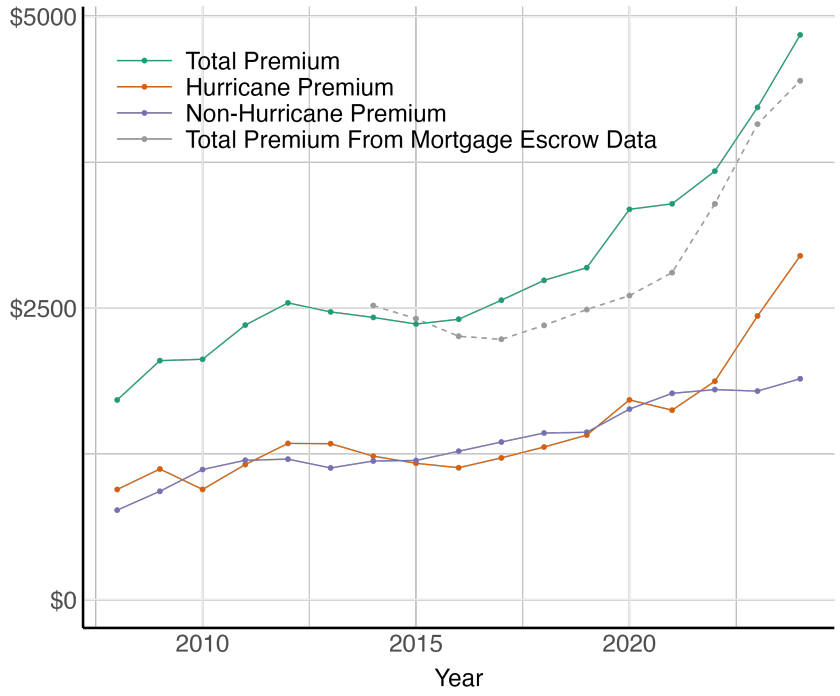

*Notes:* The figure plots reinsurance prices over time for comparison with average hurricane premiums and expected losses (AALs). Each is normalized based on its value in 2008. Reinsurance prices reflect the Guy Carpenter Rate On Line Index for U.S. Property Catastrophe Risk. Rate On Line measures the premium per dollar of reinsurance purchased.

Figure 10: 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.

Figure 11: Florida Home Insurance Price Index, 2008–2024




*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).

Figure 12: Price Index By Structure Type

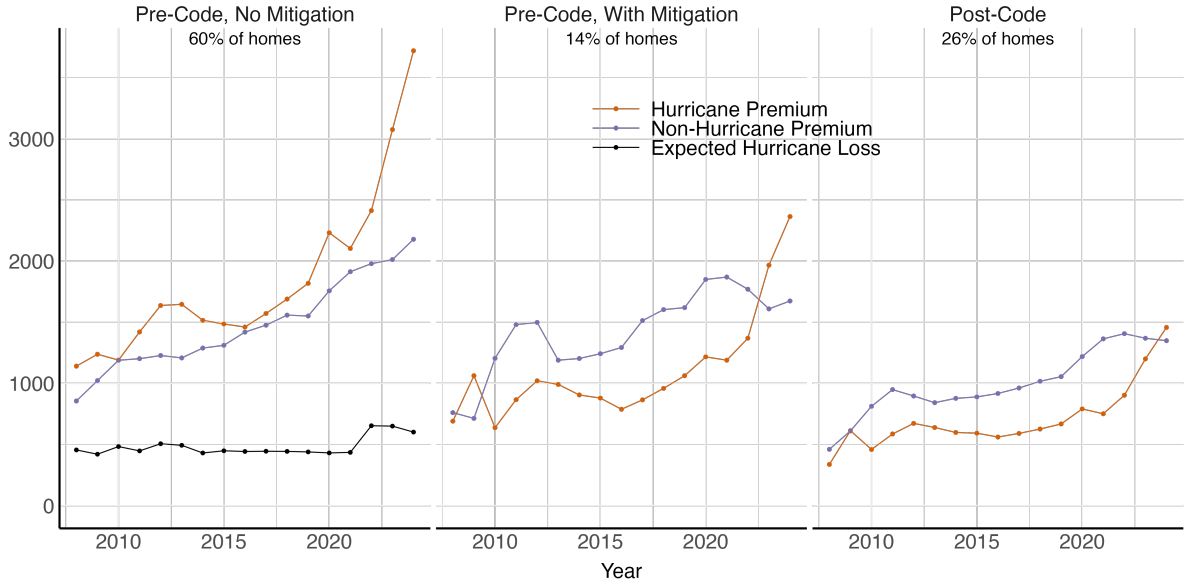



Figure 13: Price Index For Citizens vs. Private Market

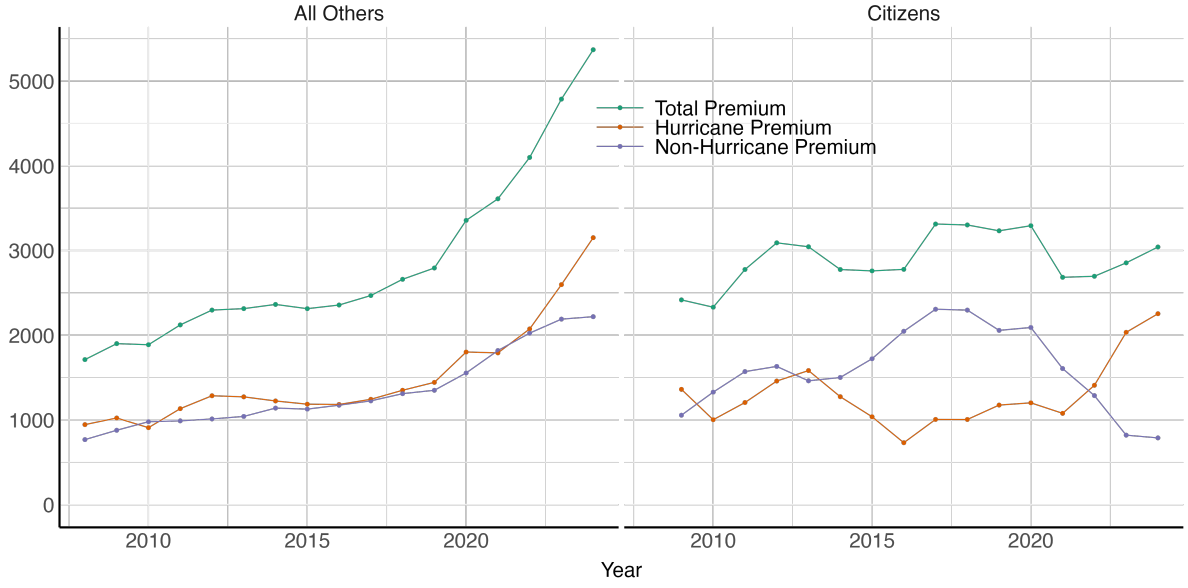


Table 1: Florida Insurers in the Dataset

| 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%) | |

Table 2: Florida Insured Housing Stock by Construction and Vintage

| | Masonry | Frame | Other/Unknown |
|---|---|---|---|
| **2007** | | | |
| Pre-Code, No Mitigation | 0.57 | 0.16 | 0.05 |
| Pre-Code, With Mitigation | 0.05 | 0.00 | 0.00 |
| Post-Code | 0.13 | 0.03 | 0.01 |
| **2012** | | | |
| Pre-Code, No Mitigation | 0.47 | 0.14 | 0.04 |
| Pre-Code, With Mitigation | 0.10 | 0.01 | 0.00 |
| Post-Code | 0.17 | 0.05 | 0.02 |
| **2017** | | | |
| Pre-Code, No Mitigation | 0.43 | 0.14 | 0.04 |
| Pre-Code, With Mitigation | 0.10 | 0.01 | 0.00 |
| Post-Code | 0.20 | 0.06 | 0.02 |

*Notes:* Table summarizes snapshots of the population of insured Florida homes in 2007, 2012, and 2017. Panels report the share of homes by construction materials and vintage in each of these years. "Pre-Code" refers to homes built before 2001. "With Mitigation" refers to pre-code homes that have been substantially retrofitted to reduce hurricane vulnerability.

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 by the 2006 AALs for each zip code.

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

| | Mean | SD | p5 | p50 | p95 |
|---|---|---|---|---|---|
| **1990 Masonry Home, No Wind Retrofit** | | | | | |
| Hurricane Premium | 2,121 | 2,362 | 265 | 1,316 | 6,362 |
| Non-Hurricane Premium | 1,518 | 1,074 | 641 | 1,224 | 3,309 |
| Hurricane Expected Loss (RMS/AIR) | 491 | 373 | 96 | 384 | 1,245 |
| Hurricane Expected Loss (Model Used by Insurer) | 489 | 419 | 89 | 358 | 1,342 |
| Hurricane Expected Loss (All Models) | 505 | 398 | 76 | 372 | 1,298 |
| **1990 Masonry Home, Maximum Wind Retrofit** | | | | | |
| Hurricane Premium | 695 | 724 | 81 | 449 | 2,071 |
| Non-Hurricane Premium | 1,157 | 720 | 456 | 983 | 2,480 |
| **2005 Masonry Home** | | | | | |
| Hurricane Premium | 746 | 760 | 113 | 523 | 2,058 |
| Non-Hurricane Premium | 1,053 | 716 | 401 | 847 | 2,384 |

*Notes:* Dataset contains 222,264 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.

Table 5: Price of Hurricane Risk – Passthrough of a Major Model Update

| | Hurricane Premium (1) | Non-Hurricane Premium (2) |
|---|---|---|
| RMS, AIR AAL | 5.82*** (0.658) | -0.536 (0.329) |
| Company-Year FE | ✓ | ✓ |
| Company-Territory FE | ✓ | ✓ |
| Observations | 8,913 | 8,913 |
| Dependent variable mean | 3,424.9 | 2,337.3 |
| $R^2$ | 0.97 | 0.96 |

*Notes:* Table shows two separate OLS regressions. The dataset is restricted to years 2021 and 2023. All regressions include weights equal to the firm's implied number of customers by territory. Standard errors are clustered by county.

Table 6: Average Price of Hurricane Risk

| | Hurricane Premium | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Constant | -108.8 (77.6) | | | |
| RMS, AIR AAL | 4.14*** (0.173) | 4.51*** (0.107) | | |
| RMS, AIR AAL × 2008-2013 | | | 3.06*** (0.151) | 3.58*** (0.153) |
| RMS, AIR AAL × 2014-2019 | | | 4.44*** (0.131) | 4.13*** (0.124) |
| RMS, AIR AAL × 2020-2024 | | | 5.81*** (0.274) | 5.25*** (0.284) |
| Company-Year FE | | ✓ | ✓ | ✓ |
| Panel | Unbalanced | Unbalanced | Unbalanced | Balanced |
| Observations | 46,290 | 46,290 | 46,290 | 28,649 |
| Dependent variable mean | 2,496.9 | 2,496.9 | 2,496.9 | 2,400.0 |
| $R^2$ | 0.48 | 0.76 | 0.79 | 0.80 |

*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.

Table 7: Average Price of Hurricane Risk, Additional Specifications

| | Hurricane Premium | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| RMS, AIR AAL | 4.51*** (0.107) | | |
| All-Model Mean AAL | | 3.96*** (0.113) | |
| AAL from Firm's Reported Vendor | | | 4.16*** (0.077) |
| Company-Year FE | ✓ | ✓ | ✓ |
| Observations | 46,290 | 46,290 | 46,290 |
| Dependent variable mean | 2,496.9 | 2,496.9 | 2,496.9 |
| $R^2$ | 0.76 | 0.77 | 0.76 |

*Notes:* Table shows four separate 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.

Table 8: Average Price of Hurricane Risk by Insurer Type

| | | Hurricane Premium | |
|---|---|---|---|
| Insurer Type | Florida Domestics | Diversified Companies | Citizens |
| | (1) | (2) | (3) |
| RMS, AIR AAL × 2008-2013 | 2.90*** (0.084) | 4.80*** (0.200) | 2.06*** (0.238) |
| RMS, AIR AAL × 2014-2019 | 5.01*** (0.228) | 3.68*** (0.099) | 3.73*** (0.620) |
| RMS, AIR AAL × 2020-2024 | 7.15*** (0.268) | 5.34*** (0.220) | 4.19*** (0.811) |
| Company-Year FE | ✓ | ✓ | ✓ |
| Observations | 20,772 | 23,939 | 1,579 |
| Dependent variable mean | 2,336.1 | 2,700.8 | 1,521.2 |
| $R^2$ | 0.84 | 0.80 | 0.67 |

*Notes:* Table shows two separate OLS regressions. The dataset is restricted to years 2021 and 2023. All regressions include weights equal to the firm's implied number of customers by territory. Standard errors are clustered by county.

# 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. These forms are publicly available from the commission for model review years 2011 and later. 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 (2006–2021) 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 Advanced Risk Analysis. 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 | 2020–2024 |
|---|---|---|---|
| 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

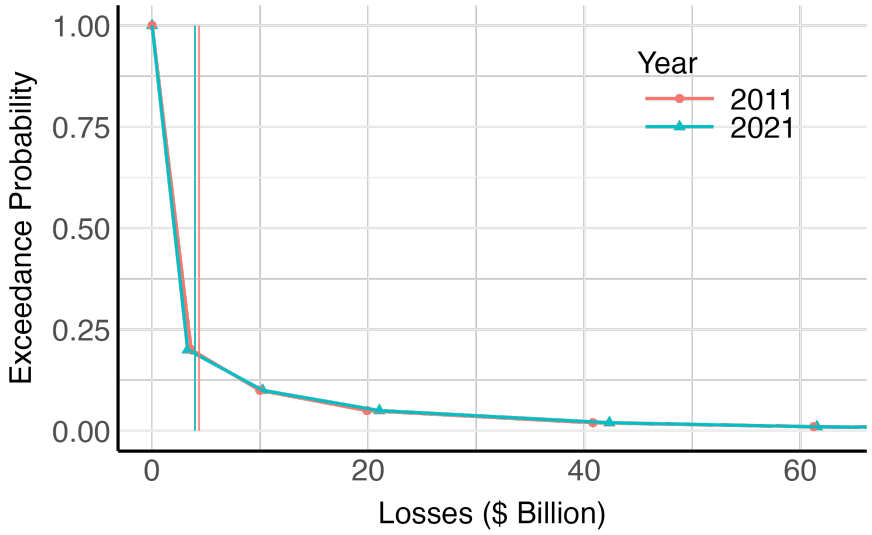
Appendix Table 5: Median Insured Value by Construction and Vintage

| | Masonry | Frame | Other/Unknown |
|---|---|---|---|
| **2007** | | | |
| Pre-Code, No Mitigation | 188,819 | 177,140 | 195,100 |
| Pre-Code, With Mitigation | 249,559 | 238,315 | 263,000 |
| Post-Code | 259,032 | 236,645 | 249,800 |
| **2012** | | | |
| Pre-Code, No Mitigation | 206,955 | 201,322 | 232,314 |
| Pre-Code, With Mitigation | 250,248 | 235,057 | 236,396 |
| Post-Code | 270,200 | 248,177 | 277,750 |
| **2017** | | | |
| Pre-Code, No Mitigation | 218,313 | 211,686 | 247,881 |
| Pre-Code, With Mitigation | 270,781 | 241,750 | 250,000 |
| Post-Code | 281,191 | 266,700 | 287,200 |

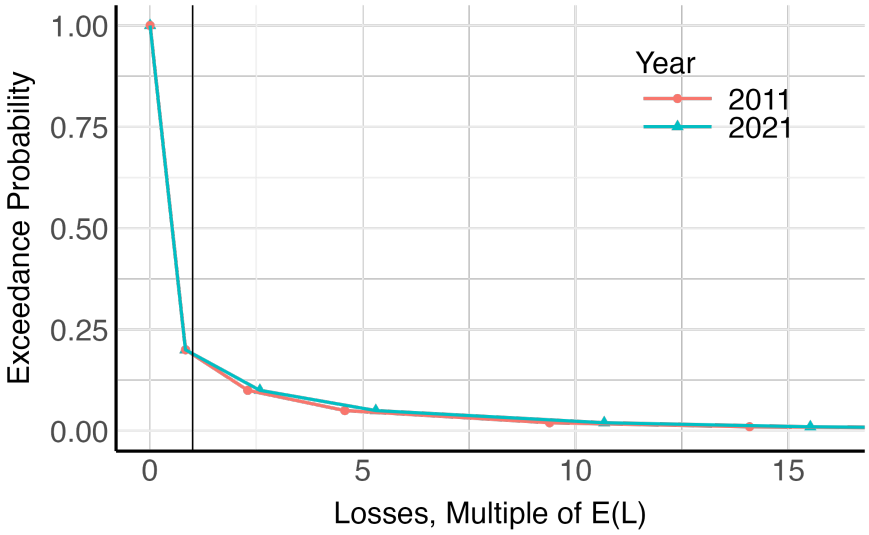
*Notes:* Table summarizes FHCF data that provide snapshots of the population of insured homes in 2007, 2012, and 2017. "Pre-Code" refers to homes built before 2001. "With Mitigation" refers to pre-code homes that have been substantially retrofitted to reduce hurricane vulnerability. Table reports the median coverage limit on the home structure (Coverage A) for each of these home types over time.

## 2 Exceedance Curves

Appendix Figure 1: 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 2011 and 2021. 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 $3.56 billion in 2011 and $3.97 billion in 2021. 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 2011 and 2021.

Appendix Table 6: Exceedance Curves by Model Vendor and Year

Panel (A): Florida Portfolio

| | AIR | | RMS | |
|---|---|---|---|---|
| Probability | 2011 | 2021 | 2011 | 2021 |
| 1.0000 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.2000 | 0.83 | 0.83 | 0.82 | 0.88 |
| 0.1000 | 2.30 | 2.58 | 2.73 | 2.69 |
| 0.0500 | 4.58 | 5.31 | 5.46 | 5.24 |
| 0.0200 | 9.39 | 10.67 | 10.17 | 9.86 |
| 0.0100 | 14.09 | 15.52 | 14.70 | 14.73 |
| 0.0040 | 21.61 | 23.06 | 22.37 | 23.04 |
| 0.0020 | 27.82 | 28.51 | 30.04 | 30.72 |
| 0.0010 | 34.94 | 35.38 | 39.64 | 40.08 |
| 0.0005 | 41.60 | 42.36 | 51.05 | 51.52 |
| 0.0002 | 51.24 | 54.95 | 68.09 | 69.64 |
| 0.0001 | 61.46 | 68.71 | 81.86 | 85.01 |

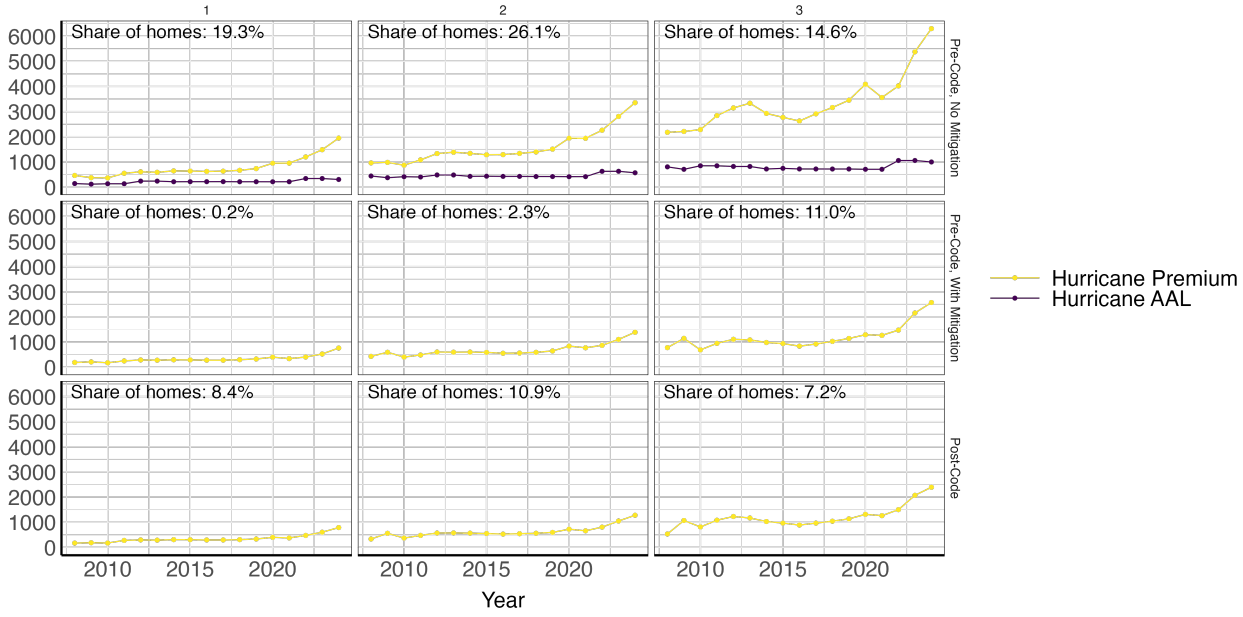
Panel (B): Notional Portfolio

| | AIR | | RMS | |
|---|---|---|---|---|
| Probability | 2011 | 2021 | 2011 | 2021 |
| 1.0000 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.2000 | 0.91 | 1.04 | 1.09 | 1.14 |
| 0.1000 | 2.40 | 2.89 | 3.00 | 2.97 |
| 0.0500 | 4.55 | 5.55 | 5.41 | 5.28 |
| 0.0200 | 9.03 | 10.02 | 9.32 | 9.16 |
| 0.0100 | 12.76 | 13.35 | 12.84 | 12.88 |
| 0.0040 | 19.71 | 18.60 | 18.39 | 18.75 |
| 0.0020 | 25.09 | 22.09 | 23.56 | 24.03 |
| 0.0010 | 30.82 | 24.65 | 29.84 | 30.37 |
| 0.0005 | 35.55 | 29.10 | 37.28 | 37.92 |
| 0.0002 | 43.54 | 34.63 | 48.19 | 49.48 |
| 0.0001 | 55.36 | 43.77 | 57.05 | 59.12 |

*Notes:* Values are in multiples of the model's expected loss.

# 3 Additional Figures and Tables

Appendix Figure 2: Hurricane premium index by home type and hurricane hazard




*Notes:* Each row shows results for one home type and each column shows results for one tercile of county-level hurricane hazard (county average hurricane AAL).