California Homeowner Insurance Market Design

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June 4, 2025

Abstract

The California homeowner insurance market is collapsing. In the face of increasing wildfire risk, many homeowners insurance companies have exited the market or dramatically scaled back their portfolios, leaving thousands of households without coverage. Consequently, California's Fair Access to Insurance Requirements (FAIR) Plan, which operates as the state's insurer of last resort, is now bearing over $450 billion in exposure, as of September 2024. Existing statewide policies, such as premium caps imposed under Proposition 103, have only exacerbated the problem, accelerating private insurer exits and shifting the financial burden of homeowner insurance onto the state and its taxpayers. This paper proposes a novel allocation model and clock auction mechanism for the homeowner insurance market in California. This solution, rooted in matching and auction theory, aims to allocate insurers geographically diverse portfolios with approximately equal per-home expected loss. To account for insurers' different preferences over risk, the clock auction allows them to trade from their initial allocations in a truthful and Pareto efficient manner. This approach addresses core market design failures by promoting risk diversification, curbing insurer market exits, and ultimately expanding coverage for homeowners. Moreover, this mechanism provides a scalable framework for private insurers providing coverage in other high-risk environments.[1]

1 Introduction

The severity of California's wildfire crisis has reached unprecedented levels in recent years. As rated by number of structures destroyed, the top four most destructive fires have all occurred in the last eight years since 2017 (ABC, 2025). The vulnerabilities of California's insurance market were brought to the fore of public attention by the Palisades and Eaton fires in January of 2025. Together, the two fires burned approximately 37,500 acres, took 29 lives, and cost between $76 and $131 billion in property losses (Kaysen,

[1] Here is the link to our video presentation. Please note that we made slight modifications to modeling assumptions post filming (we modified burn risk represented by each risk tier and increased premium pricing in our simulations). However, the gist of our project remains the same. https://drive.google.com/file/d/1iMduhRhUwTOCw1OxjyUUF8coHKALYRxA/view?usp=sharing

2025). These fires, fueled by periods of prolonged drought and intensely high winds, are now viewed as the most expensive wildfires in California's history, with overall economic damages amounting to as much as $250 billion (Vincent, 2025). As wildfire seasons have extended from five to seven months and high-risk acreage continues to grow, California's home insurance market has been placed under an unsustainable amount of stress — thus calling for a comprehensive review of the market's current design (WFCA, 2024).

Due to mounting losses, many of California's largest insurance carriers have chosen to withdraw from the market. Eight of the twelve largest providers have either capped their risk exposure or exited the market, with State Farm alone dropping 1,600 policies in the high-risk Palisades region in July 2024 (Picchi, 2025). In the absence of sufficient coverage from private insurers, many have turned to the FAIR Plan, a state-mandated program that offers limited coverage to homeowners unable to find private insurance. Between 2019 and 2023, the FAIR Plan has experienced a doubling in policies, jumping from roughly 155,000 to 339,000 (California DOI, 2025). The Plan's exposure is now nearing $460 billion, straining both its short-term and long-term financial health. Although there have been policy efforts to balance affordability with access to coverage in the form of price caps and subsidies, their impact has largely been counterproductive. In reality, such policies have worsened the situation by suppressing prices, accelerating market exits and transferring financial risk to citizens.

In the status quo, the homeowner insurance market has failed to balance affordability, accessibility, and profitability. Rising climate-related risks coupled with regulatory constraints on premium pricing have led to a breakdown in efficient, market-clearing allocations: homeowners are increasingly priced out or denied coverage; insurers are exiting due to capital risk; state-run solutions, such as California's FAIR plan, are becoming unsustainable.

2 Background

2.1 Stakeholder Analysis: Homeowner's Insurance in California in the Status Quo

There are three primary stakeholders in California's homeowner insurance market.

1. **Insurers**: Within the homeowner insurance market, the primary risk-bearers in California are private insurance companies. These insurers are constrained by a myriad of regulations that limit their ability to accurately price and diversify their portfolios. The leading constraint in this case is Proposition 103 — a 1988 ballot initiative which mandated Department of Insurance approval for any rate increases

(California DOI, 2025). This newly introduced approval system altered the dynamics of California's insurance market, effectively creating a rate cap, barring the use of modern catastrophe modeling in underwriting and decoupling price premiums from the actual wildfire risk. The impact was so consequential in fact, that between 2017 and 2022, California was the worst state in the country for "rate suppression," having the biggest gap between "the actuarially indicated rate and the rate approved by regulators" (Bourne, 2025).

Moreover, California's insurance regulations also limit insurers' ability to reflect reinsurance rates in their rates. Reinsurance, essential for shielding insurers from catastrophic events, has become increasingly expensive as wildfires grow more frequent and severe. Unable to pass these costs on to policyholders, insurers faced compounding costs. This effect is best contextualized by the reality that catastrophic losses have increased from $4 billion in 2016 to $15 billion in 2017, while net profit margins for property and casualty insurance hover around 5% — leaving insurers with little room for error (California DOI, 2022). Insurers must also account for large amounts of off-book risk imposed by their mandatory participation in California's FAIR Plan. This hidden exposure adds yet another layer of uncertainty and capital risk for insurers, further deterring them from participating in the market.

Most critically, the recent rising frequency and intensity of wildfires has broken existing underwriting models. State data continues to underestimate actual wildfire exposure: today internal insurer models suggest up to 30% of California homes face high wildfire risk, compared to the state's outdated estimates of only 12% (Hoffman, 2025). In layman's terms, should a $1 million home experience an increase in risk from 1-in-400-year event to 1-in-50-year event, the insurance premium would balloon from $2,500 to $20,000 per year.

Together, these pressures have pushed even the largest and richest insurers to reduce exposure in California markets, or exit entirely. In order for a redesigned mechanism to be successfully adopted and implemented, these measures need to be accounted for by enabling more accurate risk-pricing, creating diversified risk pools, and reducing hidden liabilities.

2. **Homeowners**: For California homeowners, the wildfire insurance crisis is manifesting as a dual shock of affordability and availability. As wildfire risk intensifies, premiums have risen dramatically — this is especially true for high-value properties in vulnerable areas. Such price surges are financially unsustainable for the majority of households thus pushing homeowners to seek out alternatives to the formal insurance market. The existing underwriting models only compound the crisis as they fail to account for parcel-level risk mitigation efforts such as home hardening, defensible space, and

community fire breaks. Despite new state initiatives to encourage and subsidize these interventions, insurers have been slow to integrate them into pricing structures. As private companies exit the market, many homeowners are exposed to catastrophic financial losses from the recent wildfires and create a huge strain on the state-run FAIR plan, the insurer of last resort. In effect, homeowners have become collateral damage as the insurance system is unable to distribute wildfire risk in an equitable and sustainable manner. Without intervention, both the human and economic costs will continue to escalate.

3. **The State (via the FAIR Plan)**: The FAIR Plan is California's solution to the state's insurance crisis, providing basic fire coverage to homeowners unable to secure insurance through the private market. It offers minimal coverage at an average premium of $3,200 per year, with some high-risk properties facing rates as high as $10,000 (Maher, 2024). While homeowners can add supplemental options like liability coverage, the FAIR Plan remains limited in scope and is often more expensive than standard private insurance.

   It is crucial to recognize that the FAIR Plan is not state-funded. Rather, it is financed by private insurers who offer policies and participate in California's market. When claims exceed the available funding, these licensed insurers are subject to additional assessments. This system has created a problematic feedback loop where insurers are exiting the market due to growing risk, and the remaining market participants are becoming more and more exposed to FAIR Plan liabilities. This pressure is only growing; in 2022, the FAIR Plan received 270,000 applications, many from homeowners dropped by their insurers (Maher, 2024). While waiting for approval, mortgage companies are led to impose forced-placement insurance which carries costs of up to $2,700 per month.

   In the aftermath of the devastating Palisades and Eaton wildfires in 2025, the FAIR Plan is now facing an estimated $4 billion in total losses, prompting a $1 billion emergency assessment to remain it solvent (Kaufman, 2025). Companies like State Farm, which handles roughly 20% of the entire California market, were hit with $200 million in charges, despite not underwriting the affected policies (Darmiento, 2025). The financial burden will only increase as the risk and loss estimates worsen.

2.2 Why Existing Market Designs Fail

The core reason that California's market is nearing collapse is because there is a misalignment of incentives, and stakeholders are struggling to balance risk exposure with equitable pricing. This was largely due to issues arising from the two dominant mechanism approaches: free actuarial pricing and mandated cross subsidization. Both models, when implemented, lead to breakdowns in coverage, efficiency, or participation, or at its worst, a combination of a few.

Free actuarial pricing occurs when insurers are able to set premiums purely based on risk. However, for high-risk properties, this could result in massive premium hikes. In fact, industry experts state that, "insurers will show up if they can price freely" (Hoffman, 2025). In theory this offers a market solution; but in practice, this approach renders high market coverage economically infeasible for a large portion of homeowners, leaving many uninsured.

On the other hand, the mandated cross-subsidy approach attempts to limit obstacles to greater affordability through the redistribution of risk. Under this model, low-risk homeowners are actually overcharged to offset losses from their high-risk counterparts. The market begins to unravel as there is now greater incentive for low-risk homeowners to opt out of the market altogether.

Our proposed solution — an initial allocation and subsequent clock auction mechanism — offers all stakeholders a structured middle ground. In this design, each insurance company is allocated a geographically diversified portfolio with a similar expected loss per home to other insurance companies. They are mandated to offer a premium to each home proportional to the expected loss presented by the home, although the premium is sufficiently high to encourage continued participation in the market. Finally, through a descending clock auction, insurers are able to tailor their portfolios according to their different levels of risk aversion by "buying" or "selling" policies in their allocated portfolios. This mechanism spreads risk, allows for price discovery through trading, and results in a Pareto efficient allocation of homes to insurers.

2.3 A Word on the Economic Theory Behind Insurance

To understand the exodus of homeowner's insurance companies from California, we must first allow a quick digression to explain the basic economic theory behind insurance and insurer's utility functions. Transactions between private insurers and homeowners rely on two phenomena: risk aversion and risk pooling on the part of insurance companies.

We begin with the most fundamental definition of risk aversion:

Introducing Risk Aversion

Definition: Risk Aversion

An agent is risk averse if and only if they face a concave utility function over consumption.

A well-known utility function for modeling risk-averse preferences is the exponential utility function, also known as constant absolute risk aversion (CARA) (Rao, 2020). The CARA utility function is defined as:

$$u(x) = \frac{1 - e^{-ax}}{a} \quad \text{for } a \neq 0$$

- $u(x)$: utility function dependent on variable x, which often represents wealth or consumption level, or another quantity of interest
- a: risk aversion parameter, also known as Arrow's coefficient (must satisfy $a \neq 0$), where a is defined as:

$$a = -\frac{u''(x)}{u'(x)}$$

There is a special case where $a = 0$, and the utility becomes linear:

$$u(x) = x \quad \text{(Agent is risk-neutral, as } u''(x) = 0\text{)}$$

In interpreting this, a measures how rapidly marginal utility of an additional dollar as wealth increases. We will use a as a measure of risk aversion later in our analysis of simulation results.

If x is a random outcome over a normal distribution with mean μ and variance σ^2, so $x \sim \mathcal{N}(\mu, \sigma^2)$, then:

$$\mathbb{E}[u(x)] = \begin{cases} \frac{1 - e^{-a\mu + \frac{a^2\sigma^2}{2}}}{a} & \text{for } a \neq 0 \\ \\ \mu & \text{for } a = 0 \end{cases}$$

The certainty equivalent, or the minimum units of x an agent will take for certain instead of taking on the risk of receiving $x \sim \mathcal{N}(\mu, \sigma^2)$, is:

$$x_{CE} = \mu - \frac{a\sigma^2}{2}$$

Thus, the certainty equivalent of an agent with CARA utility depends on two key inputs: risk aversion and variance of the outcome. Differences in the certainty equivalents of homeowners and insurance companies create opportunity for trade. The agent with a higher certainty equivalent can take $x \sim \mathcal{N}(\mu, \sigma^2)$ off the hands of the agent with a lower certainty equivalent. Therefore, a homeowner and an insurer contract into insurance policies only if at least one of two conditions is fulfilled:

1. The insurance company is less risk averse than the homeowner, reflected in different α values in the case of CARA utility.

2. Insurance companies pool risk, so they face less variance per policy than the homeowner does.

To analyze the payoff of a general insurance company, who does not necessarily have CARA utility, we set up the following model.

Utility of Insurer

For convenience, we first introduce some foundational notation that will be serviceable throughout the paper:

- $\mathcal{I} = \{1, \ldots, N\}$: Set of all homes, indexed by i
- $\mathcal{J} = \{1, \ldots, J\}$: Set of insurance companies, indexed by j
- $I_j \subset \mathcal{I}$: Set of homes insured by company j

Suppose an insurance company $j \in J$ covers a set of homes I_j. Let l_i be the loss from an arbitrary home $i \in I_j$. Suppose that l_i values are independent and identically distributed with: [a]

$$\mathbb{E}[l_{i,j}] = \mu, \quad \mathrm{Var}(l_{i,j}) = \sigma^2$$

Let L_j denote the total losses incurred by insurance company j:

$$L_j = \sum_{i \in I_j} l_{i,j}$$

The average loss per home for insurer j is:

$$\frac{L_j}{|I_j|} = \mu$$

with variance:

$$\mathrm{Var}\left(\frac{L_j}{|I_j|}\right) = \frac{\sigma^2}{|I_j|}$$

Assume insurer j has a utility function $u_j(\cdot)$ that is concave (i.e., $u_j''(\cdot) < 0$). Then, applying a second-order Taylor approximation for expected utility of random loss l_i around μ:

$$
\begin{aligned}
\mathbb{E}\left[u_j\left(\frac{L_j}{|I_j|}\right)\right] &\approx \mathbb{E}\left[u_j(\mu) + u_j'(\mu)\left(\frac{L_j}{|I_j|} - \mu\right) + \frac{1}{2}u_j''(\mu)\left(\frac{L_j}{|I_j|} - \mu\right)^2\right] \\
&= u_j(\mu) + u_j'(\mu) * \mathbb{E}\left[\frac{L_j}{|I_j|} - \mu\right] + \frac{1}{2}u_j''(\mu) * \mathbb{E}\left[\left(\frac{L_j}{|I_j|} - \mu\right)^2\right] \\
&= u_j(\mu) + u_j'(\mu) * 0 + \frac{1}{2}u_j''(\mu) * \mathrm{Var}\left(\frac{L_j}{|I_j|}\right) \\
&= u_j(\mu) + \frac{1}{2}u_j''(\mu) * \frac{\sigma^2}{|I_j|}
\end{aligned}
$$

Clearly, for a risk-averse insurer, reducing the variance of loss improves expected utility. That is:

$$
\text{As } |I_j| \uparrow, \quad \mathrm{Var}\left(\frac{L_j}{|I_j|}\right) \downarrow \quad \Rightarrow \quad \mathbb{E}[u_j(L_j/|I_j|)] \uparrow
$$

[a] Indeed, our model is currently limited in that it does not account for burn risk correlation between homes. However, we take active measures in designing our model to introduce geographic diversity among the policies an insurance company takes on in an attempt to mitigate risk correlation. More sophisticated models may account for risk differently.

Therefore, even if the individual household and the insurance company share the same concave utility function $u(\cdot)$, the insurance company enjoys higher expected utility from covering a given home, as it is able to pool risks across many policies. By contrast, a household can be thought of as an insurer with $|I_j| = 1$, facing the full variance σ^2, while an insurer with $|I_j| = N$ benefits from variance reduction to σ^2/N.

In theory, this allows for gains from trade, and homeowner's insurance companies would not leave the market. However, theory does not align with reality due to the aforementioned premium caps implemented by the California government. Furthermore, homeowner's insurance companies currently incur high marketing, transaction, and legal costs, which impede the transfer of risk from homeowners to insurers.

We propose an alternative mechanism that results in full coverage of homes, assigns a premium to insurance companies, and then allows for gains from trade among insurance companies with different preferences over risk in a descending clock auction.

3 Model Description and Rationale

3.1 General Overview

There are three parts to our model. We initially allocate homes with a focus on geographic risk diversification and equalizing the expected loss per home each insurance company faces, while respecting their preferences for how many homes they would like to cover. Then, we assign premiums transparently. Each homeowner must pay a premium proportional to the expected loss their home faces, which is based on its burn risk and its property value. This avoids the issue in the status quo where homes facing low risk may have to bear the burden of homes facing high risk. In this case low-risk homes may exit the market, causing a form of market unraveling. Finally, we allow insurance companies to trade and realize gains from their differentiated preferences over risk via a descending clock auction. In this auction, one insurer can put a home on the market that they do not wish to cover. Then, other insurers can bid on this policy. The price drops continuously as the auction proceeds. The last bidder that remains in the auction is the winning bidder and gets paid the terminal price of the auction in exchange for assuming responsibility for covering the home.

The latter part of our model takes inspiration from clock auctions used in the European Union Emission Trading System (ETS) (EC, 2025). ETS operates as a cap-and-trade program, placing an upper limit on the total emissions allowed while still letting companies trade credits. Firms that can reduce emissions cheaply do so and sell their excess permits; those facing higher costs opt to buy. This system incentivizes cost-effective risk reduction, aligns incentives across all participants, and ensures an efficient allocation of burden. Our trading market for fire risk mirrors this logic: rather than emissions, we allocate fire exposure, allowing insurers to trade risk in pursuit of optimized, diversified portfolios.

Like ETS, this mechanism leverages auction formats — in particular, clock auctions — to determine price per unit dynamically based on real-time supply and demand. This ensures transparent price discovery and minimizes strategic manipulation.

3.2 Risk Classification

Furthermore, a working model for insurance allocation must be based upon a thorough risk classification system. In our context of wildfire risk, the considered inputs are 1) environmental exposure, 2) property-level risk, and 3) historical loss experience. By incorporating such factors into our model we ensure accurate assessments of wildfire vulnerability across regions which allows for more sustainable matching and trading.

1. The first consideration is environmental exposure. For the purpose of this project, our model will be utilizing information from the California Fire Hazard Severity Zones (FHSZ), which provides a foundational classification tool. FHSZ groups properties into moderate (yellow), high (orange), and very high (red) risk zones. As the California Fire Marshal's office updates its hazard maps often with local climate data and improved fire risk modeling, the FHSZ will only become a better reflection of accurate wildfire risk across the state.

2. As environmental exposure is insufficient to calculate total wildfire risk, property-level qualifications

are considered, specifically a home's design and mitigation efforts. Such factors can look like defensible space and home hardening, type of construction/building materials, and climate mitigation credits. More often than not, insurance models fail to account for forest treatment in models which comes at a tremendous cost, but new regulation is now requiring models to incorporate such information.

Construction quality and materials further influence vulnerability. Roof composition, siding flammability, and structural durability all factor into the risk score. Incorporating this data allows for a finer-grained differentiation of properties within the same hazard zone.

A future extension of our model includes the issuance of tradable "risk credits" for properties that implement fire proofing measures. These credits could be integrated into insurer portfolios, incentivizing proactive mitigation efforts and allowing insurers to directly input portfolio risk scoring and trading incentives into the model.

3. The final dimension of the risk analysis comes from historical insurance performance data. On a micro-level, homeowner specific claim histories serve as important underwriting inputs. They allow insurers to differentiate between applicants in their preference lists based on historic behavior and outcomes. Macro-level trends, such as regional fire historicals, provide additional data worth considering when pricing insurance premiums. For example, in the years 2017, 2018, and 2020, more structures were destroyed by fires than in the entire decade 2007 through 2017 (emLab, UC Santa Barbara). Past experience is a central component in any calculation for pricing and must be embedded in any potential allocation mechanism.

From these three factors, insurance companies ascertain a burn risk for each home r_i—a measure of the probability a home will burn down in the next year.

For each homeowner i, we observe:

$$
\begin{aligned}
&e_i \in \mathbb{R}_{\geq 0} && \text{(environmental exposure)} \\
&s_i \in \mathbb{R}_{\geq 0} && \text{(property-level risk)} \\
&c_i \in \mathbb{N}_0 && \text{(claims/loss history)}
\end{aligned}
$$

Then, the burn risk r_i is a composite of the $e_i, s_i,$ and c_i:

$$r_i = \alpha e_i + \beta s_i + \gamma c_i, \quad \alpha, \beta, \gamma > 0$$

This approach to risk assessment encompasses the drivers of risk for homeowner insurance companies. That said, our simulations rely primarily on publicly-available FHSZ environmental exposure data; property-level assessments and past claims data are difficult to track down and often proprietary. We therefore simplify risk r_i to primarily focus on environmental exposure and property value in our simulation; however, policymakers and insurers would be well-advised to form a more comprehensive assessment of risk.

4 Formal Model

4.1 Formal Three-Part Model

1. Initial Allocation: We first introduce some simple notation for our model.

Model Set Up

In addition to the variables we defined in previous sections, which we continue to use here, we introduce the following:

- $\mathcal{C} = \{1, \ldots, C\}$: Set of counties in California, indexed by c
- Number of homes in a county c: N_c
- Number of homes covered by an insurer j located in county c: $N_{j,c}$
- Market share of Insurer: $M_j = \frac{N_j}{N}$
- Property value: v_i
- Burn risk: r_i

Now, we shall introduce our formal allocation model.

Initial Allocation

1. Each home $i \in I$ is assigned a composite risk score:

$$r_i = \alpha e_i + \beta s_i + \gamma c_i, \quad \alpha, \beta, \gamma > 0$$

2. For each $i \in I$, calculate the expected loss from wildfire: $\ell_i = r_i * v_i$
3. In each county $c \in C$, assign homes to insurance companies such that two conditions are met: (1) For each insurance company $j \in J$, for each county $c \in C$, i is assigned $M_j * N_c$ homes in county c.

(2) For some tolerance $t \in \mathbb{R}_{>0}$, the total expected loss per house is no greater than t between any two insurance companies.

See simulation section 2.5 for one mechanism that accomplishes this, although this part of our model is mechanism agnostic.

2. Insurance Risk Premiums, RP: In addition to paying the value of their expected loss, homeowners pay an additional fee to offset the risk to insurers. We propose the following mechanism to determine insurance premiums.

Setting Insurance Premia

1. Set some $k > 0$ such that each home $i \in I$ is required to pay $RP_i = (1+k)\mathbb{E}(l_i)$ for coverage. k may be set by the state government, in keeping with precedent of the state government of California setting price caps on premia.
2. For each insurance company $c \in C$, calculate the $\sum_{i=1}^{N_c} RP_i$ as a proportion of their variance. This serves as an approximation of the compensation they receive per-unit of risk they accept—an idea that will be formalized and useful later.

3. Descending-Price Clock Auction: Although the initial allocation process is standardized and does not account for the different risk preferences of insurance companies, we allow for gains from trade to tailor the portfolios of each insurance company to their risk tolerance.

In particular, we use a descending price clock auction to unlock gains from trade.

Clock Auction

Model Notation:

- Let $t \in \mathbb{R}_{>0}$ be the time elapsed since the start of the auction at time t_0.
- Let $p_i(t) \in \mathbb{R}_{\geq 0}$ denote the price clock for home i at round t.
- Let $u_j(i, p_i(t))$ be the utility of company j for home i at price $p_i(t)$.
- Let $D_j(t) = \{i \in \mathcal{I} : u_j(i, p_i(t)) \geq 0 \text{ and } u_j(i, p_i(t)) \geq u_j(i', p_{i'}(t)) \ \forall i' \in \mathcal{I} \backslash \{i\}\}$ be the set of homes most preferred by insurer j at round t.
- Let $D_i(t) = \{j \in \mathcal{J} : i \in D_j(t)\}$ be the set of companies demanding home i at round t.

Auction Procedure (at each round t):

1. **Information Disclosure:** For every home i on the market, its expected loss $\mathbb{E}(l_i)$ known to every insurer $j \in J$.

2. **Price Initialization**: Set the price of each home sufficiently high, for example to twice the expected loss: $2 * \mathbb{E}(l_i)$.

$$p_i(0) = 2 * l_i \quad \forall i \in \mathcal{I}$$

3. **Demand Revelation:** Each insurance company $j \in \mathcal{J}$ bids for the home it most prefers at current prices:

$$D_j(t) = \arg\max_{i \in \mathcal{I}} \{u_j(i, p_i(t))\} \quad \text{if } u_j(i, p_i(t)) \geq 0$$

4. **Excess Demand Check:** For each home $i \in \mathcal{I}$, define:

$$\text{Excess}_i(t) = \begin{cases} 1 & \text{if } |D_i(t)| > 1 \\ 0 & \text{otherwise} \end{cases}$$

5. **Price Update:** If any home has excess demand, update:

$$p_i(t+1) = \begin{cases} p_i(t) - \delta & \text{if Excess}_i(t) = 1 \\ p_i(t) & \text{otherwise} \end{cases} \quad \text{where } \delta > 0$$

6. **Stopping Rule:** If $\text{Excess}_i(t) = 0 \ \forall i \in \mathcal{I}$, terminate and assign each home i to the unique $j \in \mathcal{J}$ such that $i \in D_j(t)$.

5 Features of Our Allocation and Auction Model

5.1 Features of the Initial Allocation

There are a number of attractive features of each part of our model. We begin by analyzing the desirable properties of our initial allocation mechanism.

Initial Allocation: We propose an initial allocation mechanism that guarantees full coverage, maximizes the geographic diversity of each insurance company's portfolio and equalizes expected losses across insurance companies, subject to fulfilling market share constraints.

1. First, it is trivial that, by design, our allocation ensures full coverage.

Proof. For each county $c \in C$, the total number of homes allocated is:

$$\sum_{j \in J} M_j * N_c = N_c * \sum_{j \in J} M_j = N_c * 1 = N_c$$

So all N_c homes in county c are covered. Summing over all counties:

$$\sum_{c \in C} \sum_{j \in J} M_j * N_c = \sum_{c \in C} N_c = N$$

Hence, all N homes across counties are fully allocated.

According to the existing academic literature of risk sharing, in an insurance system without transaction costs, full coverage is the efficient outcome for all insured homeowners that are more risk averse than an insurance provider (Gollier, 2013). We develop this theory in the appendix, A1.

2. Next, we'll show that our initial allocation fulfills market share constraints.

Market Share Constraint

Definition: Market Share Constraint An allocation $\alpha : I \to J$ respects market share constraints if

$$\forall j \in J, N_j = M_j * N$$

where, as before, N_j is the number of homes assigned to j from our allocation α.

Proof. Our initial allocation respects market share constraints.

In our model: $\forall c \in C$, $\forall j \in J$, $M_j = \frac{N_{j,c}}{N_c}$.

Then, $\forall j \in J$, $N_j = \sum_{c \in C} N_{j,c} = \sum_{c \in C} M_j * N_c = M_j \sum_{c \in C} N_c = M_j * N$.

Thus, $\forall j \in J, N_j = M_j * N$.

Our allocation fulfills the market share constraints.

3. Next, we concern ourselves with geographic diversity and show that our initial allocation is maximally geographically diverse.

Geographic Diversity

- For each insurance company $j \in J$ and county $c \in C$, define the share of j's portfolio in county c as:

$$P_{j,c} := \frac{|\{i \in I : \alpha(i) = j \wedge c(i) = c\}|}{|\{i \in I : \alpha(i) = j\}|} = \frac{N_{j,c}}{N_j}.$$

- Let $f : [0,1] \to \mathbb{R}$ be a twice-differentiable function satisfying:[a]

$$f'(x) < 0 \quad \text{and} \quad f''(x) < 0.$$

Definition: Geographic Diversity We say that an allocation α^* is maximally geographically diverse subject to market share and full coverage constraints if it solves:

$$\max_{\alpha} \sum_{j \in J} \sum_{c \in C} f(P_{j,c}) \quad \text{subject to market share and full coverage constraints}$$

[a]We choose this function f to be strictly decreasing to represent a penalty function for having too much of a portfolio concentrated in one county. Additionally, we let it be strictly concave to penalize more harshly as concentration increases. This reflects how the risk correlation has increasingly harmful consequences as it increases, because one catastrophic event can then threaten the bottom line of companies, not just their short-term margins.

Proof. We show that our initial allocation $\alpha : I \to J$ is maximally geographically diverse. An allocation $\alpha : I \to J$ is maximally geographically diverse (subject to market share and full coverage constraints) if it maximizes

$$\sum_{j \in J} \sum_{c \in C} f(P_{j,c}) \text{ subject to market share and full coverage constraints}$$

Simplifying, we may as well maximize $\sum_{j \in J} f(P_{j,c})$ for each $j \in J$, because for every insurer, the geographic diversity penalty in one county does not impact that in another.

Using our definition of $P_{j,c}$, we equivalently seek to maximize

$$\sum_{j \in J} f\left(\frac{N_{j,c}}{N_j}\right) \quad \text{subject to the full coverage constraint } \sum_{j \in J} N_{j,c} = N_c.$$

Since $f''(x) < 0$, the function f is strictly concave. To maximize the sum of concave functions over a linear constraint, we should equalize the marginal terms. That is, the optimum occurs when the arguments $\frac{N_{j,c}}{N_j}$ are equal across all $j \in J$.

Indeed, in our allocation, we have that for all $j \in J$, $N_{j,c} = M_j * N_c$ and $N_j = M_j * N$. Thus, it's the case that our allocation equalizes $\frac{N_{j,c}}{N_j} = \frac{N_c}{N}$ for all $j \in J$, hence maximizing geographic diversification.

5.2 Features of Insurance Premium Determination

This part of the model does not impact the strategic decision-making but is simply included to determine insurers' incentives to continue participating in our model. In our simulation, we calculate the total revenue each insurance company can expect with an allocation generated from our model and compare to real-world data.

Since companies cannot do anything to alter their insurance premiums—it is exogenously determined by their market share, allocated homes, and a state-sanctioned risk parameter—it does not have strategic implications for our model.

5.3 Features of Insurance Market Descending Clock Auction

1. Our descending clock auction is a threshold auction.

   Proof: We characterize an auction as a threshold auction if two conditions hold.

   - Whenever a bid b would be winning for any bidder, any higher bid by the same bidder would also win. Indeed, take an arbitrary bidder $j \in J$. Suppose j places a winning bid b_j at some time $t > 0$. This suggests that at time t, $b_j = p(t)$, and b_j is the only bid at time t.

     Suppose that $b_j^* > b_j$. Then, assuming sufficiently high initial prices, $b_j^* = p(t^*)$ for some t^*. Since p is a strictly decreasing function in our clock auction, $p(t^*) > p(t)$ suggests that $t^* < t$. Suppose, by contradiction, that b_j^* is not winning. Then, there exists another bidder that places a bid at some time prior to or at t^*. In this case, the descending clock auction would certainly have terminated by time $t^* < t$, and b_j would not be a winning bid, a contradiction of our assumption. As such, we find that b_j^* must be winning.

   - **Corollary:** Since the descending clock auction is a threshold auction, it is also a truthful auction. Like other truthful auctions, our auction allocates each home to the insurance company that values it most.

2. Our descending clock auction is Pareto efficient.

   Proof: Suppose, by contradiction, that the final allocation is not Pareto efficient. Then, suppose there exists a pair of insurers $j_1, j_2 \in J$ with portfolios I_{j_1} and I_{j_2} such that both j_1, j_2 could benefit from a trade.

   Thus, the allocation is not Pareto efficient if and only if there exists a home $i \in I_{j_1}$ and price p such that:

$$\mathbb{E}(u_{j_2}(I_{j_2} \cup \{i\})) + u_{j_2}(p) > \mathbb{E}(u_{j_2}(I_{j_2}) \text{ and}$$

$$\mathbb{E}(u_{j_1}(I_{j_1} \backslash \{i\})) - u_{j_1}(p) > \mathbb{E}(u_{j_1}(I_{j_1}))$$

Then, when the price drops to p in our descending clock auction, j_2 will place a bid of p and the trade will occur. If the auction is terminated before p at a higher price $p' > p$, then j_1 will accept said bid p' and trade i away. Either way, this results in a contradiction insofar as home i will never be in j_1's portfolio I_{j_1}.

Hence, the allocation must be Pareto efficient.

6 Design of Simulation

6.1 Risk Quantification

The California Fire Hazard Severity Zone (FHSZ) Map has been endorsed by the Government of California (Cal Fire, 2025). Different approaches were taken to model fire hazard in wildland and non-wildland areas. Non-wildland areas are the concern of our paper and include urban and agricultural areas. As mentioned before, the FHSZ Map takes into account the environmental conditions that increase wildfire likelihood and intensity, such as nearby vegetation, slope of the land, fire history, and more.

With the exception of proprietary tools for measuring fire risk, the FHSZ is the most well-accepted approach to gauge the fire risk of an area. Following in the example of the California government, we will use the FHSZ model to evaluate wildfire risk.

In particular, there are three risk designations under the FHSZ system:

- Moderate Risk: 0.05-0.5% burn risk (risk of burning in the next year)
- High Risk 0.5-1% burn risk
- Very High Risk 1-3% burn risk

Although published FHSZ data does not directly specify the probability that a home in a given area will burn, we use FHSZ as an approximation of burn risk in our simulations.

6.2 Initial Allocation

We make the following approximations:

Simulation Set Up

Home-Level Attributes to Determine Expected Loss of House $i \in I$

- Randomize burn risk based on risk category.

$$r_i \sim \begin{cases} \text{Uniform}(0.0005, 0.005) & \text{if mod} \\ \text{Uniform}(0.005, 0.01) & \text{if high} \\ \text{Uniform}(0.01, 0.003) & \text{if vhigh} \end{cases}$$

- Randomize property value based on the county average using a normal distribution with standard deviation of $50,000$.

$$v_i \sim \text{Normal}(\mu_{c(i)}, \sigma^2) \quad \text{where } \mu_{c(i)} = \text{average home value in county } c(i)$$

We assume there are 8 homeowner's insurance providers on the market.
Indeed, looking empirically, eight homeowner's insurance companies provided 70.9% of coverage in California in 2023. For our simulation, we shall have 8 homeowner's insurance companies with percentage coverage scaled from the empirical data, so that they provide 100% of the homeowner's insurance in California.

Insurance Company	**Simulated Company**	**Scaled Coverage (%)**
State Farm (19.9%)	A	28.06
Farmers (14.9%)	B	21.00
Liberty Mutual (6.5%)	C	9.17
CSAA (6.5%)	D	9.17
Mercury (6.1%)	E	8.60
Allstate (5.5%)	F	8.18
Auto Club (5.5%)	G	8.18
USAA (5.4%)	H	7.63

Table 1: Homeowner's Insurers in California and Simulated Insurers

Then, we run the following procedure.

1. Determine the total number of homes to simulate. We chose to simulate 10,000.

2. Import data from the Californian government database documenting the acreage of LRA land classified as moderate risk, high risk, and very high risk in each county.

3. The number of homes assigned to each county is proportional to the amount of LRA-designated acreage in that county. Within each county, we divide homes across three wildfire risk tiers (moderate, high, very high) based on the proportion of acreage in each tier.

4. Now, for each home, we know which county it is in and which risk tier it belongs to. We determine its expected loss from wildfire by taking the product of burn risk and its property value. To get its burn risk, we look at the risk tier it belongs to. If it belongs to moderate risk, it has a burn risk taken at random between 0.05% and 0.5%. If it belongs to high risk, it has a burn risk taken at random between 0.5% and 1%. If it belongs to very high risk, it has a burn risk taken at random between 1% and 3%.

   Its property value is determined based on a normal distribution of the property values in its county.

5. Finally, this algorithm randomly allocates n homes across the 8 insurers subject to two conditions.

   a. In each county, an insurance company is assigned a number of homes proportional to their market size. Once they reach the number of homes equal to their market share of 10,000, they are not assigned any additional homes.

   b. We equalize the expected loss per home each company faces as much as possible. Due to randomization, there may be certain allocations in which the expected loss per home differs across different companies. We set up a post-allocation corrective mechanism in which we set a tolerance of 100.

   Our corrective loop iteratively reduces the discrepancy in expected loss per home across insurers by swapping homes. In each iteration, it identifies the insurer with the highest and lowest average expected loss, then swaps the home with the highest expected loss from the high-loss insurer with the home with the lowest expected loss from the low-loss one, if doing so improves balance. The process stops once the difference in average expected loss is within a specified tolerance (we chose 100) or no beneficial swap is possible.

6.3 Calculating Premiums

For the purposes of our simulation, we allow insurers to charge each home 120% of the expected loss of the home. This figure was primarily determined through trial-and-error. We find in our results and analysis that such a premium would allow insurance companies to make more than they are in the status quo, mitigating the risk of insurer exodus.

This revenue calculation was performed as follows:

1. We run our initial allocation process 20 times, each time calculating the revenue each insurance company $j \in J$ makes on every run. We take the average revenue of each insurance company afterwards.
2. To compare with real-world data, we rescale these averaged revenues. Since there are approximately 15 million homes in California and we run our allocation on 10,000 homes, we scale each insurer's revenues up by $\frac{15000000}{10000} = 1500$. We then scale each insurer's revenue down by $\frac{70.9}{100}$, as these 8 insurers represent 70.9% of the market, not 100%.
3. We conduct a comparison to the revenues of the top 8 aforementioned homeowner's insurance companies in the status quo.

For additional data, we back-solve for a measure of how much insurers are being compensated on top of their expected losses for the variance they accept. Indeed, this figure corresponds to the insurer's compensation for taking on risk (per unit of variance):

$$\frac{R_j - \mathbb{E}(L_j)}{Var(L_j)} \text{ where } R_j \text{ is the revenue of insurer } j \text{ and } L_j = \sum_{i \in I_j} l_i.$$

Indeed, this serves as a direct approximation of the Arrow-Pratt coefficient when we use a Taylor expansion for the pay-out of insurance company j.

Arrow-Pratt Risk Aversion Coefficient

Arrow-Pratt Coefficient

The Arrow coefficient, which we introduced at the beginning of the paper, is given by

$$a(\mu_j) = -\frac{u_j''(\mu_j)}{u_j'(\mu_j)}$$

- The greater the value of $a(\mu_j)$, the more risk-averse the insurer is. The lower the value of $a(\mu_j)$, the less averse they are.

We begin with the insurer's participation condition:

$$\mathbb{E}[u_j(L_j)] + u_j(R_j) \geq 0$$

That is, the expected utility of bearing total loss and risk associated with L_j plus the utility of receiving revenue R_j must be non-negative for insurer j to participate.

From the second-order expansion of utility that we developed in Section 2.3, we have that the expected utility of insurer j from their entire portfolio is:

$$\mathbb{E}[u_j(L_j)] \approx u_j(\mu_j) + \frac{1}{2}u_j''(\mu_j) * \mathrm{Var}(L_j)$$

Since the revenue R_j is deterministic and not too significantly marked up, we approximate its utility using a first-order Taylor expansion around the same point μ_j:

$$u_j(R_j) \approx u_j(\mu_j) + u_j'(\mu_j)(R_j - \mu_j)$$

Substituting into the participation condition:

$$u_j(\mu_j) + \frac{1}{2}u_j''(\mu_j) * \mathrm{Var}(L_j) + u_j(\mu_j) + u_j'(\mu_j)(R_j - \mu_j) \geq 0$$

$$2u_j(\mu_j) + \frac{1}{2}u_j''(\mu_j) * \mathrm{Var}(L_j) + u_j'(\mu_j)(R_j - \mu_j) \geq 0$$

We normalize utility (because it's ordinal) so that $u_j(\mu_j) = 0$, yielding:

$$u_j'(\mu_j)(R_j - \mu_j) + \frac{1}{2}u_j''(\mu_j) * \mathrm{Var}(L_j) \geq 0$$

Dividing through by $u_j'(\mu_j) > 0$:

$$(R_j - \mu_j) + \frac{1}{2} * \frac{u_j''(\mu_j)}{u_j'(\mu_j)} * \mathrm{Var}(L_j) \geq 0$$

Recalling the Arrow coefficient:

$$a(\mu_j) = -\frac{u_j''(\mu_j)}{u_j'(\mu_j)}$$

We obtain:

$$R_j - \mu_j \geq \frac{1}{2}a(\mu_j) * \mathrm{Var}(L_j) \quad \Rightarrow \quad a(\mu_j) \approx \frac{2(R_j - \mu_j)}{\mathrm{Var}(L_j)}$$

Thus, by calculating $\frac{R_j - \mu_j}{\mathrm{Var}(L_j)}$ for each $j \in J$, we find the maximum Arrow coefficient an insurer can have and still be willing to participate in our market.

6.4 Descending Clock Auction

Having now allocated the homes to insurers, we allow them to freely conduct trades reflective of their respective preferences for risk and then update their expected revenues. We make a number of simplifications within this simulation to reduce processing time, relying on our proofs from the formal model to justify such simplification.

1. Initialization: Each home i is initially priced at:

$$p_i = 2 * \mathbb{E}[l_i]$$

   where $\mathbb{E}[l_i]$ is the expected loss of home i, determined by its burn risk and property value.

2. Risk Aversion Sampling: Each insurer $j \in J$ is assigned a risk aversion score A_j drawn independently from a uniform distribution:

$$A_j \sim \mathcal{U}[0.5, 10]$$

   This score remains fixed during a given auction run and reflects the insurer's sensitivity to risk.[2]

3. Penalty Computation: For each home i, a penalty score is computed for each insurer j:

$$P_{ij} = \frac{1}{2} * A_j * \frac{\text{Var}(l_i)}{N_j}$$

   where $\text{Var}(l_i)$ is the variance of the expected loss for home i, and N_j is the number of homes already assigned to insurer j (used here to reflect portfolio diversification). The variance is calculated assuming the burn probability π is uniformly distributed over a tier-specific interval:

$$\text{Var}(l_i) = \frac{(\pi_{\max} v_i - \pi_{\min} v_i)^2}{12}$$

4. Assignment Rule: Each home i is re-assigned to the insurer j with the lowest penalty P_{ij}, who is deemed to be the winning bidder.

5. Simulation Execution: This procedure is repeated across 20 independent randomizations of insurer risk preferences. For each randomization:

   - A new set of risk aversion scores $\{A_j\}$ is generated.

[2] This represents a wide range of risk preferences to illustrate the power of trade. However, we also run the simulation on a more limited set and discuss our findings in the results section.

- 10 homes are sampled without replacement.
- For each home, we record the current owner and the new winning insurer.

The process results in 200 home-level allocations across all risk preference scenarios.

6. Outcome Reporting: The simulation outputs include:
   - A summary of home allocations before and after the auction, indicating initial owner, winning bidder, and whether the winning bidder had the lowest risk aversion in that round.
   - A final summary of the proportion of total wins attributed to each insurer across all 200 allocations.

7 Simulation Results and Analysis

We have simulated the wildfire insurance allocation mechanisms discussed above. The git repository can be found at this link: https://github.com/Chelseahu12/ECON136.git

To try the simulations, simply clone the repository, and use make [insert simulation you want to try; we have four total] in a Linux terminal to run the program.

Before running, please review the README.md and install dependencies.

Analysis of Initial Allocation

We primarily assess insurer's willingness to participate by considering their expected losses per home, revenues before trade, and revenues after trade.

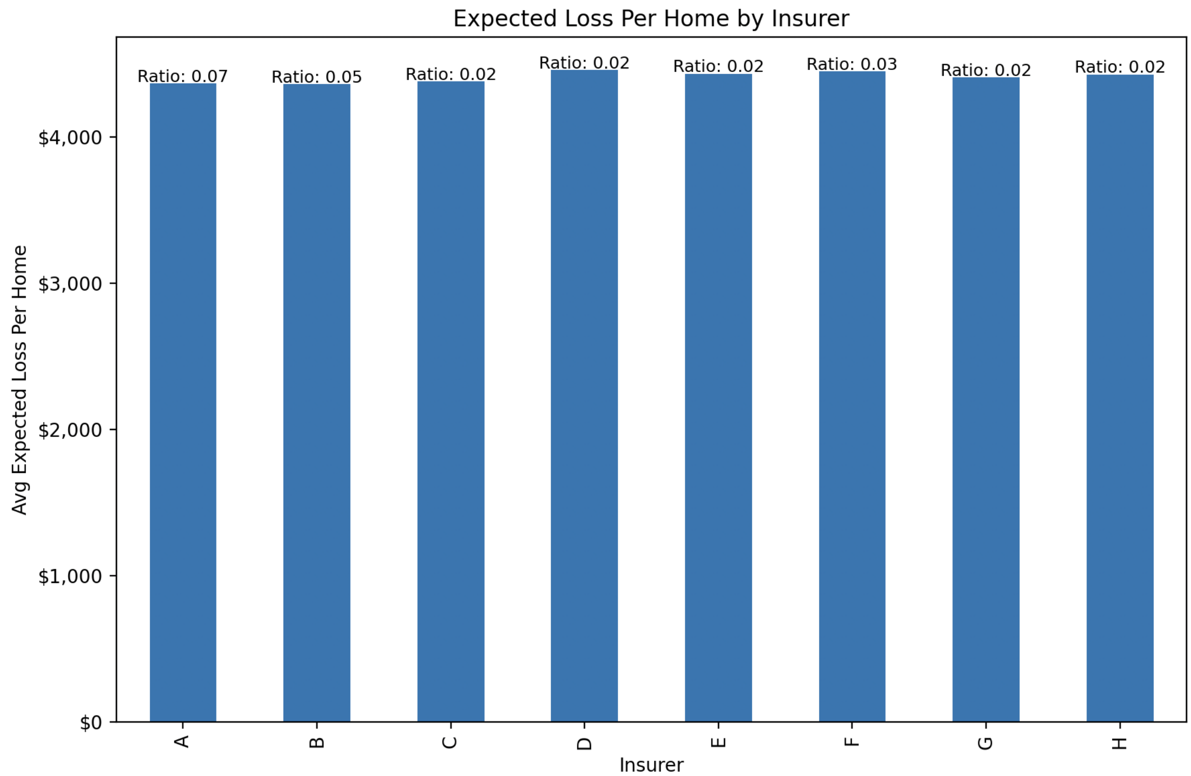

Figure 1: Average Expected Loss per Home by Insurer with 1/2 * Arrow Coef

Expected Loss Per Home:

We see that our initial allocation mechanism guarantees that each insurer's expected loss per home is within $100 of every other insurer, as desired.

Revenues:

These initial allocations yield superior revenues for insurers than they face in the status quo.

Insurance Company	**Avg Adjusted Revenue ($)**	**2022 CA Written Premiums ($)**
State Farm (19.9%)	13 062 266 352.03	7 838 080 636.00
Farmers (14.9%)	9 725 056 903.50	7 022 146 440.00
CSAA (6.5%)	4 375 987 363.43	3 280 898 772.00
Liberty Mutual (6.5%)	4 307 207 260.15	4 018 189 682.00
Mercury (6.1%)	4 135 369 241.89	3 244 191 870.00
Allstate (5.5%)	4 002 096 873.68	4 585 883 976.00
Auto Club (5.5%)	3 879 725 531.32	3 695 226 979.00
USAA (5.4%)	3 834 093 419.72	3 228 283 000.00

Table 2: California Insurance Companies - Simulation Revenue Comparison
[3]

This suggests that insurers are willing to participate in our market, so long as their risk parameter (Arrow coefficient) is less than 0.04. Much of the current literature on risk theory models a moderately risk averse agent with an Arrow coefficient of 0.01, so we take our results favorably (Dionne, 2013; Mas-Colell, Whinston, Green, 1995). With minor deviations due to randomization, large insurers have lower variance and therefore more favorable premium compensation per unit variance they take on. This reflects a general feature of insurance markets where risk pooling is advantageous for insurers.

Gains from Trade:

Insurance markets characterized by perfect information and the absence of transaction costs produce an equilibrium in which the least risk-averse agents fully insure more risk-averse agents. This is approximately, but not exactly, the outcome we see when running a simplified simulation of the descending clock auction.

We can rationalize this mathematically; the winning bidder is generally the one with the lowest expected disutility from covering the additional home. This calculation is simple:

$$\mathbb{E}(u_j(l)) \approx u_j(\mathbb{E}(l)) + \frac{u_j''(\mathbb{E}(l))Var(\mathbb{E}(l))}{N_j}$$

Therefore, the agent reporting the lowest $|\frac{u_j''(\mathbb{E}(l))}{N_j}|$ value is the winning bidder. This is not directly proportional to $u_j''(\mathbb{E}(l))$, as it favors larger companies that can pool risk more effectively.

Indeed, when the range of risk aversion scores $u_j''(\mathbb{E}(l)$ is reduced to 0-0.1, the only winning bidders across 100 runs are the leading insurers A and B. However, when the range is widened to 0.5-10, insurers A, B, C, F, G, H all win some number of bids.

In randomizing risk preferences 20 times and randomly selecting 10 homes for the companies to bid on each time, the only winning bidder who did not have the lowest risk aversion score was Insurance Company A, which held the greatest number of policies. Additionally, the proportion winning bids that may be attributed to each insurance company is summarized below:

Insurer	**Proportion of Wins**
A	0.35
B	0.20
C	0.05
F	0.10
G	0.15
H	0.15

Table 3: Proportion of Wins by Insurer over 100 Risk Preference Randomizations

Therefore, our model appears to favor large insurance companies with the greatest number of policies. This consolidation is part of risk-pooling, however, and we do not come to a normative judgment on whether the benefits of market dominance outweigh the harms in this case.

8 Conclusion and Directions for Further Research

Our allocation model and clock auction offer a starting point and framework to tackle the homeowner's insurance crisis in California through market design principles. Although we find several aspects of our model to be desirable for insurers and homeowners, there are a few notable limitations to our current model that provide opportunity for further research.

- Our model currently does not account for risk correlation. We assume that burn risks are independent and identically distributed throughout this paper; however, this assumption dramatically simplifies the risk that insurers take on. It is in the interest of insurance companies to de-correlate risk through diversification of their portfolios. While our model attempts to account for this procedurally by maximizing geographic diversification within the allocated portfolios of each insurer, a more sophisticated model may model risk in a more comprehensive and realistic manner.

- Our model also does not account for the acquisition or transaction costs insurers face. Acquisition costs may include marketing to consumers and building brand reputation. Transaction costs in the homeowner's insurance market may include the costs of auditing a home or legal fees. The existing academic literature around insurance posits that with non-zero transaction costs, a socially optimal level of indemnity does not involve full coverage but rather partial coverage (Gollier, 2013).

- We similarly simplify the utility functions faced by both homeowners and insurers. We adopt the well-accepted EU model, in which we assume that both homeowners and insurers seek to maximize their expected utility. Moreover, we employ a second-degree Taylor approximation of their utility functions. In the future, researchers should analyze empirical data to better gauge when companies decide to cut coverage. This information may help economists approximate the break-even points of insurers and allow for the use of regression tools to fit a utility function to the empirical data.

Nevertheless, faced with a rapid exodus of insurers from the California market, policymakers ought to draw from the theory and techniques we employ to guarantee full coverage, geographic diversification, and appropriate premiums. Additionally, by allowing for trade afterwards through a descending clock auction, they may allow companies that may currently be on the brink of exiting to tailor their portfolios to realize additional gains.

Homeowner's insurance must be widely accessible to the population of California. Without it, individuals will be left unprotected in the face of ever increasing wildfire risk, no doubt with ramifications to the Californian housing market writ large. It is imperative that policymakers explore novel market design solutions to address a concern that is on the minds of thousands across the state of California.

9 Appendix

9.1 A1

Indeed, in 1979, economist Autur Raviv developed a model to find the optimal policy for the insure (Dionne, 2013):

Optimal Insurance Design

This is a stochastic optimization question for the insured that tells us how much insurance they should receive per dollar of loss:

$$\text{Maximize:} \quad \mathbb{E}\left[u(w_0 - l + I(l) - RP)\right]$$

$$\text{subject to:} \quad \mathbb{E}\left[I(x) + c(I(x))\right] \leq \Pi$$

- w_0: initial wealth of the insured
- l: random loss
- $I(l)$: indemnity function (insurance payout for loss x)
- RP: premium paid for insurance
- $c(I(l))$: transaction cost of indemnity (increasing and convex)
- Π: upper bound on total cost (e.g., actuarial premium limit)

The first-order condition for the optimal indemnity function $I(x)$, under convex transaction costs $c(\cdot)$, is:

$$I'(l) = \left[1 + \frac{c''(I(l))}{1 + c'(I(l))} * T(w_0 - l + I(l) - P)\right]^{-1}$$

- $I'(l)$: marginal indemnity — how payout increases with additional loss
- $T(z)$: absolute risk tolerance of the insured at wealth level z

where the absolute risk tolerance is defined as:

$$T(z) = -\frac{u'(z)}{u''(z)}$$

- $u(\cdot)$: utility function of the insured [a]

When we ignore transaction costs, clearly, $I'(l) = 1$ and signifies that the indemnity should increase proportional to the loss; in other words, it is optimal for the insured to receive full coverage.

[a] Note that $T(z)$ is the negative inverse of Arrow's coefficient, which we discuss later

9.2 A2

Symbol	Meaning
I	Set of homes, indexed by $i \in I$
J	Set of insurance companies, indexed by $j \in J$
C	Set of counties, indexed by $c \in C$
N_I	Total number of homes ($\|I\|$)
N_J	Total number of insurance companies ($\|J\|$)
N_C	Total number of counties ($\|C\|$)
e_i	Environmental exposure of home i ($e_i \in \mathbb{R}_{\geq 0}$)
s_i	Structural/property-level risk of home i ($s_i \in \mathbb{R}_{\geq 0}$)
c_i	Claims or loss history for home i ($c_i \in \mathbb{N}_0$)
r_i	Burn risk for home i: $r_i = \alpha e_i + \beta s_i + \gamma c_i$
v_i	Property value of home i
μ_i	Expected loss of home i: $\mu_i = r_i \cdot v_i$
RP_i	Risk premium charged to home i: $RP_i = (1 + k) \cdot \ell_i$
I_j	Set of homes insured by company j, $I_j \subset I$
N_j	Total number of homes covered by insurer j: $N_j = \|I_j\|$
$N_{j,c}$	Number of homes insured by company j in county c
N_c	Total number of homes in county c
M_j	Market share of insurer j: $M_j = \frac{N_j}{n_I}$
μ_j	Expected total loss of insurer j: $\mu_j = \mathbb{E}[L_j]$
L_j	Total losses faced by insurer j: $L_j = \sum_{i \in I_j} \ell_i$
$u_j(\cdot)$	Utility function of insurer j, assumed concave
$a(\mu_j)$	Arrow-Pratt risk aversion coefficient: $a(\mu_j) = -\frac{u_j''(\mu_j)}{u_j'(\mu_j)}$
$p_i(t)$	Price of home i at auction time t
$u_j(i, p_i(t))$	Utility to insurer j of covering home i at price $p_i(t)$
$D_j(t)$	Set of homes insurer j demands at time t
$D_i(t)$	Set of insurers demanding home i at time t
δ	Decrement step size in clock auction price updates
A_j	Risk aversion score of insurer j used in simulation
$P_{i,j}$	Penalty score assigned to home i for insurer j in auction

Table 4: Notation used throughout the paper

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Additionally, we'd like to thank Prof. Paul Milgrom for an excellent course on market design principles, as well as the lovely teaching staff who helped guide the writing of this paper.