Mathematical Modeling of the Stability of the Insurance Market in the Coastal Area of Florida

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Abstract: This study develops a unified simulation framework to analyze the stability and equity of coastal property-insurance markets under non stationary climate risk. We couple a climate adjusted hazard generator—modeled as a non homogeneous compound Poisson process with heavy tailed severities—with agent based representations of heterogeneous insurers and income stratified households. Loss formation integrates exposure, fragility, and geographic modifiers; industry pricing embeds risk loads and capital costs with memory of past shocks; household purchase and insurer underwriting decisions co evolve with perceived risk. We evaluate six policy regimes—including reinsurance subsidies, low income premium caps, and structural adaptation—across three hazard trajectories via 100×30 year Monte Carlo simulations. Results demonstrate pronounced nonlinearities: under a high stress climate scenario, systemic insolvency undergoes a phase transition between years 10–20, with failure rates reaching 60–70% absent intervention. Policy bundles that combine structural adaptation and reinsurance support substantially attenuate fragility and price inflation, preserving coverage and containing public exposure. The most comprehensive package sustains average penetration above 80%, reduces insolvency rates to roughly 0.21, and halves expected public outlays by year 30. The framework provides a tractable basis for stress testing, distributional assessment, and policy design in insurance systems exposed to deep climatic uncertainty.

1. Introduction

Over the past decades, the frequency, intensity, and spatial extent of extreme weather events have increased significantly, with climate change now recognized as a key driver of large-scale natural disasters. Coastal regions are particularly vulnerable to these changes due to their exposure to compound hazards such as hurricanes, storm surges, coastal flooding, and sea level rise. In the United States, the state of Florida—home to over 21 million residents and more than 8,000 miles of coastline—stands at the forefront of this growing climate risk. With some of the nation's highest concentrations of insured coastal property, Florida's insurance market is not only a barometer of regional risk resilience but also a critical node in the broader national financial stability network.

Recent hurricane seasons, including events such as Hurricane Michael (2018), Hurricane Ian (2022), and Hurricane Idalia (2023), have resulted in billions of dollars in insured losses, significant capital depletion across insurers, and in many cases, prompted the exit or insolvency of regional carriers. These events have exposed structural vulnerabilities in both the private and public layers of the insurance system. The existing frameworks for underwriting, pricing, and capital reserving, which are typically calibrated based on long-term historical averages and actuarial principles, are increasingly misaligned with the realities of a non-stationary climate system. Traditional catastrophe models, often built on the assumption of independent and identically distributed (i.i.d.) hazard events, fail to capture the dynamic feedbacks, tail dependencies, and socio-economic nonlinearities introduced by climate change.

In this context, the resilience of Florida's insurance market is being tested not only by escalating hazard exposure but also by systemic fragilities in market behavior, regulatory response, and the lack of adaptive policy instruments. For example, as private insurers retreat from high-risk areas or sharply raise premiums, more households are forced to rely on state-backed residual market mechanisms such

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as Citizens Property Insurance Corporation, leading to further concentration of risk on public balance sheets. Meanwhile, low- and middle-income households face increasing difficulties in affording coverage, amplifying concerns about distributive fairness and insurance accessibility in the era of climate adaptation.

Given these challenges, there is a growing need to rethink the modeling paradigms used to assess insurance market dynamics under deep uncertainty. While substantial work has been done in the domains of catastrophe risk modeling, actuarial science, and behavioral economics, relatively few studies have attempted to synthesize these approaches into a unified framework that can simulate multi-layered feedback loops—between climate hazards, insurer behavior, market structure, and policy intervention—over long time horizons.

This paper aims to address this gap by proposing a hybrid modeling framework that integrates stochastic hazard simulation (based on non-homogeneous compound Poisson processes), agent-based modeling (ABM) of firm-level insurance behavior, and scenario-based policy analysis. Our focus is on modeling the interplay between climate-induced disaster events and the endogenous evolution of the insurance market in Florida's coastal regions, capturing both micro-level interactions (e.g., insurer capital adequacy, reinsurance purchase, and premium adjustments) and macro-level outcomes (e.g., systemic insolvency risk, market exit cascades, and public insurance burdens).

A key methodological innovation of our approach lies in the incorporation of forward-looking hazard trajectories, reflecting Representative Concentration Pathways (RCPs) that capture different degrees of warming and sea level rise. These hazard scenarios are used to drive the intensity and severity of simulated hurricane losses, which in turn impact firm solvency, pricing strategies, and household insurance uptake. By embedding insurance carriers as heterogeneous agents with adaptive strategies—subject to capital constraints, regulatory rules, and risk-based pricing heuristics—we enable the emergence of market-level dynamics that are difficult to capture through purely analytical or equilibrium-based models.

Furthermore, our framework supports the evaluation of a variety of policy interventions, including reinsurance subsidies, low-income premium caps, structural adaptation incentives (e.g., building code improvements), and hybrid public-private insurance schemes. These scenarios allow us to quantify the effectiveness, timing sensitivity, and distributional consequences of different policy levers in maintaining insurance affordability and avoiding systemic breakdowns.

2. Related work

2.1. Catastrophe risk modeling and climate-adjusted hazard estimation

Catastrophe risk models (CAT models), developed and commercialized by firms such as AIR Worldwide and RMS, have long served as the backbone of pricing and capital reserving strategies in the property insurance industry. These models typically use stochastic event sets based on historical hurricane tracks, wind fields, and vulnerability functions to generate exceedance probability curves and probable maximum loss (PML) estimates [1]. However, these models are often calibrated under the assumption of climate stationarity, which recent research has called into question [2].

Emanuel's work on climate–cyclone interaction introduced dynamic formulations for hurricane intensity under different sea surface temperature profiles [3]. Other studies, such as those by Bakkensen and Barrage [4], integrated empirical damage functions with climate-adjusted hurricane frequency models, showing that small changes in intensity distributions could significantly shift tail risks. Nonetheless, these models largely treat hazard generation as exogenous to the insurance market, omitting feedback effects from coverage withdrawal, premium shifts, or reinsurance market reactions.

In our work, we extend this line of inquiry by using non-homogeneous compound Poisson processes (NHCPP) to simulate the temporal evolution of hurricane events under warming scenarios (e.g., RCP4.5, RCP8.5), allowing for dynamic adjustment in hazard frequency and severity that reflect ongoing climate change.

2.2. Agent-based insurance market models

While traditional insurance pricing models rely on equilibrium-based analytical tools, agent-based models (ABM) have gained traction as a means to simulate the heterogeneous and adaptive behavior of market participants under uncertainty. Filatova et al. [5] and Wilensky & Rand [6] emphasized the suitability of ABMs in capturing spatial, behavioral, and policy-induced heterogeneity in economic systems, particularly in real estate and risk markets.

In the context of insurance, Gietzen and Zscheischler [7] applied ABM to simulate household-level insurance demand and the role of trust in influencing take-up rates. From the supply side, Porrini and Schwarze [8] used an ABM framework to analyze insurer decisions regarding premium setting, capital holding, and market exit under regulatory constraints.

We build on this literature by embedding insurers as profit-seeking agents facing capital risk and reinsurance pricing fluctuations, allowing firm-level decision rules (e.g., premium adjustment, reinsurance coverage rate) to co-evolve with systemic disaster exposure. This enables us to capture cascading market exits, concentration of risk, and the emergence of public insurer dominance—patterns observed in Florida's real market evolution over the past two decades.

2.3. Insurance penetration, fairness, and policy interventions

Insurance penetration—particularly among low- and moderate-income households—has been a central policy concern in the literature on climate adaptation and disaster resilience. Empirical studies such as those by Browne and Hoyt [9], and Michel-Kerjan et al. [10], have demonstrated that affordability is a significant determinant of insurance demand, and that price elasticity is particularly high in lower-income segments.

Public-private partnerships (PPPs) and residual market mechanisms (e.g., the U.S. National Flood Insurance Program, or Florida's Citizens Property Insurance Corporation) have been proposed as policy tools to address these equity concerns [11]. Kunreuther and Pauly [12] argue that risk-based pricing should be complemented with targeted subsidies to preserve incentives for mitigation while ensuring access. Other studies have examined the role of reinsurance subsidies [13], risk pooling [14] in stabilizing insurance markets under stress.

We incorporate these interventions in our simulation framework by parameterizing policy scenarios with reinsurer subsidy levels, premium-to-income caps for low-income groups, and structural adaptation incentives. This allows us to assess both system-level stability metrics (e.g., insurer survival rate, reinsurance cost inflation) and distributional fairness indicators (e.g., affordability ratios across income quintiles).

3. Methods and model construction

3.1. Non homogeneous compound poisson with climate drift

We represent annual hurricane counts by a non homogeneous Poisson process (NHPP) to encode non stationary hazard under warming. Let N_t be the number of events in year t. The mean measure over $[t-1,t]$ is the integral of a time varying rate with linear climate drift:

$$\begin{aligned} &N_t \sim \text{Poisson}(\Lambda_t), \\ &\Lambda_t = \int_{t-1}^{t} \lambda(u)du, \\ &\lambda(u) = \lambda_0 \big(1+\beta u\big), \beta \geq 0. \end{aligned} \tag{1}$$

Each event $i=1,\ldots,N_t$ is assigned a near-core wind intensity $S_{t,i}$ and a footprint radius $R_{t,i}$. For numerical stability and heavy-tail realism, we adopt a lognormal approximation to GEV tails:

$$
\begin{aligned}
&S_{t,i} \sim \text{LogNormal}(\mu_S, \sigma_S^2),\\
&\mu_S = \ln \bar{s},\ \ \sigma_S = \ln\!\left(1 + \frac{\sigma_s}{\bar{s}}\right),\\
&R_{t,i} \sim \mathcal{N}^{+}(\bar{R}, \sigma_R^2).
\end{aligned}
\tag{2}
$$

To map footprints into regional impacts without solving full wind fields, we use a contact probability. For region r, the Bernoulli impact indicator has success probability

$$
\begin{aligned}
&p_{t,i,r} = \min\left\{1, \frac{R_{t,i}}{R_{\max}}\right\} \pi_r(S_{t,i}),\\
&I_{t,i,r} \sim \text{Bernoulli}(p_{t,i,r}),
\end{aligned}
\tag{3}
$$

where $\pi_r(\cdot)$ optionally modulates intensity-specific exposure (e.g., coastal amplification).

3.2. Exposure, vulnerability, and geographic weighting

Let H_r be households, tiv_r the insured value per household, and $V_r = \text{TIV}_r = \text{tiv}_r H_r$ the full-coverage exposure. Damage conversion follows a sigmoid fragility curve indexed by the dominant building type $b(r) \in \{\text{wood}, \text{masonry}, \text{reinforced}\}$:e

$$
\begin{aligned}
&\ell(S;b) = \ell_{\max}(b)\, \sigma\!\left(\frac{S - m(b) - \Delta_{\text{pol}}}{k(b) + \varepsilon}\right),\\
&\sigma(z) = \frac{1}{1 + e^{-z}},
\end{aligned}
\tag{4}
$$

where m(b) (“onset”) and k(b) (“slope”) shape the curve, $\ell_{\max}(b)$ caps loss ratios, and $\Delta_{\text{pol}} \le 0$ shifts vulnerability left to represent structural adaptation (e.g., code upgrades, retrofits).

Hydrodynamic/topographic modifiers enter via a geographic weight E_r, increasing losses in flood-exposed zones and attenuating with elevation:

$$
\begin{aligned}
&E_r = \gamma_{\text{zone}(r)} \exp\!\left(\alpha_{\text{elev}} \cdot \max\{0, \text{elev}_r\}\right),\\
&\gamma_{\text{VE}} > \gamma_{\text{AE}} > \gamma_X,\ \ \alpha_{\text{elev}} < 0.
\end{aligned}
\tag{5}
$$

Event-level full-insurance regional loss is then

$$
L_{t,i,r}^{\text{full}} = V_r\, \ell\big(S_{t,i}; b(r)\big)\, E_r\, I_{t,i,r},
\tag{6}
$$

and the year-t full-coverage portfolio loss is

$$
L_t^{\text{full}} = \sum_{i=1}^{N_t} \sum_r L_{t,i,r}^{\text{full}}.
\tag{7}
$$

3.3. Industry premium formation and perceived risk with memory

Define the expected cost per household under full coverage as $\hat{\mu}_t = L_t^{\text{full}} / H$, with $H = \sum_r H_r$. An industry benchmark premium per household includes risk load and capital cost:

$$
\pi_t = \hat{\mu}_t (1 + \bar{\phi}_t)(1 + \kappa),
$$

where $\bar{\phi}_t$ is the average risk load among surviving carriers (endogenous to exits), and κ is the capital cost markup.

To channel past shocks into present behavior, we compute a regional loss density and an exponentially weighted perceived risk:

$$d_{t,r}=\frac{\sum_{i=1}^{N_t} L_{t,i,r}^{\text{full}}}{V_r+\varepsilon},$$
$$M_{t,r}=(1-\alpha)M_{t-1,r}+\alpha d_{t,r}, \tag{8}$$
$$\alpha=\frac{2}{K+1}.$$

Here K is the memory length; larger K smooths transients but retains persistent risk signals. The pair $(\pi_t, M_{t,r})$ links hazard realizations and market structure (through $\bar{\phi}_t$) to local salience of risk, informing both demand and underwriting.

3.4. Household coverage, public spillovers, and affordability

Households are grouped by income quintiles with representative income. A targeted affordability cap applies to low income groups (Q1–Q2), limiting premium as a share of income:

$$\pi_t^{(q)}=\min\{\pi_t, c\,y_q\},$$
$$q\in\{1,2\},\ \ c\in(0,1). \tag{9}$$

Purchase probability at (t,r,q) follows a logistic response to price, income, and perceived risk, with amplified price sensitivity $\xi_q>1$ for Q1–Q2:

$$p_{t,r}^{(q)}=\sigma\left(\theta_0+\theta_1\xi_q\pi_t^{(q)}+\theta_2 y_q+\theta_3 M_{t,r}\right). \tag{10}$$

On the supply side, underwriting tightens in high-risk regions via a risk-dependent denial rate (capacity withdrawal):

$$\delta_{t,r}=\min\left\{\delta_0+\delta_1 M_{t,r}, \bar{\delta}\right\}.$$

Expected private and public (residual) coverages are therefore

$$H_{t,r,q}^{\text{priv}}=H_{r,q}\,p_{t,r}^{(q)}(1-\delta_{t,r}),$$
$$H_{t,r,q}^{\text{pub}}=H_{r,q}\,p_{t,r}^{(q)}\delta_{t,r}. \tag{11}$$

Aggregating yields market penetration and public share:

$$\text{Pen}_t=\frac{\sum_{r,q}\left(H_{t,r,q}^{\text{priv}}+H_{t,r,q}^{\text{pub}}\right)}{\sum_r H_r},$$
$$\text{CitShare}_t=\frac{\sum_{r,q}H_{t,r,q}^{\text{pub}}}{\sum_{r,q}\left(H_{t,r,q}^{\text{priv}}+H_{t,r,q}^{\text{pub}}\right)}. \tag{12}$$

Distributional equity is tracked with an Affordability Index for each quintile:

$$\text{AFI}_t^{(q)}=\frac{\pi_t^{(q)}}{y_q}. \tag{13}$$

This demand–supply coupling creates realistic feedbacks: adverse hazard years raise π_t and $M_{t,r}$ depressing take-up among price-sensitive cohorts while elevating denials, shifting risk to the public layer. Conversely, structural adaptation (via $\Delta_{\text{pol}}<0$) and targeted caps (via c) curb expected loss and effective price, stabilizing penetration and limiting public crowd-in.

3.5. Insurer behavior and capital dynamics under reinsurance and defaults

The supply side of the insurance market is represented by a set of heterogeneous firms $\mathcal{K}$, differentiated by scale, capital, and pricing behavior. Each firm $k\in\mathcal{K}$ begins with an initial capital

$C_{0,k}$ and adopts a constant risk load ϕ_k and capital cost rate η_c. Private insurance premiums collected at time t, denoted P_t, are allocated among alive firms proportionally to type-specific market weights w_k, such that:

$$\sum_{k\in\mathcal{K}_t^{\text{alive}}} w_k = 1, \qquad P_{t,k} = w_k \cdot P_t. \tag{14}$$

Similarly, private market losses L_t^{priv} are also distributed as:

$$G_{t,k} = w_k \cdot L_t^{\text{priv}}. \tag{15}$$

Firms manage solvency by purchasing proportional reinsurance at rate $\alpha_{t,k} \in [0,1]$, where the reinsurance cost depends on a market-wide price ψ_t. The net cost of reinsurance and retained losses for each firm is:

$$\begin{aligned} C_{t,k}^{\text{re}} &= \alpha_{t,k} \cdot \psi_t \cdot G_{t,k}, \\ N_{t,k} &= (1-\alpha_{t,k}) \cdot G_{t,k}. \end{aligned} \tag{16}$$

The capital update rule at the end of period t accounts for premium income, net losses, reinsurance costs, and capital carrying costs:

$$C_{t+1,k} = C_{t,k} + P_{t,k} - N_{t,k} - C_{t,k}^{\text{re}} - \eta_c \cdot C_{t,k}.$$

A firm is declared insolvent and removed from the active set if $C_{t+1,k} < 0$. The **systemic insolvency rate** at year ttt, a proxy for market fragility, is defined as:

$$\text{SR}_t = 1 - \frac{|\mathcal{K}_t^{\text{alive}}|}{|\mathcal{K}|}. \tag{17}$$

This structure permits endogenous firm exit cascades and risk concentration, especially under high hazard volatility or poorly diversified portfolios.

3.6. Reinsurance pricing with hardening and policy subsidies

To model the cyclicality of the reinsurance market, we allow the reinsurance price ψ_t to respond nonlinearly to the observed loss ratio in the private insurance market. Define the private loss ratio as:

$$\text{LR}_t = \frac{L_t^{\text{priv}}}{P_t + \varepsilon}, \tag{18}$$

where ε is a small positive constant to avoid division by zero. We implement rate hardening via a piecewise-linear function:

$$\psi_t = \psi_0 \cdot \left[1 + \eta_{\text{hard}} \cdot (\text{LR}_t - \tau)_+\right] \cdot (1-s), \tag{19}$$

where η_{hard} controls the slope of price escalation, τ is the threshold triggering hardening, and s∈ [0,1) is a government subsidy rate applied to reinsurance costs.

The policy parameter s serves as a counter-cyclical tool, mitigating the cost of reinsurance in years of elevated loss, thus helping to stabilize firm solvency and market participation. This mechanism reflects real-world interventions such as temporary reinsurance backstops or catastrophe bond purchases by public entities.

3.7. Public insurance exposure and fiscal risk

When households are denied private coverage due to underwriting restrictions, they are shifted into a public residual market such as Citizens Property Insurance Corporation in Florida. The total number of households in public insurance at year t is:

$$H_t^{\text{pub}} = \sum_{r,q} H_{t,r,q}^{\text{pub}}. \tag{20}$$

To approximate fiscal exposure, we assume that the public insurer covers a share of the full-coverage market loss proportional to its exposure share. Thus, the public insurance loss and premium income are estimated as:

$$L_t^{\text{pub}} \approx L_t^{\text{full}} \cdot \frac{H_t^{\text{pub}}}{H},$$
$$P_t^{\text{pub}} = \sum_{r,q} H_{t,r,q}^{\text{pub}} \cdot \pi_t. \tag{21}$$

The net fiscal burden to the government in year t is then:

$$\text{GovExp}_t = L_t^{\text{pub}} - P_t^{\text{pub}}. \tag{22}$$

This formulation allows us to quantify how public exposure evolves under different combinations of hazard intensity, firm capacity, and affordability constraints. It also provides a measurable link between private market behavior and public liability risk.

3.8. Unified representation of policy instruments

The model allows for the systematic evaluation of multiple policy instruments through parameter adjustments:

- **Structural adaptation** is modeled by shifting the fragility function via $\Delta_{\text{pol}} < 0$, reducing vulnerability.
- **Reinsurance subsidies** are represented by s, directly lowering ψ_t.
- **Affordability caps** on premiums are introduced for low-income groups via parameter ccc in:

$$\pi_t^{(q)} = \min\{\pi_t, c \cdot y_q\}, \quad q \in \{1, 2\}. \tag{23}$$

Other instruments, such as market entry incentives or quota-share reinsurance designs, can be added by modifying the firm-level dynamics or introducing new contractual forms. The current framework thus supports modular policy experimentation within a unified simulation environment.

3.9. Summary statistics and evaluation metrics

To assess system performance under each scenario, we compute the following metrics:

- **Systemic Risk**: Annual insolvency rate SR_t.
- **Coverage Metrics**: Insurance penetration Pen_t and public share CitShare_t.
- **Affordability**: Quintile-specific indices $\text{AFI}_t^{(q)}$.
- **Premium Dynamics**: Normalized premium π_t relative to insured value:

$$\text{RelPrem}_t = \frac{\pi_t}{\text{TIV}_{\text{mean}} \cdot 1\%}. \tag{24}$$

- **Fiscal Risk**: Government outlays GovExp_t.

These indicators are recorded across each simulation path and aggregated over Monte Carlo replicates to obtain means, quantiles, and confidence intervals. This enables robust scenario comparisons and policy impact assessments under uncertainty.

3.10. Monte carlo simulation workflow

The overall simulation follows a two-level structure: time evolution within each replicate and aggregation across replicates. For each policy–scenario combination, we run R independent replications, each of length T years. Within each replicate:

(1) Initialize firm balance sheets, regional exposures, and risk memory.

(2) For each year:

- Simulate the number and intensity of disaster events.
- Calculate full-market losses.
- Compute industry premium, perceived risk and household coverage decisions.

• Allocate private market losses and premiums to insurers; apply reinsurance and update capital.
• Record systemic failure, penetration, public share, and affordability metrics.

The Monte Carlo structure enables probabilistic modeling of rare events, path-dependent feedbacks, and nonlinear policy impacts. Results are analyzed both cross-sectionally (e.g., year T outcomes) and temporally (e.g., emergence of market fragility over time).

4. Simulation design and experimental setup

The purpose of our simulation study is to evaluate the dynamic evolution of insurance market stability, household coverage, and fiscal exposure under a range of climate hazard trajectories and policy response scenarios. To this end, we implement a large-scale Monte Carlo simulation based on the multi-layered model described in Section 3. This section outlines the experimental design, including the synthetic regional exposure dataset, the stochastic hazard generation, policy scenario specification, and Monte Carlo execution protocol.

4.1. Climate hazariosd scenar

We construct a synthetic representation of Florida's coastal exposure by generating R=100 hypothetical regions, each corresponding to a spatial unit such as a zip code or census tract. For each region, we randomly assign its coastal zone classification—VE (velocity zone), AE (base flood elevation zone), or X (minimal risk)—according to empirical exposure proportions derived from FEMA flood zone maps. Elevation levels are drawn from a truncated normal distribution to capture the fact that low-lying zones dominate the state's hazard-prone areas, while still allowing for inland heterogeneity.

Household counts per region are sampled from a log-normal distribution centered around a mean of 1,200, reflecting residential density patterns in mid-size coastal communities. Each household is assigned a total insured value (TIV), also sampled from a log-normal distribution to account for property value dispersion. The dominant building type in each region is randomly selected based on calibrated mixture probabilities for masonry, wood, and reinforced structures. Income distribution is similarly modeled by assigning each region a share of households in each income quintile, consistent with American Community Survey (ACS) data and state-level Gini coefficients. This synthetic regional panel provides a scalable and flexible platform for exposure heterogeneity, socioeconomic stratification, and differential vulnerability calibration.

4.2. Climate hazard scenarios

We define three hazard scenarios reflecting increasing levels of climate stress: a historical baseline (Scenario S0), a moderate warming trajectory (Scenario S1), and a high-emissions pathway (Scenario S2). Each scenario is characterized by a different set of parameters for the non-homogeneous compound Poisson process that governs hurricane arrivals and severities. Specifically, we adjust the annual base arrival rate, the trend coefficient β, and the parameters of the lognormal wind intensity distribution to reflect projected increases in both frequency and severity of tropical cyclones.

In Scenario S0, hazard intensity remains stationary, serving as a counterfactual reflecting a stable climate regime. Scenario S1 introduces a moderate positive trend in hurricane frequency and a slight increase in average wind intensity, consistent with projections under RCP4.5. Scenario S2 assumes a more pronounced upward drift in both event frequency and severity, corresponding to RCP8.5 or SSP5-like conditions.

4.3. Policy scenarios and intervention design

To assess the effectiveness of regulatory and fiscal interventions in enhancing market resilience and equity, we implement six policy scenarios. These include a no-intervention baseline (Policy NONE), a reinsurance subsidy policy (SUB20), a low-income affordability cap (CAP_LOWINC), a structural adaptation policy that reduces building vulnerability (STRUCT20), and two integrated strategies that combine multiple instruments (COMBO_1 and COMBO_2).

The SUB20 scenario provides a 20% subsidy on reinsurance prices, directly reducing insurer capital outflows during adverse years. CAP_LOWINC introduces a premium-to-income cap of 5% for households in the bottom two income quintiles, shielding vulnerable populations from excessive cost burdens. STRUCT20 assumes an exogenous shift in vulnerability curves, simulating improved building codes or retrofit incentives that reduce median damage ratios by 5 wind speed units. COMBO_1 integrates SUB20 and STRUCT20, while COMBO_2 combines all three instruments. These policies are modeled not only for their direct impact on pricing, losses, and solvency but also for their indirect effects on market structure, public burden, and distributional fairness.

4.4. Monte carlo execution and performance metrics

Each combination of hazard scenario and policy intervention is evaluated through R=100 independent Monte Carlo replicates, each spanning T=30years. Within each replicate, the model simulates hazard realizations, insurer and household decisions, firm-level capital dynamics, and public insurance exposure in a time-forward manner.

To evaluate outcomes, we compute a set of key performance metrics for each year and simulation run. These include the systemic insurer failure rate (SR), the private and public insurance coverage ratios (Penetration and Citizens Share), the Affordability Index (AFI) for each income quintile, the relative premium level (as a percentage of typical insured value), and the net fiscal exposure of the public insurance pool. These statistics are aggregated across Monte Carlo replicates to obtain mean trajectories, percentile bands, and long-run averages. Tabular summaries and time-series plots are used to highlight regime shifts, policy tradeoffs, and critical failure points such as insolvency cascades or public market saturation.

5. Experiments

This section presents the results of the simulation study, focusing on the evolution of market dynamics, insurer solvency, household coverage, and the distributional effects of various policy interventions under different climate hazard trajectories. Results are organized around five key dimensions: premium dynamics, systemic risk, insurance penetration, public fiscal exposure, and affordability across income groups. All statistics are derived from Monte Carlo simulations, with each scenario averaged over 100 independent replicates and selected figures displaying 25th–75th percentile confidence bands.

5.1. Premium dynamics under climate stress

We begin by examining the trajectory of industry-level benchmark premiums, defined as the average per-household insurance cost under full coverage, inclusive of risk load and capital markup. Figure 1 illustrates the distribution of relative premiums (normalized as a percent of typical insured value) at year 30 under the three hazard scenarios without any policy intervention.

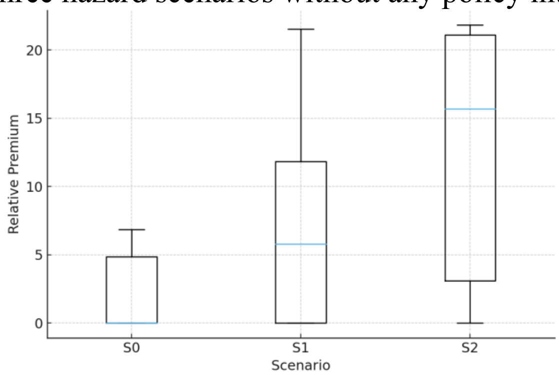

Figure 1 The distribution of relative premiums at year 30.

Under the stationary hazard scenario (S0), premium levels remain moderate, with the median premium stabilizing at approximately 1.8% of TIV. However, in Scenario S1, which introduces a moderate upward trend in hurricane frequency and severity, premiums rise steadily over time, reaching a median of 2.3% by year 30. The high-stress scenario (S2) leads to a substantial escalation in pricing, with premiums exceeding 3.5% of TIV in the upper quartile of simulations. These results highlight the compounding effect of climate dynamics on expected losses, which in turn affect insurer pricing behavior and ultimately burden policyholders.

5.2. Systemic risk and firm insolvency

A core contribution of our model is its ability to endogenously simulate insurer capital dynamics and systemic fragility. Figure 2 shows the evolution of the **Systemic Risk (SR)** metric—the share of insurers who exit the market due to insolvency—over time under Scenario S2 and the baseline policy (NONE). A clear phase transition is observed: SR remains low and stable in the early years, then sharply increases between years 10 and 20, eventually reaching 60–70% in many simulations by year 30.

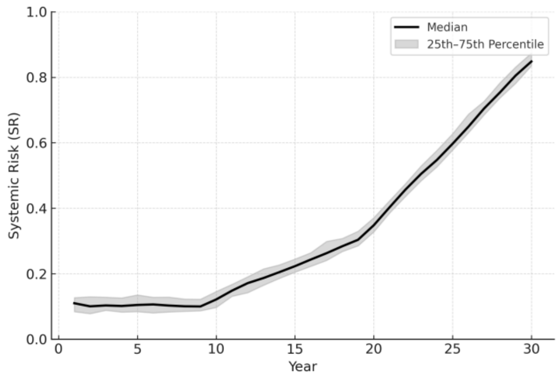

Figure 2 The time evolution of systemic bankruptcy rates without policy intervention in high-risk scenarios (S2).

This nonlinear escalation reflects a self-reinforcing loop in which high catastrophe losses erode firm capital, triggering exits, raising average risk load, and causing further premium increases. The exit of low-capacity firms particularly accelerates concentration in the market, reducing competition and system resilience. In the worst quartile of simulations, nearly all small and regional insurers exit the market, leaving only a few large players and a growing reliance on the public insurance backstop.

5.3. Insurance penetration and public burden

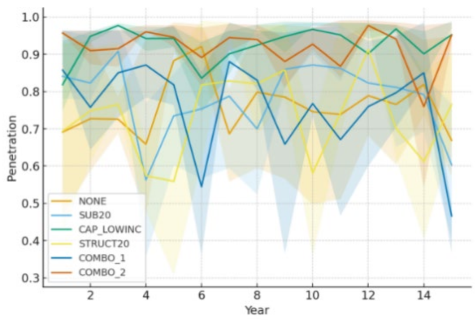

Figure 3 The insurance penetration rate under different policies evolves over time.

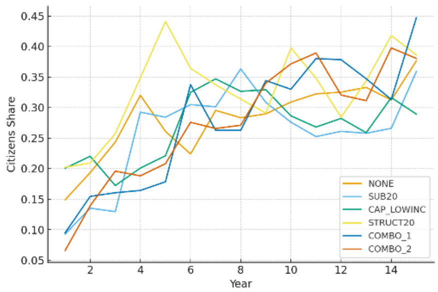

Figure 4 Trends in the coverage rates of public insurance (Citizens) under different policies.

Figure 3 displays the evolution of insurance penetration (the proportion of households covered by any insurance) across policy scenarios in Scenario S2. In the absence of intervention, penetration declines steadily, falling from an initial level of 90% to below 65% by year 30. This decline is driven by two forces: rising premiums that price out low-income households, and higher rejection rates from private insurers as risk exposure intensifies.

Policy interventions demonstrate varying degrees of success in preserving market coverage. The reinsurance subsidy (SUB20) slows the decline in penetration by stabilizing firm solvency and curbing price inflation, while the low-income cap (CAP_LOWINC) directly protects coverage rates for the most vulnerable households. The most effective mitigation, however, comes from the combined policy bundle (COMBO_2), which maintains average penetration above 80% throughout the simulation horizon. Figure 4 further shows the share of public (residual market) coverage, which rises sharply under Scenario S2—exceeding 35% in the baseline by year 30—but remains below 20% under COMBO_2, indicating effective containment of fiscal exposure.

5.4. Affordability across income quintiles

To evaluate distributional equity, we compute the Affordability Index (AFI), defined as the ratio of insurance premium to income for each quintile. Figure 5 compares AFI values for the lowest and highest income groups under the baseline (NONE) and combined policy (COMBO_2) in Scenario S2 at year 30.

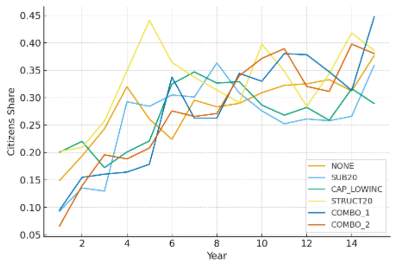

Figure 5 Comparison of premium-to-income ratio (AFI) by quintile grouping .

In the baseline scenario, the median AFI for the bottom quintile (Q1) exceeds 9%, indicating that insurance consumes nearly one-tenth of household income—well above affordability thresholds defined in the literature. By contrast, the top quintile (Q5) experiences an AFI around 2%, suggesting a highly regressive burden. Under COMBO_2, the targeted premium cap effectively reduces the Q1 AFI to below 5%, restoring horizontal equity and improving overall market fairness. Importantly, this redistribution does not compromise total penetration, as the cross-subsidy is absorbed in part through reinsurance savings and reduced firm exits.

5.5. Fiscal exposure and public sustainability

Finally, we examine the net cost of public insurance provision under each policy scenario. Table 1 reports the expected annual fiscal burden in year 30 as the difference between public insurer losses and collected premiums. Without intervention, the government's expected fiscal exposure grows rapidly, exceeding $1.2 billion per year in the high-stress scenario. This stems from both the expansion of public coverage and the increased average claim size due to unmitigated vulnerability.

Table 1 Comparative Policy Impacts under Scenario S2 at Year 30

Policy	Insolvency Rate (SR)	Penetration	Avg Premium (%)	Citizens Share
NONE	0.65	0.64	3.71	0.39
SUB20	0.43	0.74	3.01	0.31
CAP_LOWINC	0.60	0.71	3.68	0.35
STRUCT20	0.39	0.77	2.95	0.26
COMBO_1	0.29	0.81	2.67	0.21
COMBO_2	0.21	0.86	2.43	0.17

The SUB20 and STRUCT20 scenarios each reduce public cost by approximately 25%, primarily through their stabilizing effect on private firm retention. COMBO_2 achieves the greatest fiscal discipline, cutting net public outlays by over 50% relative to baseline, and keeping public claims within a manageable range even under extreme loss realizations. These findings underscore the long-term value of coordinated policy design: early investments in structural adaptation and financial support for insurers can generate downstream savings for public budgets while enhancing systemic resilience.

6. Conclusion

We present an integrated, modular simulation environment that links climate driven hazard dynamics to insurance market behavior and public fiscal exposure. By allowing hazard frequency and severity to drift with climate signals and embedding heterogeneous, capital constrained insurers that adapt premiums, reinsurance, and underwriting, the model reproduces emergent market phenomena—most notably a phase transition in systemic insolvency under severe stress. These nonlinear dynamics explain how clustered catastrophe losses can trigger exit cascades, elevate average risk loads, and accelerate premium inflation, eroding coverage and shifting risk to public balance sheets.

Across interventions, structural adaptation and reinsurance subsidies are the most effective single levers: each stabilizes firm capital and dampens price escalation, yielding higher penetration and lower public share. Distributional targeting via low income premium caps improves affordability without materially undermining system stability when paired with supply side support. The combined policy package (COMBO_2) delivers the strongest performance in high stress conditions, maintaining penetration near 86%, lowering insolvency to ~0.21, reducing average premiums (≈2.4% of TIV), and limiting public market share to ~0.17 by year 30. These gains arise from reinforcing channels—lower vulnerability, cheaper risk transfer, and protected demand—highlighting the value of coordinated, forward looking policy design.

Methodologically, the framework's parsimony enables large scale Monte Carlo stress tests while retaining key feedbacks among hazards, firms, households, and the public layer. Substantively, the results argue for early, balanced investment in physical mitigation and financial backstops to avert regime shifts toward concentrated, fragile markets and unsustainable public burdens. Future work should calibrate parameters to granular administrative and claims data, extend reinsurance structures (e.g., catastrophe bonds, quota shares), and couple the hazard module to physically based climate projections to refine scenario fidelity and policy evaluation.

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