**Finance and Economics Discussion Series**

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

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**2026-016**

Please cite this paper as:
Heitfield, Erik (2026). "Model Uncertainty and the Pricing of Hurricane Risk in Florida ," Finance and Economics Discussion Series 2026-016. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2026.016.

# Model Uncertainty and the Pricing of Hurricane Risk in Florida

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2025-12-26

**Abstract** This paper examines how model uncertainty affects the price of catastrophe risk insurance. We use unique data on expected loss rate projections from seven hurricane risk models approved by regulators for use in Florida property insurance rate setting to quantify model uncertainty. By combining these data with newly published information on local property insurance markets, we are able to empirically test the relationship between model uncertainty and insurance premiums across Florida ZIP codes and over time. Controlling for confounding variables and time-invariant latent factors that may be correlated with observed variables, we find strong empirical support for the hypothesis that greater dispersion among model forecasts leads to higher homeowners insurance premiums. Our findings suggest that, had model dispersion been ten percent lower than that observed in 2021, a typical Florida homeowner would have saved $50 to $90 on her annual homeowners insurance premium.

**Kewords:** risk management, home insurance, hurricanes, model uncertainty

**JEL Codes:** D83, G22, G32, G41

## 1 Introduction

Insuring risks arising from low-probability, high-severity hazards such as earthquakes, terrorist attacks, and hurricanes is notoriously difficult. Very large loss events are harder to diversify, risk averse investors require high premiums to offload deep tail risk, and insurers must hold far more capital relative to expected losses to cover potential claims than they do for more commonplace hazards such as auto accidents. Less appreciated is the fact that since these events are by definition quite rare, insurers and investors also have much less information with which to make judgments about the distribution of future losses.

The uncertainty associated with forecasting future catastrophe events can be separated into two broad components. *Aleatoric uncertainty* refers to that component of uncertainty inherent to a system that cannot be eliminated even with perfect data and correctly specified models. In contrast, *epistemic uncertainty* refers to uncertainty arising from lack of knowledge about the system that could be reduced given further research. One manifestation of epistemic uncertainty is that different catastrophe risk models may project different loss distributions, even if they are derived from similar or the same underlying data. We commonly call this source of uncertainty model uncertainty or model risk.

This paper examines how model uncertainty, as distinct from aleatoric uncertainty, influences pricing in catastrophe risk insurance markets. Using unique data on hurricane loss projections from seven catastrophe risk models approved by Florida regulators for use in setting homeowners insurance prices, we measure dispersion in model loss projections across ZIP codes and over time. By combining these data with recently published information on local property insurance markets from the Treasury Department's Federal Insurance Office, we investigate the relationship between model uncertainty and homeowners insurance premiums.

Our analysis makes three main contributions to our understanding of effects of model uncertainty on insurance pricing. First, our review of detailed documentation and test deck results for hurricane risk models shows that there is significant dispersion among model loss forecasts at the level of individual ZIP codes, and that these differences can primarily be attributed to differing assumptions and judgments applied by model developers rather than to sampling error or differential access to available data. Second, using a stylized model of insurance price-setting and regulation in the presence of model uncertainty, we show that greater dispersion among model forecasts can lead to higher premiums either because insurers are averse to ambiguity, or because they are able to "cherry pick" among available models to relax regulatory constraints. Finally, we show that there is a strong empirical relationship between model uncertainty and homeowners insurance premiums. Controlling for confounding variables including expected losses, house prices, and community demographics, as well as latent variables that may be correlated with observed variables, we find strong statistical support for the hypothesis that greater dispersion among model forecasts leads to higher homeowners insurance premiums. Our findings suggest that, had model uncertainty been ten percent lower than that observed in 2021, a typical Florida homeowner would have saved $50 to $90 on her annual homeowners insurance premium.

Understanding the drivers of catastrophe insurance pricing is important because, while the challenges of insuring catastrophe risks are substantial, the social benefits of doing so are also very large. Insurance is a critical source of community resilience following disasters. Insurance payouts enable households and businesses to meet short-term liquidity needs and provide capital necessary for rebuilding (You and Kousky 2024), allowing local economies where insurance is broadly available to recover more quickly from natural disasters (von Peter, von Dahlen, and Saxena 2024). By providing an efficient mechanism for transferring risk, insurance also supports the functioning of important asset markets such as real estate. The social benefits of insuring catastrophe risks are so large that when salient risks become uninsurable in private markets, governments are frequently called upon to fill the gap.[1]

Homeowners insurance markets have come under severe strain in large parts of the United States as devastating wildfires in western states and hurricanes and flooding elsewhere have led to high insurance losses. Nationwide data on 246 million insurance policies collected by the Federal Insurance Office (2025) shows that premiums increased by 8.7 percent in real terms from 2018 to 2022, with consumers in ZIP codes with the highest insurance losses facing higher rates of premium increases and policy cancellations. Using mortgage escrow data to infer home insurance premium payments, Keys and Mulder (2024) find that a doubling of U.S. reinsurance prices from 2018 to 2023 coincided with a significant increase in the sensitivity of property insurance premiums to measures of local disaster risk.

Insurers will naturally seek to charge higher premiums in markets exposed to higher and more volatile losses, but economic research on ambiguity aversion and information frictions suggests that aleatoric risk may not be the only factor at play. Foundational work by Ellsberg (1961) demonstrates that individuals systematically prefer risks with known probabilities over those with unknown or ambiguous probabilities. Building on this resarch a rich theoretical literature on agent decision making has developed in which agents are assumed to either have smooth preferences over multiple probability distributions (Klibanoff, Marinacci, and Mukerji 2005) or to optimize against worst-case plausible alternatives to possibly erroneous models (Hansen and Sargent 2001). Models of dynamic asset pricing suggests that asset values should embed additional premiums to compensate for ambiguity about future returns (Chen and Epstein 2002; Epstein and Schneider 2007). A number of papers including Zhao and Zhu (2011), Gollier (2014), and Dietz and Walker (2019) have applied notions of ambiguity aversion to describe insurer behavior. While specific predictions vary depending on modeling assumptions, the consensus of this research is that rational ambiguity-averse insurers can be expected to charge higher prices, limit coverage, or both in markets with greater ambiguity.

Despite the large body of theoretical research on ambiguity aversion in insurance, empirical work on the subject has been limited. Using data from a survey of practicing actuaries, Cabantous (2007) finds that insurance professionals recommend charging higher premiums in scenarios where they have ambiguous or conflicting information about loss probabilities. Calibration studies such as that by Dietz and Niehörster (2021) have used data from loss forecasts to compute implied

[1]In the United States, the National Flood Insurance Program, the Terrorism Risk Insurance Act, the Florida Hurricane Catastrophe Fund, and the California Earthquake Authority are notable examples of government-sponsored catastrophe insurance programs established to provide coverage when fully private markets were unable to do so.

premiums and show how they relate to assumptions about the nature and magnitude of insurers' ambiguity aversion, but, importantly, they do not test whether ambiguity aversion influences actual transaction prices.

Models of strategic behavior in the presence of information asymmetries suggest an alternative mechanism by which uncertainty about underlying risk processes may lead to higher insurance prices. Agents may act in accordance with standard expected utility theory but may have access to different information about loss probabilities. Applying insights from Harrison and Kreps (1978) that asset prices in markets with disagreement reflect the valuations of pessimistic traders when more optimistic traders face constraints, recent work by Boomhower et al. (2024) argues that similar selection forces can operate when insurers differ in their ability to measure risks. Using data on property insurance rate submissions in California, they study how differences in competing firms' underwriting processes affect the pricing and availability of wildfire insurance. Firms that employ more granular wildfire risk models are able to compete effectively in high risk markets, whereas those with coarser models set higher prices or withdraw from such markets to avoid adverse selection. As a result, markets where there is greater uncertainty about risk processes are more concentrated and have higher average premiums than similarly risky markets where there is greater consensus among competitors about loss probabilities.

Another possibility, explored in this paper, is that model uncertainty gives firms subject to rate regulation an opportunity to behave strategically in their interactions with state insurance regulators. Economists have long recognized that price regulation creates incentives for firms to manipulate costs (Averch and Johnson 1962; Braeutigam and Panzar 1993). Furthermore, evidence from the global financial crisis (Cohen and Manuszak 2013) and the Florida insurance market (Sastry, Sen, and Tenekedjieva 2023) shows that when credit rating agencies disagree, firms can improve regulatory outcomes or lower borrowing costs by "cherry picking" the most optimistic ratings. Many states allow insurers to use catastrophe models to support requests for premium rate increases. In circumstances where rate regulation is a binding constraint and model forecasts diverge, insurers may be able to justify more aggressive rate increases by selecting more pessimistic models.

The remainder of this paper is organized as follows. In Section 2 we describe how hurricane risk models are used and regulated in homeowners insurance markets. Section 3 explains what can be deduced about the level and sources of differences among these models from regulatory filings. Section 4 develops a stylized model to illustrate how either ambiguity aversion or cherry picking behavior may lead to higher premiums in markets where hurricane loss projections are more dispersed. In Section 5 and Section 6 we present our empirical analysis of the relationship between model uncertainty and homeowners insurance premiums in Florida. Section 7 draws conclusions from our findings.

## 2 The role of catastrophe risk models in homeowners insurance markets

Catastrophe risk models play both a direct and an indirect role in the pricing of homeowners insurance in disaster-prone areas. Primary insurers make use of catastrophe models to evaluate risks to individual properties, which directly informs their underwriting decisions, and for portfolio planning and capital allocation purposes, which affects where they choose to market policies. Models may also have an indirect effect in primary insurance markets through their employment by reinsurance firms, rating agencies, and investors. Their use in this context affects the cost to primary insurers of offloading tail risk and obtaining financing, which can pass through to primary market prices (Keys and Mulder 2024).

In the U.S., property insurance is regulated at the state level. Individual state insurance commissions set rules governing the use of catastrophe models for capital management and underwriting. The National Association of Insurance Commissioners (NAIC), which promulgates standards and model rules that may be adopted by state insurance regulators, has recommended that risk-based regulatory capital charges include model-based adjustments for earthquake, hurricane, and wildfire catastrophe risks. Regulations covering the use of catastrophe risk models in homeowners insurance rate-setting vary markedly by state. For example, until recently in California the use of models for rate-setting was heavily constrained, with rules requiring that insurers justify proposed rate changes with historical data rather than forward-looking models.[2] Elsewhere regulators may require insurers to disclose their use of models and comply with supervisory standards, but do not typically certify or audit models directly.

Florida has what is likely the nation's most detailed and rigorous processes for regulating catastrophe risk models. Following extensive property losses and the failure of several insurers in the wake of hurricane Andrew, in 1995 Florida legislators established the Florida Commission on Hurricane Loss Projection Methodology (FCHLPM), an independent body tasked with evaluating models used for projecting hurricane and flood losses in the state. Hurricane models must be approved by the Commission to be used in support of state insurance rate filings. To obtain approval, vendors must submit detailed model documentation to the Commission. After reviewing this information to ensure that the model meets with its standards, the Commission issues a "letter of acceptability" to the vendor. As of 2025, hurricane models by CoreLogic, Impact Forecasting, Karen Clark and Company, Moody's (formerly RMS), and Verisk (formerly AIR) are approved for use in Florida. In addition, a hurricane model developed by researchers at the Florida International University is used by regulators in their review of rate filings. The Florida Public Hurricane Model (FPHM) has also been reviewed and approved by the Commission. The FCHLPM makes much of the information used in its model certification process available to the public, providing a high level of transparency into the technical details of vendors' hurricane models.

## 3 Epistemic uncertainty in hurricane loss forecasting

For each model it reviews, the FCHLPM requires vendors to submit written responses to questionnaires probing every aspect of their modeling methodology. The Commission also requires vendors to produce quantitative information on the output of their models. These data include statewide loss cost estimates, projected losses for particular storm scenarios, and ZIP code level projected loss costs for different types of homes. This detailed qualitative and quantitative

[2] In December 2024 California passed new legislation allowing insurers to use wildfire risk models in statewide rate setting. Prior to this change models could be used for rate segmentation but not for setting overall rate levels.

information provides a rare perspective on how catastrophe models are designed, and on their similarities and differences.

Figure 1 compares projected losses per dollar of exposure to frame homes by ZIP code for each of seven vendor models approved for use in Florida in 2021. All models tend to predict higher loss costs in the same ZIP codes, but the forecasts are not as highly correlated as one might expect. Figure 2 shows how the models assess risk in different locations differently. A couple of models project very steep risk gradients from north to south, while others show smoother transitions. Likewise, some models project much higher losses in coastal areas relative to inland areas than others. Differences across model forecasts within ZIP codes are not small. As shown in Figure 3, the lowest loss cost projections for ZIP codes in the top risk quartile are similar to the average loss projections for ZIP codes in the third risk quartile. These forecasts reflect the work of some the top catastrophe modeling firms and academics in the world and all have been subject to a rigorous regulatory approval process. Why are their forecasts so different?

The answer is that forecasting hurricane losses is subject to epistemic uncertainty, as well as aleatoric uncertainty. It is well understood that the location and severity of future hurricanes is inherently unknowable, and would be so even if forecasters had access to virtually infinite quantities of data on weather patterns.[3] But there is also much we do not know about how storms propagate and about how weather conditions translate into property losses, and this uncertainty yields ample opportunities for different forecasters to arrive at different conclusions from the same data.

Most catastrophe risk models used in insurance underwriting share a similar architecture consisting of three components: a hazard module, a vulnerability module, and a financial module (see Figure 4). The hazard module relies on a catalogue of catastrophe events, called a *stochastic event set*, consisting of information on the location, severity, and probability of possible events. All Florida hurricane models build stochastic event sets from the National Oceanic and Atmospheric Administration's (NOAA) HURDAT database, which includes Atlantic Basin storm track information dating back to the 1850s. Each modeling firm applies is own filters and adjustments to the raw storm track data. For example, some firms discount older data because they believe they are less representative of current climate conditions. Storm track data provide only high level information on the location and severity of storms. Vendors combine this data with more fine-grained geospatial information on local topology and hydrology and apply engineering models to estimate intensity parameters at individual exposure locations.

Monte Carlo draws from the stochastic event set and engineering models are then passed to the vulnerability module, which links physical parameters from a simulated event such as wind speed or water depth to "ground-up" losses on a property. There is substantial heterogeneity among the vulnerability modules used in Florida, with different vendors relying to different degrees on a mix of statistical analysis of historical data, engineering studies, and expert judgment. All models account for a variety of building characteristics such as construction type, above ground elevation,

[3] In a now famous address before the American Association for the Advancement of Sciences, meteorologist Edward Lorenz (1972) coined the phrase "the butterfly effect" after discovering that weather forecasts only a few days in the future were sensitive to miniscule rounding errors in input data.

and number of floors, and some attempt to capture the effects of risk mitigation such as storm shutters and roof truss straps.

Once ground-up losses are estimated, data are passed to the financial module which calculates insurance losses to individual properties or a portfolio of properties for a given event. Nonlinearities in the mapping from property damage to insured losses arising from deductibles, caps, co-pays and other policy features are incorporated at the exposure level. At the portfolio level, the financial module captures the effects of reinsurance and other risk ceding arrangements. Some vendors also attempt to embed broader economic factors, such as the effects of increases in demand for labor and construction materials following large-scale disasters, into their financial modules. The process of simulating events and computing ground-up and insured losses is repeated many times, yielding simulated loss distributions for individual exposures and portfolios. From these simulated distributions vendors compute a variety of standard risk metrics including average annual loss, occurrence probability, and probable maximum loss (called value-at-risk in other contexts).

We know that differences in forecasts across models do not primarily reflect the consequences of sampling variation because all vendors have access to substantially the same data. Rather, they reflect differences in modeling approaches, assumptions, and judgments. Though all seven Florida hurricane models use the same storm track data and similar information on property locations and characteristics, they employ different methodologies at each stage of the risk assessment process. They use different adjustments to stochastic event set data, they use different engineering models to project broad storm track data onto intensity parameters at the property level, they use different approaches to translate those parameters into ground-up losses, and they make different economic assumptions when transforming ground-up losses into insured losses.

# 4 How does model uncertainty affect insurance premiums?

As discussed in Section 2, hurricane risk models play a central role in Florida homeowners insurance regulation. Similar to most other states, homeowners insurance policy terms and rates must be approved by the state insurance regulator before or shortly after they come into effect. Florida statute requires that rates not be "excessive, inadequate, or unfairly discriminatory" and must rely on hurricane loss estimates produced by catastrophe models approved by the FCHLPM (Florida Legislature 2024a, 2024b). Florida law further requires that a public model be made available to all insurers and the state insurance regulator "for the purpose of calculating rate indicators in rate filing" and other purposes (Florida Legislature 2024c). In this section we develop a stylized model to illustrate how, in this context, either ambiguity aversion or cherry picking by regulated insures may lead to higher insurance premiums in markets where there is greater dispersion among hurricane model projections.

## 4.1 Model uncertainty and market structure

Consider a market where $N$ insurers compete by selling identical insurance contracts that pay \$1 in the event of a loss or \$0 otherwise. Each insurer's marginal cost is its expected payout, which, given our normalization of the insurance contract size, is simply the probability, $p$, that a claim will be filed. The true claim probability is unknown, however, and a range of models are available that produce estimates of the claim probability over the interval $\left[\underline{p}, \bar{p}\right]$. Model uncertainty is captured by the length of this interval. When considering comparative statics with respect to model uncertainty, we will focus on the more interesting case where the upper end of the range of model forecasts changes.

Though contracts have identical terms, we assume that search frictions and other switching costs cause consumers to view contracts from different insurers as differentiated products, leaving room for some pricing power by insures. This market structure is described using a standard Salop circle model where each firm is separated by an interval of width $1/N$.[4] Consumers are uniformly distributed across the unit circle. The value to consumer $i$ of a contract sold by firm $j$ is a linear function which is decreasing in the insurance premium $\pi_j$ and the distance between consumer $i$ and firm $j$. For simplicity, we assume all consumers share the identical valuation functions.

The market is subject to price regulation. Prior to setting its premium, insurer $j$ must submit a model claim probability, $p_j$, to the regulator. The regulator then approves a maximum premium that the firm can charge, according to the fixed rule $\lambda(p)$. We assume that the rule is known in advance and is applied equally to all insurers. Thus, the timing of decisions in our stylized model is as follows:

1. Firm $j$ submits a model $p_j$ to the regulator.
2. The regulator approves a premium cap $\lambda(p_j)$ for the firm.
3. The firm sets a premium $\pi_j \leq \lambda(p_j)$.
4. Consumers select policies and losses are realized.

The selections of $p_j$ and $\pi_j$ each occur simultaneously for all firms; firms do not observe one-another's actions before choosing their own actions.

## 4.2 Firm preferences

A firm's behavior depends on its preferences and beliefs about the true claim probability. For simplicity we assume that all firms share the same prior belief $p_0 \in [\underline{p}, \bar{p}]$ about the likelihood of a claim. We consider two alternative descriptions of firm preferences.

**Ambiguity Neutral**

Firms are risk neutral and insensitive to ambiguity. A firm facing an uncertain payoff function, $\Pi(p, \pi)$, seeks to maximize its expected payoff given its beliefs about the true claim probability

$$\max_{p,\pi} \mathrm{E}_{p_0}[\Pi(p, \pi)]$$

**Ambiguity Averse (Gilboa and Schmeidler 1989)**

Firms are risk neutral but are averse to ambiguity. A firm facing an uncertain payoff function, $\Pi(p, \pi)$, operates according to a min-max strategy in which it seeks to maximize its expected payoff given the worst possible claim probability

[4]Because market structure is not the main focus of this model, we take the number of firms and their location in product space as exogenous, though it is straightfoward to derive an equilibrium in which firms choose entry and location subject to a fixed entry cost.

$$\min_{\hat{p}\in[\underline{p},\bar{p}]} \max_{p,\pi} \mathrm{E}_{\hat{p}}[\Pi(p,\pi)]$$

Notice that in this simple framework the only distinction between ambiguity neutral firms and ambiguity averse firms is the claim probability used in determining expected payoffs. Ambiguity neutral firms use a fixed probability that does not depend on model uncertainty, while ambiguity averse firms use a worst-case probability that may depend on the range of models available.

## 4.3 Price regulation

The regulator seeks to constrain prices so that they are neither "excessive" nor "inadequate". A natural way to capture this idea is to establish a cap on the markup above marginal cost that an insurer can charge. The problem for the regulator is that it does not know a firm's marginal cost and is subject to the same model uncertainty as the firms themselves. In our simple framework the regulator has two options: it can either rely on its own estimate of the claim probability or accept the firm's estimate.

**Regulator Model**

The regulator makes use of its own model to determine the claim probability, $p_R$, and caps premiums at a "fair" markup $\mu$ above this estimate.

$$\lambda(p) = (1+\mu)p_R$$

**Firm Model**

The regulator accepts the firm's proposed estimate of the claim probability, $p$ and caps premiums at a "fair" markup $\mu$ above this estimate.

$$\lambda(p) = (1+\mu)p$$

In practice the regulator likely operates using a mixture of both approaches, relying on the Florida Public Hurricane Model for its own assessment, but also considering loss data reported by firms based on models approved by the FCHLPM. The two exteme cases defined here serve to pin down the range of options available to the regulator. We also consider the possibility that the permitted markup, $\mu$, is so high that the rule is not a binding constraint on firm pricing.

## 4.4 Equilibrium outcomes

In the absence of regulatory constraints, the optimal price response by firm $j$ given claim probability $\hat{p}$ and the premium $\pi_{-j}$ charged by rivals is

$$\pi_j(\pi_{-j};\hat{p}) = \frac{1}{2}\left(\pi_{-j} + \frac{1}{N} - \hat{p}\right) \tag{1}$$

The regulatory constraint for firm $j$, $\lambda_j$, is binding when $\lambda_j \le \pi_j(\pi_{-j};\hat{p})$. In this case the firm will set $\pi_j^* = \lambda_j$ and would prefer a higher constraint. In a symmetric equilibrium all firms will choose

$$\pi^*(\hat{p}) = \min\left(\hat{p} + \frac{s}{N}, \lambda\right) \tag{2}$$

where $s > 0$ is a demand parameter describing search frictions and $\lambda$ is the regulatory constraint common to all firms.

As discussed earlier, the value of $\hat{p}$ that firms use in setting prices depends on whether they are ambiguity averse, and, if they are, on the level of model dispersion. An immediate implication of Equation 2 is that when regulation is binding model uncertainty does not affect equilibrium pricing in the price-setting subgame. For a given binding price cap $\lambda$, ambiguity averse firms will act in exactly the same way as ambiguity neutral firms. On the other hand, when regulation is not a binding constraint, ambiguity averse firms will set prices using a more conservative claim probability, $\bar{p}$, rather than their prior, $p_0$, so that greater model uncertainty (higher $\bar{p}$) leads to higher prices.

Depending on the rule applied by regulators, model uncertainty may also affect pricing through its effect on the premium constraint faced by firms. When the markup constraint is binding, firm $j$ would prefer a higher constraint, so if $\lambda(p)$ is increasing in $p$ it has an incentive to offer the regulator a more conservative model. Importantly, this incentive exists whether or not the firm is ambiguity averse. When the regulator sets rate caps using firm-submitted models and these caps are binding, all firms are incentivized to offer $\bar{p}$, the most conservative model available, regardless of their own beliefs about the true claim probability or their willingness to accept ambiguity. Firm preferences and beliefs do matter in the premium setting stage of the game, however, insofar as they determine the point at which the regulatory constraint begins to bind. The regulatory constraint will be binding under a broader range of circumstances when firms are ambiguity averse.

Proposition 4.4.1 describes how model uncertainty affects equilibrium premiums. Details of the proposition are proved in the appendix.

**Proposition 4.4.1**: The directional effect of an increase in model uncertainty (higher $\bar{p}$) on equilibrium insurance premiums, $\pi^*$, is summarized by the following table:

| Regulatory Constraint | Ambiguity Neutral | Ambiguity Averse |
|---|---|---|
| None or not binding | 0 | + |
| Markup cap over regulator model | 0 | 0 |
| Markup cap over firm models | + | + |

Greater dispersion among model projections can be expected to contribute to higher insurance premiums either when regulatory constraints are slack and insurers are ambiguity averse, or when regulators take firm-provided loss estimates into account when approving rate requests. Proposition 4.4.1 has implications for interpreting the causes of identified relationships between model uncertainty and insurance premiums. When regulatory constraints are binding the behavior of ambiguity averse firms will be the same as that of ambiguity neutral firms. Since firm preferences can only be inferred from firm behavior, it is not possible to parse out the relative contributions of ambiguity aversion and cherry picking in an environment such as the one explored in this paper, where regulatory constraints are binding in all markets.[5]

# 5 Data sources and variable construction

Either ambiguity aversion or cherry picking may lead to a positive relationship between model uncertainty and insurance premiums. To test this hypotheses we combine data on catastrophe model loss forecasts with newly published data on insurance premiums.

## 5.1 Outcome variable

While the NAIC regularly publishes data on insurance premiums and other market statistics aggregated to the state level, until recently little data on homeowners insurance pricing was available at a more granular level. Visibility into local insurance markets improved dramatically in early 2025 when the Federal Insurance Office (2025) published a report on the U.S. homeowners insurance market detailing findings from a first-of-its-kind nationwide data collection of insurance polices in effect from 2018 to 2022. With about 48 million policies per year, the collection is designed to cover 80 percent of premiums paid in the U.S. for the most common types of homeowners insurance policies. Along with its own analysis of these data, the FIO publicly released a large subset of the data it had collected, aggregated to the ZIP code level. Variables in the dataset include average premiums, claims frequency and severity, and policy cancellation rates.

To preserve anonymity, FIO's public data release does not include information for ZIP codes for which data on fewer than ten insurers or 50 policies were collected. As shown in Figure 5, ZIP codes included in the data set tend to be more populous. As a result, while the 560 Florida ZIP codes in the FIO data cover only 55 percent of the 1013 ZIP code tabulation areas (ZCTAs) constructed by the Census Bureau in 2020, these ZIP codes represent 76 percent of the state's population. Covered ZIP codes are distributed across the state and represent all of the state's major metropolitan areas. Coverage is weakest in primarily rural areas, particularly those in the Florida panhandle. Sample selection issues arising from FIO's data masking rules are a concern, and may limit the extent to which findings that rely on these data can be extended to highly concentrated insurance markets.

Our outcome variable, the cost of homeowners insurance in a ZIP code, is average premiums per policy which the FIO computes as total premiums written for HO-3 and HO-5 insurance policies divided by the number of such policies in force at the end of a reporting year. Values are expressed in nominal terms.

## 5.2 Treatment variable

Data on hurricane catastrophe model forecasts come from the FCHLPM. Among the material that model vendors must provide to the Commission are zero deductible loss cost projections by ZIP code. Using model submission forms made available to the public by the FCHLPM, we have

[5] Proposition 4.4.1 suggests that one may be able to separately identify ambiguity aversion and cherry picking incentives by exploiting exogenous variation in regulatory policies. For example, future research might compare firm behavior in high-regulation and low-regulation states.

compiled these projections data for all seven vendor models approved for use in Florida in 2019 and 2021.

Vendors report separate loss cost projections for frame homes, masonry homes, and mobile homes. Both frame and masonry homes are popular in Florida, but we were unable to obtain public data on the stock of homes of each type, so to compute a single loss projection for each vendor in each ZIP code we used a simple average of the loss cost projections for frame and masonry homes. The within-vendor correlation between projections for the two types of structures is greater than 99 percent for all vendors, so the relative weights placed on each projection has no material effect on the relationship between measured loss costs and other variables.[6]

We use the coefficient of variation (CV) to measure the dispersion in vendor loss cost projections in each ZIP code. Computed as the standard deviation divided by the mean of vendor forecasts, CV is a unit-free measure of dispersion. This is our key treatment variable. Other measures of model uncertainty considered but not reported include the normalized spread between the maximum and median model loss and the normalized interquartile range of model losses. All approaches to measuring dispersion yield similar results.

## 5.3 Control variables

To control for observable differences across ZIP codes, we gathered information on house prices from Zillow and demographic and geographic information from the Census Bureau. Zillow publishes monthly estimates of typical home values at the ZIP code level for most regions of the U.S. Estimated home values are derived from the firm's proprietary machine learning models which are trained on information from multiple listing services, government records, and user data.[7] ZIP code demographic variables come from the 2020 Current Population Survey and the 2022 American Community Survey. Unlike other variables in this analysis, we do not have separate observations of demographic variables for 2019 and 2021. The Census Bureau's TIGER/Line database provides boundary shapefiles and geographic information for ZIP code tabulation areas.

## 5.4 Summary statistics

Table 1 reports summary statistics for ZIP code characteristics, and Figure 6 and Figure 7 show marginal distributions for our outcome and treatment variables. A few features of the data warrant attention, as they influence the specifications of our models and the interpretation of our results. Premiums per policy are positively correlated with home prices because people with more valuable homes buy more insurance coverage. Average projected loss costs are also positively correlated with home prices because, in Florida, proximity to the ocean conveys significant positive amenity values. Though these variables tend to move together, they are not so highly correlated that we cannot identify conditional relationships among them. The marginal distributions of home prices, premiums, and expected loss costs across ZIP codes are each highly skewed.

[6] We confirmed this by running versions of our models with alternative weights and the results were unchanged.

[7] Zillow publishes series for a number of different structure types and market segments. This analysis uses the "ZHVI Single-Family Homes" series, which reflects a trimmed mean of forecast home prices in a region. Monthly data are averaged to obtain yearly values. See Zillow (2025) for further details on the house price index construction methodology.

Our regression equations are specified in logs to reduces the potential influence of outliers and heteroskedasticity. Some vendors made major updates to their models between 2019 and 2021 leading to substantial changes in some loss cost forecasts, and hence, to the distribution of forecast CVs across ZIP codes. From an identification perspective these updates are fortuitous, as they generate intertemporal variation in our treatment variable which we can leverage to gauge the effects of changes on model uncertainty over time.

# 6 Measuring the effect of model uncertainty on homeowners insurance premiums

The key challenge in identifying a causal effect of model uncertainty on insurance premiums is that other observable and unobservable factors may be correlated with both model uncertainty and insurance premiums. Failure to properly control for these factors could lead us to erroneously attribute their effects to our measures of model uncertainty. We include a number of control variables to limit confounder effects. Insurers can be expected to charge higher prices in areas with higher expected losses, which we capture with the mean of model loss cost forecasts for each ZIP code. Standard economic models that do not incorporate ambiguity aversion also predict that risk averse investors will require a premium for insuring properties with more volatile or extreme losses. We do not have direct measures of loss volatility or tail risk at the ZIP code level, but for most highly skewed distributions with strictly positive support of the type used to describe storm losses, higher moments can be expressed as functions of the first moment.[8] Provided these functional relationships are stable across ZIP codes we can capture the influence of volatility and other higher moments by allowing for a nonlinear effect of expected losses. We do this by including a quadratic term. Owners of more expensive homes can naturally be expected to purchase more insurance coverage, all else equal, so we control for the average home price in a ZIP code. Finally, we include ZIP code average income and population density, which are likely to influence home insurance premiums for reasons unrelated to hurricane risk.

Our main outcome variable is average insurance premium per policy for single family home HO-3 and HO-5 policies in a ZIP code. Premiums are reported in dollars per year and are not adjusted for inflation. Hurricane model uncertainty, our treatment variable, is measured as the coefficient of variation of loss cost forecasts for the ZIP code.

Our basic regression specification is

$$y_{it} = d_{it}\beta_d + \boldsymbol{x}'_{it}\boldsymbol{\beta}_x + u_{it} \tag{3}$$

where $y_{it}$ is the log insurance premium in ZIP code $i$ in year $t$, $d_{it}$ is the log coefficient of variation of model projections, $\boldsymbol{x}_{it}$ is the vector of control variables, and $u_{it}$ is an error term that cannot be directly observed. In general, $u_{it}$ may be correlated across ZIP codes. Provided $u_{it}$ is conditionally uncorrelated with $d_{it}$ and $\boldsymbol{x}_{it}$, such correlation will not introduce bias in estimates of $\beta_d$ but may cause standard errors that ignore spatial correlation to understate the effects of sampling

[8] For example, if the losses for each ZIP code $i$, denoted $L_i$, have a lognormal distribution and all loss distributions share the same shape parameter, then $\mathrm{V}[L_i] = \eta(\mathrm{E}[L_i])^2$ for some constant $\eta$.

variation. To account for this, we apply the method of Conley (1999) to estimate standard errors that are robust in the presence of spatially correlated error terms.

Table 2 reports results from cross-sectional regressions for each of the two years in our sample. Coefficient estimates are reasonably stable across the two years, control variables have the expected signs, and both models show a strong positive relationship between model dispersion on predicted premiums. A concern with interpreting these results, however, is that latent factors embedded in $u_{it}$ may be correlated with the observed treatment and control variables. There are, of course, many differences across ZIP codes that we have not controlled for, and it is possible that some of these differences are related to our right-hand-side variables. It seems most plausible that unobserved confounding factors are stable within ZIP codes but vary across ZIP codes. Such factors could include, for example, exposures to hazards other than wind storms that are correlated with $\boldsymbol{x}$.

We can control for unobserved differences across ZIP codes by running a fixed effects or first differences regression, thereby exploiting within-ZIP-code variation in right-hand-side variables for identification. A disadvantage of this approach is that it precludes analysis of cross-sectional effects. However, as shown by Mundlak (1978), an equivelant approach that provides richer information is to decompose right-hand-side variables into between varation and within variation and use both components to explain the outcome variable. Coefficients on within components are identical to those produced by a regression with ZIP code fixed effects and we can gain insight into the data generating process by comparing coefficients on within and between components.

Mundlak's correlated random effects specification is derived by imposing the not unreasonable assumption that errors may depend linearly on between unit components of observed variables, but not within components. Specifically, we assume that

$$u_{it} = \bar{d}_i \gamma_d + \bar{\boldsymbol{x}}_i' \gamma_x + \epsilon_{it} \tag{4}$$

where bars denote within-ZIP-code means of right-hand-side variables and $\epsilon_{it}$ is an error term that is conditionally uncorrelated with the within components of right-hand-side variables. Substituting Equation 4 into Equation 3 yields

$$y_{it} = \bar{d}_i(\beta_d + \gamma_d) + \tilde{d}_{it}\beta_d + \bar{\boldsymbol{x}}_i'(\boldsymbol{\beta}_x + \boldsymbol{\gamma}_x) + \tilde{\boldsymbol{x}}_{it}'\boldsymbol{\beta}_x + \epsilon_{it} \tag{5}$$

where bars denote within-ZIP-code means and tildes denote deviations from within-ZIP-code means. Our goal is to estimate the treatment effect $\beta_d$. As can be seen from Equation 5, the OLS regression coefficient on the within component of the treatment variable provides an unbiased estimator for the treatment effect. Furthermore, if time-stable unobserved factors are uncorrelated with $d_{it}$ so that $\gamma_d = 0$ we should expect the estimated coefficients on within and between components of $d_{it}$ to match subject to sampling variation.

The right column of Table 3 presents results from the correlated random effects regression. For comparison purposes, we also show results for a version of the model without treatment variables and a version in which we impose the restriction that between and within treatment variable components have the same coefficient (i.e., $\gamma_d = 0$). Note that demographic control variables do not change over the two years of our panel. For these variables, only between effects can be estimated. Conley robust standard errors are reported for all coefficients.

Turning first to the interpretation of control variables, the model indicates, sensibly, that ZIP codes with more expensive homes have significantly higher insurance premiums. Population density, a proxy for urbanization, is positively related to insurance premiums. Higher-income ZIP codes have lower premiums, all else equal, consistent with findings that insurers tend to charge lower premiums to homeowners with higher credit scores (Blonz, Hossain, and Weill 2024) and the fact that community crime rates tend to be negatively correlated with income. Between-ZIP-code differences in expected loss are strongly predictive of insurance premiums, as one would expect. Measured within-ZIP-code effects of expected loss are insignificant, reflecting the fact that expected loss does not meaningfully change from year to year.

Coefficient estimates from the full model show strong positive relationships between both within- and between-ZIP-code differences in hurricane model dispersion. Measured between effects are larger than for within effects, but both are of a similar order of magnitude. With a p-value of 6.7 percent, a Wald test for equality of the within and between effect coefficients cannot reject the hypothesis that the two parameters are equal at the 95 percent confidence level. A literal interpretation of this test result would conclude that time-invariant latent factors are unlikely to influence our estimate of the treatment effect so that we can safely estimate the effect using the restricted version of our model shown in the center column of Table 3. However, there is reason for circumspection. The hypothesis test is not rejected at the 90 percent confidence level and the test statistic is computed using a conservative variance-covariance matrix constructed to be robust to spatial clustering. For these reasons we regard both the within-ZIP-code treatment effect coefficient from the full correlated random effects model and the full treatment effect coefficient from the restricted model to be plausible and defensible estimates of the effect of changes in the log of the coefficient of variation in hurricane model loss projections on log average premiums per policy.

Our parameter estimates indicate that a one percent reduction in hurricane model dispersion would result in either a 0.24 percent reduction or a 0.14 percent reduction in insurance premiums, depending on whether one uses the restricted specification or the more conservative estimate of within effects from the full model. Table 4 shows how estimated insurance premiums would change as a result of a ten percent reduction in the coefficient of variation in hurricane model loss projections. The distribution of average premiums paid is highly skewed across Florida ZIP codes so the magnitudes of projected effects expressed in dollar terms are also skewed. For the median ZIP code in 2021, the reduction in model uncertainty would lower average premium per policy by about $50 per year based on the within effect estimate of the unrestricted model and about $90 dollars per year under the full effect estimate of the restricted model.

# 7 Conclusions

We have shown that there is very substantial dispersion in projected losses produced by hurricane risk models used in Florida rate-setting, and that homeowners in ZIP codes where there is greater model uncertainty pay meaningfully higher insurance premiums than those in otherwise comparable ZIP codes. These findings have important implications for improving community resilience in disaster-prone areas.

Most directly, our findings provide quantitative evidence of the social returns to investments in better catastrophe risk models. Our review of hurricane risk model documentation and test deck results suggest that there is substantial room for improvement in the methods used for estimating the long-run likelihood and severity of future storms as well as in mapping physical measures of storm severity into economic losses. Consumers are sensitive to insurance prices and rising insurance premiums have been linked to a widening gap between insurance coverage amounts and potential catastrophe losses (Sastry et al. 2024). Reducing epistemic uncertainty in loss modeling can be expected to lower insurance premiums and narrow insurance protection gaps, enabling communities to recover more quickly from disasters.

The implications of our findings for state regulatory policies are less clear, but suggest promising avenues for further work. Using a simple model of pricing under epistemic uncertainty and model-based price regulation, we have shown that greater dispersion among loss projections can lead to higher premiums either because insurers are averse to ambiguity, or because they are able to cherry pick loss projections to relax regulatory constraints. In other settings asymmetric access to model projections among competing firms may also play a role (Boomhower et al. 2024). Without more granular data on market structure and regulatory constraints we cannot distinguish among these possible causes. If higher premiums are driven primarily by ambiguity aversion then state insurance regulators may have few tools to mitigate effects aside from promoting improvements in risk modeling. On the other hand, if higher premiums are driven primarily by asymmetric information and strategic behavior among competing firms or between firms and regulators, then state insurance regulators may have many more levers to pull. They could, for example, promote broader access to model forecasts to reduce information asymmetries, or require that blended model forecasts be used in rate-setting processes. Gauging the efficacy of such polices requires a more fulsome understanding of the mechanisms through which model uncertainty contributes to higher premiums.

# A Proof of Proposition 4.4.1

## A.1 Pricing subgame

In the absense of regulatory constraints, the pricing subgame devolves into a classic Salop circle differentiated products game with linear demand. Taking firm $j$'s marginal cost $\hat{p}_j$ as fixed, the firm's payoff function given the price $\pi_{-j}$ offered by competitors is

$$\Pi(\pi_j; \pi_{-j}) = \left(\frac{1}{N} + \frac{\pi_{-j} - \pi_j}{s}\right)(\pi_j - \hat{p}_j) \tag{6}$$

Solving first-order conditons for $\pi_j$ yields the reaction function shown in Equation 1. Since all firms are identical, we can use Equation 1 to compute the equilibrium premium charged by all firms when prices are not constrained by regulators:

$$\pi_{\cdot} = \hat{p} + \frac{s}{N} \tag{7}$$

Furthermore, since Equation 6 is quadratic in $\pi_j$, we know that for any $\pi_j < \pi_j(\pi_{-j}; \hat{p})$, the payoff is increasing in $\pi_j$. If an upper bound constraint, $\lambda_j < \pi_j(\pi_{-j}; \hat{p})$, is imposed on firm $j$ it will be binding and the firm will choose a premium equal to the constraint. Applying this reasoning to all firms yields Equation 2.

## A.2 Regulation subgame

We have just seen that when the regulatory constraint is binding any firm $j$ would receive higher payoffs in the pricing subgame if its constraint were relaxed. If the regulatory constraint $\lambda(p)$ is increasing in $p$, firm $j$ can raise its premium by offering the regulator a higher value of $p_j$. There is no offsetting cost to the firm from doing so, so the firm will be pushed toward the corner solution $p_j = \bar{p}$ if $\lambda(\bar{p}) \leq \pi_{\cdot}$. If $\lambda(\bar{p}) > \pi_{\cdot}$ the firm will offer a value of $p_j$ that is at least large enough to ensure that the constraint is not binding. Call this critical value $\tilde{p}$. Because all firms are identical they all face the same incentives and they will all offer either $p_{\cdot} = \bar{p}$ or $p_{\cdot} \geq \tilde{p}$.

## A.3 Comparative statics

Proposition 4.4.1 is simply a statement about the marginal effect of an increase in $\bar{p}$ on $\pi^*$. Turning to the first row of the table in the proposition, when the regulatory constraint is not binding and firms are ambiguity neutral, we substitute $p_0$ for $\hat{p}$ in Equation 7. $\bar{p}$ does not enter the payoff function and hence has no effect on equilibrium prices. When firms are ambiguity averse they will act in a manner consistent with the model that minimizes expected payoffs. $\hat{p}$ enters Equation 6 as a cost, so the payoff minimizing model is the most pessimistic one, $\bar{p}$. Higher $\bar{p}$ implies an increase in firms' effective marginal costs, and hence an increase in equilibrium premiums.

Turning to the second row, when regulators use their own model to determine the price constraint, $\lambda$, and this constraint is binding, all premiums are equal to $\lambda$ so $\bar{p}$ cannot affect premiums.

Finally, when regulators accept firm models so that $\lambda(p)$ is strictly increasing in $p$, we have just shown that firms have an incentive to offer the corner solution $\bar{p}$ whenever the constraint is binding. An increase in $\bar{p}$ gives firms greater opportunity to relax the constraint, leading to higher equilibrium premiums. This is true regardless of firms' effective marginal costs.

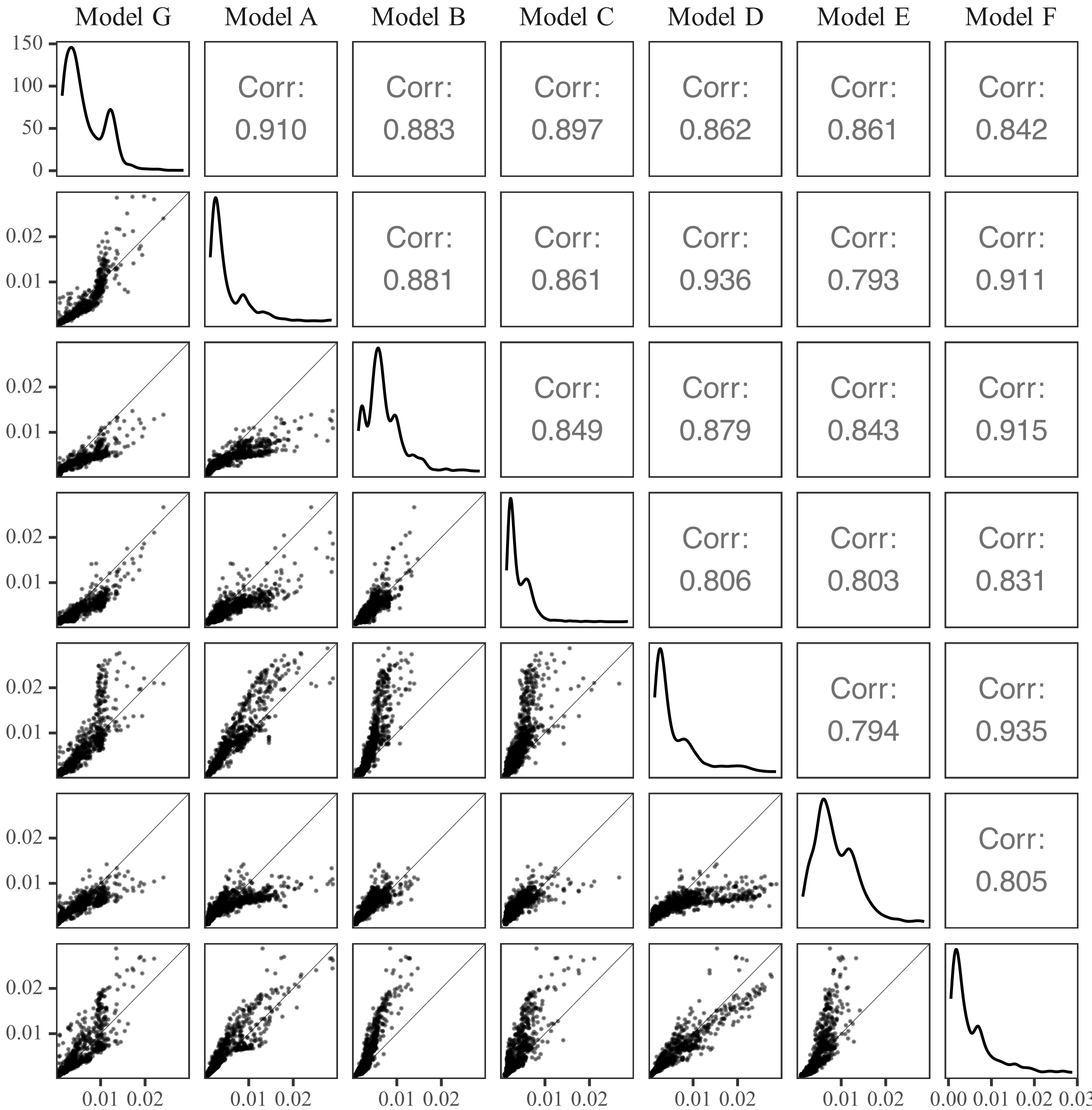


Figure 1: Pairwise comparisons of hurricane risk model projected loss cost per dollar exposure for frame homes in 2021. Each dot represents one ZIP code's projected loss cost for two models.

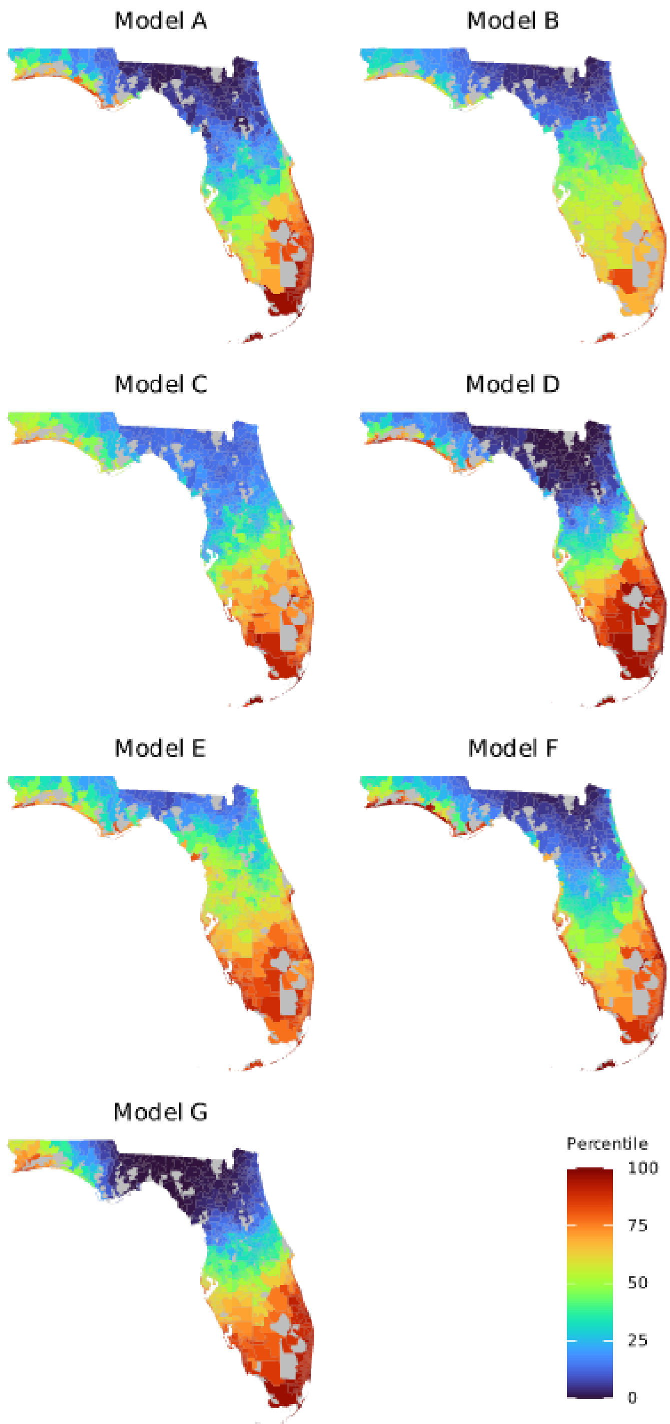


Figure 2: Projected loss costs per dollar exposure for frame homes in 2021. To aid comparisons across models ZIP codes are colored according to to their percentile rank after pooling all projections for all models.

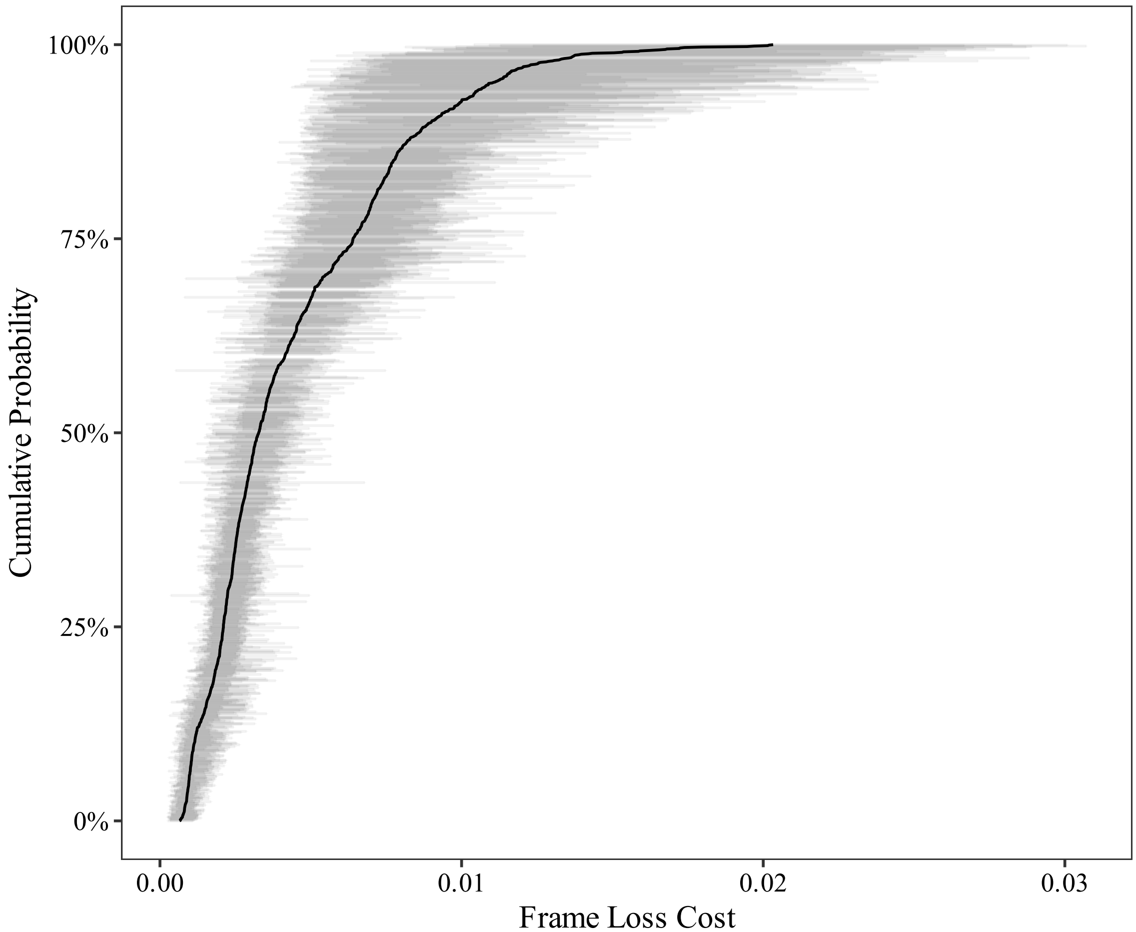


Figure 3: Cumulative density of ZIP code average frame home projected loss costs in 2021. Gray bars show ranges from lowest to highest loss cost projections for each ZIP code.

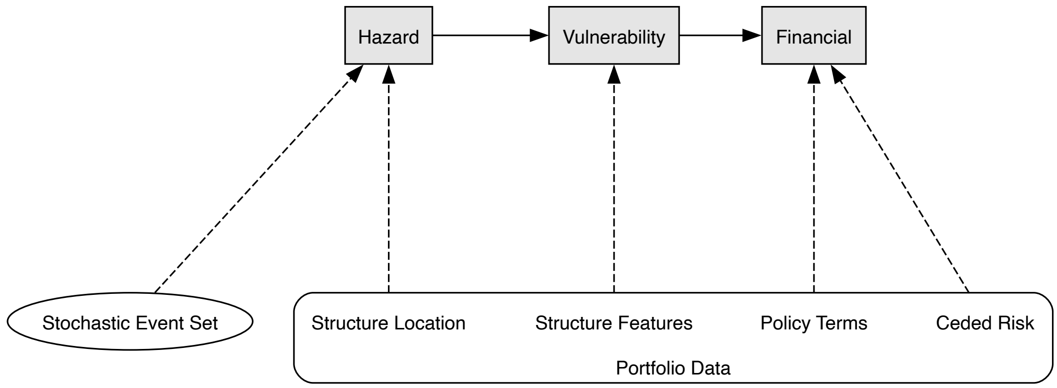


Figure 4: Architecture of a typical hurricane risk model.

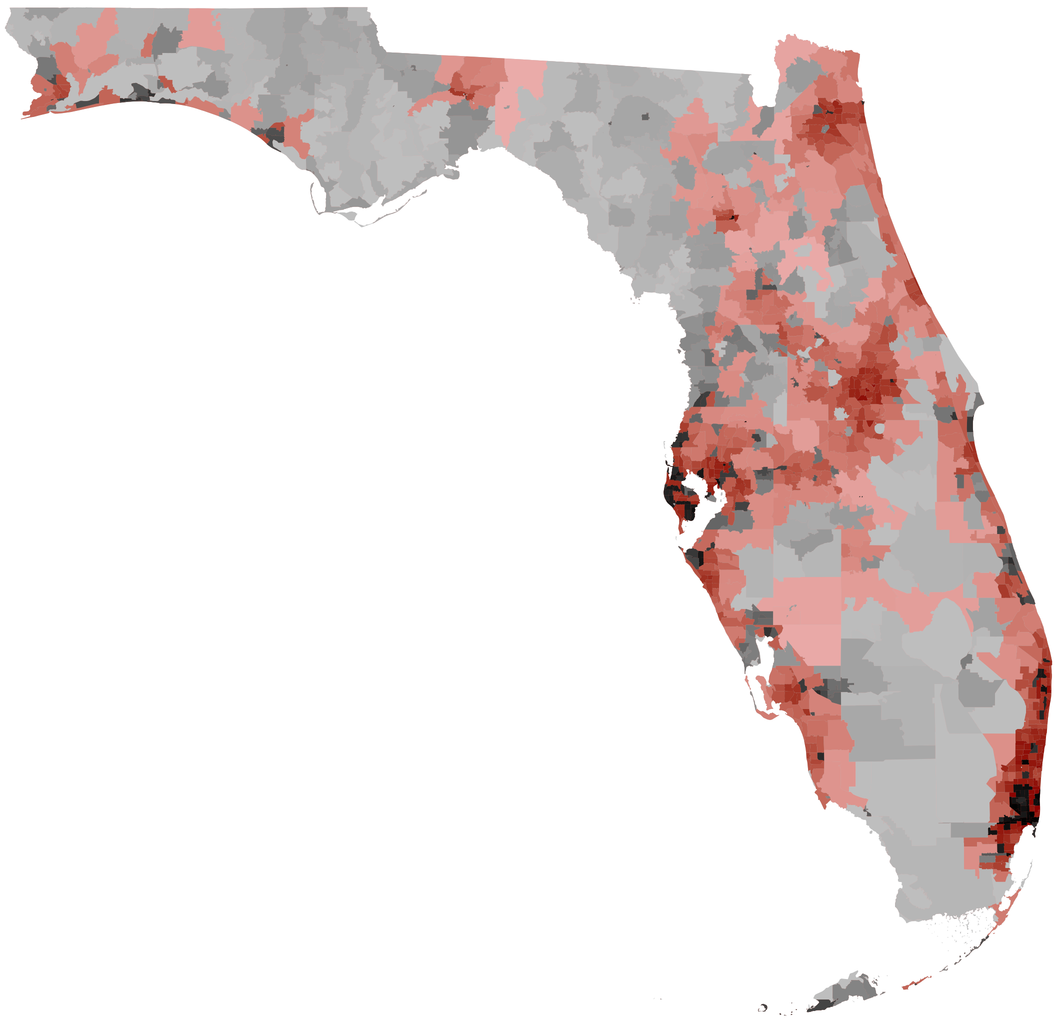

Figure 5: Florida ZIP code tabulation areas covered by the Federal Insurance Office public data release, shaded according to population density. Darker regions have higher population density. Monochrome regions are not covered by the FIO data release or do not correspond to ZIP code tabulation areas.

Table 1: Summary statistics for ZIP code variables.

| Variable | Mean | S.D. | Min. | Q1 | Q2 | Q3 | Max. |
|---|---|---|---|---|---|---|---|
| 2019 | | | | | | | |
| Premiums | 4,887 | 3,961 | 1,424 | 2,552 | 3,448 | 5,548 | 37,783 |
| House Price | 313,911 | 238,118 | 60,228 | 204,424 | 263,049 | 350,967 | 3,966,340 |
| Loss Cost Mean | 0.00421 | 0.00311 | 0.000606 | 0.002 | 0.00296 | 0.00625 | 0.0164 |
| Loss Cost CV | 0.337 | 0.0978 | 0.101 | 0.281 | 0.335 | 0.391 | 0.703 |
| 2021 | | | | | | | |
| Premiums | 4,864 | 4,477 | 1,503 | 2,322 | 3,211 | 5,286 | 40,719 |
| House Price | 393,332 | 328,841 | 89,416 | 256,615 | 324,125 | 425,019 | 5,883,793 |
| Loss Cost Mean | 0.00425 | 0.00314 | 0.000636 | 0.002 | 0.00295 | 0.0064 | 0.0163 |
| Loss Cost CV | 0.311 | 0.0918 | 0.153 | 0.244 | 0.286 | 0.359 | 0.622 |
| Demographics | | | | | | | |
| Population Density (per sq. km.) | 898 | 832 | 11 | 241 | 670 | 1,307 | 6,016 |
| Median Income | 77,080 | 24,028 | 27,876 | 60,584 | 72,036 | 89,385 | 177,917 |

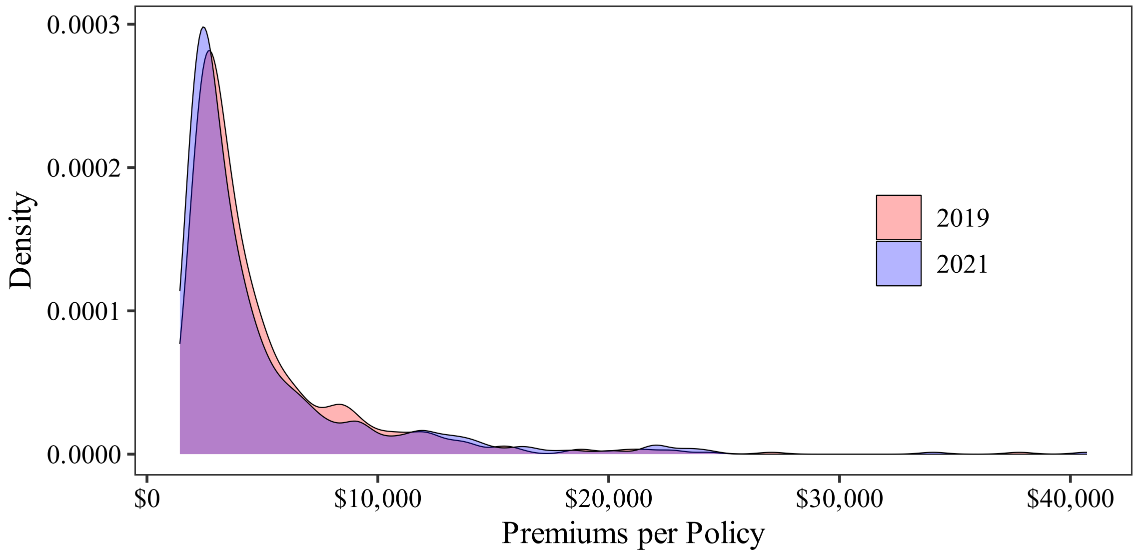


Figure 6: Distribution of ZIP code average premiums per policy, by year.

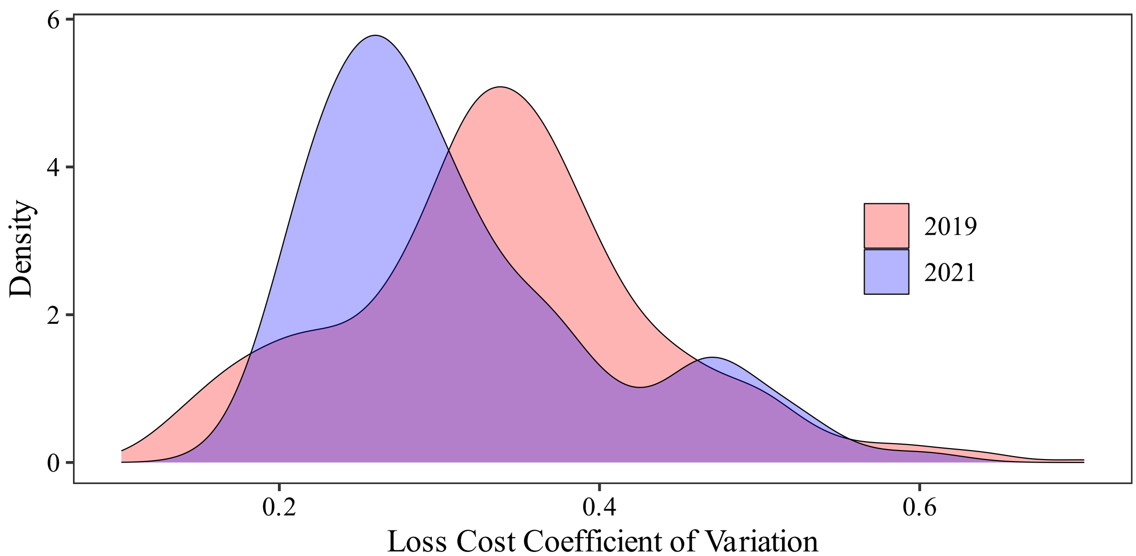


Figure 7: Distribution of ZIP code loss cost projection coefficient of variation across vendor models, by year.

Table 2: Regressions of log premiums per policy on treatment and control variables, by year.

| | sample: 2019 | sample: 2021 |
|---|---|---|
| Intercept | 10.999*** | 8.486*** |
| | (1.922) | (2.058) |
| ln(MEAN LOSS) | 2.283*** | 1.676** |
| | (0.471) | (0.533) |
| ln(MEAN LOSS)^2 | 0.164*** | 0.114* |
| | (0.038) | (0.045) |
| ln(HOUSE PRICE) | 0.626*** | 0.722*** |
| | (0.091) | (0.095) |
| ln(POP. DENSITY) | 0.038* | 0.064*** |
| | (0.015) | (0.014) |
| ln(MED. INCOME) | -0.218* | -0.245** |
| | (0.090) | (0.087) |
| ln(CV LOSS) | 0.187** | 0.360*** |
| | (0.066) | (0.090) |
| Num.Obs. | 560 | 560 |
| R2 | 0.754 | 0.806 |
| RMSE | 0.29 | 0.28 |
| Std.Errors | Conley (20km) | Conley (20km) |

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Correlated random effects regressions of log premiums per policy on treatment and control variables.

| | No Treatment | Restricted | Unrestricted |
|---|---|---|---|
| Year 2019 | 11.454*** | 10.251*** | 10.003*** |
| | (2.017) | (1.915) | (1.924) |
| Year 2021 | 11.348*** | 10.094*** | 9.869*** |
| | (2.016) | (1.920) | (1.926) |
| ln(POP. DENSITY) | 0.042** | 0.051*** | 0.053*** |
| | (0.015) | (0.015) | (0.015) |
| ln(MED. INCOME) | -0.290*** | -0.231** | -0.220* |
| | (0.081) | (0.087) | (0.090) |
| between ln(MEAN LOSS) | 2.598*** | 2.117*** | 2.024*** |
| | (0.491) | (0.469) | (0.478) |
| within ln(MEAN LOSS) | 2.951 | 0.206 | 1.465 |
| | (1.983) | (1.524) | (1.605) |
| between ln(MEAN LOSS)^2 | 0.194*** | 0.150*** | 0.142*** |
| | (0.040) | (0.039) | (0.040) |
| within ln(MEAN LOSS)^2 | 0.266 | 0.062 | 0.156 |
| | (0.167) | (0.129) | (0.137) |
| between ln(HOUSE PRICE) | 0.699*** | 0.672*** | 0.667*** |
| | (0.095) | (0.092) | (0.092) |
| within ln(HOUSE PRICE) | 0.260 | 0.592** | 0.440* |
| | (0.227) | (0.222) | (0.172) |
| ln(CV LOSS) | | 0.262*** | |
| | | (0.055) | |
| between ln(CV LOSS) | | | 0.313*** |
| | | | (0.083) |
| within ln(CV LOSS) | | | 0.142*** |
| | | | (0.022) |
| Num.Obs. | 1120 | 1120 | 1120 |
| R2 | 0.769 | 0.781 | 0.782 |
| RMSE | 0.29 | 0.28 | 0.28 |
| Std.Errors | Conley (20km) | Conley (20km) | Conley (20km) |

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 4: Effects on premiums of a ten percent decrease in hurricane model dispersion in each ZIP code. Effects are espressed as dollar reductions in fitted average premiums per policy for a ZIP code. "Restricted" effects are computed using the elasticity estimate from the restricted model. "Unrestricted" effects are computed using the within-ZIP-code elasticity estimate from the unrestricted model.

| Effect Statistic | Predicted | Restricted | Unrestricted |
|---|---|---|---|
| 2019 | | | |
| Min | 1,748 | 48 | 26 |
| Q1 | 2,752 | 75 | 41 |
| Q2 | 3,377 | 92 | 50 |
| Q3 | 5,047 | 138 | 75 |
| Max | 44,509 | 1,213 | 661 |
| 2021 | | | |
| Min | 1,811 | 49 | 27 |
| Q1 | 2,577 | 70 | 38 |
| Q2 | 3,268 | 89 | 49 |
| Q3 | 5,701 | 155 | 85 |
| Max | 53,756 | 1,465 | 799 |

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