How Are Insurance Markets Adapting to Climate Change? Risk Selection and Regulation in the Market for Homeowners Insurance

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As climate risk escalates, property insurance has a critical role to play in helping households and firms reduce risk exposure, and to recover from natural disasters when they strike. To perform these functions efficiently, insurers need to access high quality information about disaster risk and set prices that accurately reflect the costs to insure it. We use proprietary data on parcel-level wildfire risk, together with insurance premiums derived from insurers' regulatory filings, to investigate how insurance is priced and provisioned in a large market for homeowners' insurance with high levels of natural disaster risk exposure. We document striking variation in insurers' risk pricing strategies. Firms that rely on coarser measures of wildfire risk charge relatively high prices in high-risk market segments – or choose not to serve these areas at all. Empirical results show evidence of a large winner's curse, where firms with less granular pricing strategies have higher expected losses and lower net revenue per parcel. A theoretical model of a market for natural hazard insurance that incorporates both price regulation and asymmetric information across insurers helps rationalize the empirical patterns we document. Our results highlight the underappreciated importance of the winner's curse as a driver of high prices and limited participation in insurance markets for large, hard-to-model risks.

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1 Introduction

As the climate changes, natural disasters are increasing in frequency and intensity (Murray and Ebi 2012). Annual losses from natural disasters in recent years have been increasing and now exceed $120 billion.[1] With climate change, property insurance markets play an essential role to help households and businesses reduce exposure to financial impacts of disasters (Field 2012). But there are mounting concerns that private property insurance markets are not prepared to manage escalating climate risk (U.S. Department of the Treasury 2023).

In the United States, the public conversation around this issue has focused on two challenges in particular. First, damages from extreme weather events are more difficult to predict than for other insurable risks such as health outcomes or car accidents, as disaster losses are infrequent, spatially correlated, and often catastrophic (Wagner 2022b). Second, insurance markets in the United States are subject to extensive regulations that were not designed with climate change in mind. These regulations could constrain insurers' ability to set premiums at levels that keep pace with increasing climate risk exposure (Oh, Sen, and Tenekedjieva 2022).

In addition to these concerns, we elevate the consideration of a third complication. Because it is both challenging and costly to assess and price climate catastrophe risk, insurers competing in the same market may bring different risk information to their pricing and underwriting decisions. If an insurer finds it is offering a customer a lower price than its competitors, this could indicate that competitors have superior information about climate risk exposure. These information asymmetries subject firms with less sophisticated price schedules to potentially severe adverse selection, analogous to the winner's curse in the literature on common-value auctions with asymmetric information (Milgrom and Weber 1982; Engelbrecht-Wiggans, Milgrom, and Weber 1983; Hendricks and Porter 1988). Given rapid changes in climate risk and rapid innovation in risk modeling, asymmetric information between insurers may play a critical factor in market responses to climate risk. This issue has so far received little attention from policy-makers and in the public discussion about whether climate risk is "uninsurable."[2]

In this paper, we investigate how this form of adverse selection, together with binding economic regulations, affects prices and availability in a large market for natural hazard insurance. We focus on wildfire risk, the fastest-growing source of catastrophe-related damages

1. NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2024). $https://www.ncei.noaa.gov/access/billions/, DOI: 10.25921/stkw-7w73$

2. see, e.g., Coy, Peter. (2023). Why California and Florida Have Become Almost Uninsurable. *New York Times*. https://www.nytimes.com/2023/07/21/opinion/california-florida-insurance-climate-change.html.

in the United States.[3] Over the past two decades, U.S. wildfires have quadrupled in size and tripled in frequency (Iglesias, Balch, and Travis 2022). Catastrophic wildfires are now understood to be a material risk that can threaten the solvency of private property insurers.[4] This materiality notwithstanding, wildfire risk has been underexplored in the academic literature that investigates insurance market pricing, underwriting, and competition.

Our empirical setting is California's private market for homeowners insurance. California is home to an estimated 4.6 million properties with moderate to high wildfire risk exposure, a number which is expected to increase to 5.5 million – or 7.6 percent of all properties – by 2050 (First Street Foundation 2022). Since 2017, the state has seen a significant increase in average annual wildfire losses as compared to previous decades.[5] The wildfire seasons of 2017 and 2018 were particularly devastating, raising concerns about the insurability of catastrophic wildfire risk (Cignarale et al. 2019).

We begin with a descriptive analysis of California's homeowners' insurance market over the period 2009 to 2020. In the years following the 2017 and 2018 wildfire seasons, premiums have risen, the rate of policy cancellations in high-hazard areas has escalated, and participation in the California FAIR plan (a quasi-private insurer of last resort) has increased rapidly. Over this same period, we observe significant variation in the sophistication of wildfire risk modeling tools used by the largest insurers in the market.

The next section of the paper investigates the driving forces behind these observed trends. Rising premiums and stricter underwriting practices in high-hazard areas could reflect an efficient industry response to increases in assessed wildfire risk exposure. Alternatively, market and/or regulatory failures could explain these trends. Disentangling these alternative explanations is critical at a time when industry regulators are under mounting pressure to modernize and reform insurance market regulations. Our analysis proceeds in three steps. First, we develop a stylized model of insurance pricing. Canonical work on insurance markets (e.g. Stone 1973; Kreps 1990; Kunreuther 1996; Jaffee and Russell 1997) provides a relatively clear prescription for "fair and adequate" pricing in a competitive market for catastrophic risk insurance.[6] Building on these theoretical foundations, we assess the cost of providing wildfire risk insurance in terms of the expected losses, operating costs, and a loading factor that reflects the costs of attracting and holding capital surplus. Within the context of our

3. Swiss Reinsurance. (2023). Continued high losses from natural catastrophes in 2022. https://www.swissre.com/institute/research/sigma-research/sigma-2023-01/5-charts-losses-natural-catastrophes.html.

4. CoreLogic. (2022). The 2022 Wildfire Risk Report. https://www.corelogic.com/intelligence/the-2022-wildfire-report.

5. The average annual loss from 2009 to 2018 was almost $1 billion, compared to $0.40 billion from 1999 to 2008, $0.19 billion from 1989 to 1998, and $0.03 billion from 1979 to 1988 (Buechi et al. 2021).

6. For a summary of these issues, an interested reader could refer to Kunreuther and Michel-Kerjan (2011).

model, we derive and calibrate cost-based insurance pricing schedules using probabilistic estimates of expected, parcel-level wildfire losses. These calibrated risk price gradients serve as useful benchmarks in our empirical analysis.

In a second step, we leverage detailed rate cases filed with California's insurance market regulator, together with the proprietary information firms are using to assess risk exposure, to construct parcel-specific insurance premiums charged by several large insurers. These rate schedules specify a complete mapping between home or parcel characteristics and insurers' premiums. This mapping allows us to isolate the underlying relationships between firms' risk pricing and assessed wildfire risk exposure. Careful comparisons between these empirical risk price gradients and our cost-based benchmarks reveal notable differences. For the insurer with the most granular wildfire information, we find that insurance prices increase commensurately with assessed wildfire risk across a majority of homes; however, in the highest-risk segments, we document a pricing pattern consistent with rate suppression that can manifest under binding rate regulations (Harrington 1992; Jaffee and Russell 1998). Among insurers that use relatively coarse information to assess wildfire risk, pricing patterns look quite different. Implicit risk prices rise faster than assessed levels of wildfire risk exposure across otherwise similar parcels in moderate to high wildfire risk segments. Risk price gradients are noticeably less steep in the highest-risk segments.

In the third part of the paper, we investigate two possible explanations for the wildfire risk pricing patterns we observe. The first is economic regulation. California's regulatory regime has been criticized for being outdated or overly restrictive.[7] Binding economic regulations could help explain the concave pricing patterns we document in the highest-risk segments of the market. Second, risk information asymmetries on the supply side can subject less-informed firms to adverse selection. If these firms understand that they serve an adversely selected share of homes in a market segment, they should adjust their prices to account for this selection, which is a rational response to the winner's curse (Milgrom and Weber 1982; Hendricks and Porter 1988).

Because we directly observe the pricing rules that firms use to develop insurance premiums, we are uniquely positioned to estimate the size of the winner's curse in a pricing game where firms differ in the sophistication of their pricing formulas. Using a stylized Bertrand duopoly model of competition, we assess the extent of the information advantage for the insurers using the most sophisticated risk pricing strategies. Within our stylized duopoly framework,

7. See, for example, industry commentary: American Property Casualty Insurance Association. (2023). Wildfire-prone California to consider new rules for property insurance pricing. Associated Press. https://apnews.com/article/california-home-insurance-wildfire-risk-premiums-cf40911606e8e4d9c7c35ca57ca733e8.

we show that the degree of adverse selection that results is economically significant.

To explore the implications of these empirical findings, we develop an equilibrium model of the property insurance market that incorporates both asymmetric information and binding economic regulation. In this model, as in the California homeowners' insurance market, property owners are relatively uninformed about their wildfire risk exposure, but insurers can access more detailed risk information through the adoption of sophisticated modeling at a license cost. We derive the value of information for a firm and show how it varies with market share. If this cost is prohibitively high for smaller firms, the resulting information asymmetries expose less-informed firms to adverse selection. The model helps to rationalize the observed differences in firms' pricing behavior. Results of the model are that the well-informed firm captures the low-risk customers within a risk segment and that low-information firms raise their prices to avoid selling unprofitable policies to high-risk customers. It also elucidates how information asymmetries can exacerbate the effects of price regulation for relatively uninformed firms, and thus accelerate exit from high-risk segments. Finally, the model shows that price constraints may be ineffective at limiting price increases in the face of rising risk and that information provision may be a more effective approach to control prices and ensure availability.

This paper's findings are relevant to the ongoing public conversation about climate risk insurance regulation (U.S. Department of the Treasury 2023). In California, many industry observers and trade associations have attributed the lack of insurance availability in high wildfire hazard areas to excessively tight market conduct regulations that restrict prices below the expected cost of covering high-hazard homes.[8] We argue that this characterization is incomplete. Our results point to a more nuanced story where the regulatory price ceiling may be adequate in a symmetric-information market but nevertheless restrict participation in a market where some firms set prices using superior risk information. We present theory and empirical evidence consistent with a story in which adverse selection puts upward pressure on the insurance prices charged by relatively uninformed insurers. Winner's curse adjustments interact with binding economic regulations to exacerbate the effects on insurance availability in high-hazard areas. Reforms that fail to account for these interactions will not have the intended effects on insurance pricing and availability.

Our work is also related to several areas of the economics literature. First, we contribute to the literature on natural disaster insurance. Early work by Jaffee and Russell (1997) and

8. See, for example: American Agents Alliance. (2023). California Needs Regulatory Reform and Quick Rate Review to Halt Personal Lines Meltdown. https://www.insurancejournal.com/news/west/2023/06/02/723845.htm.

Kunreuther (1996) examines the causes of private market failures in catastrophe insurance and the conditions that must be established to make these markets viable. More recent work has investigated the response of insurance markets to catastrophic events (Klein and Kleindorfer 1999; Born and Viscusi 2006), the pricing of climate risks (Gourevitch, Kousky, and Liao 2023), and the performance of public markets for catastrophic flood insurance (Gallagher 2014; Wagner 2022a; Bradt, Kousky, and Wing 2021; Hennighausen et al. 2023; Mulder 2021). Building on this prior work, we study the pricing and availability of wildfire risk insurance in a private, albeit regulated, market setting.

In addition, this paper builds on an expansive literature on asymmetric information and adverse selection in selection markets (Akerlof 1970; Einav, Finkelstein, and Cullen 2010). Given rapid innovations in generative artificial intelligence and associated analytics, competition between insurers with different risk rating strategies raises questions around selection and policy interactions (Einav, Finkelstein, and Mahoney 2021). Prior work has examined the possibility that proprietary risk information imposes costs on competitors who subsequently face an adversely selected pool of customers, both in the context of auto loans (Einav, Jenkins, and Levin 2012) and auto insurance (Jin and Vasserman 2021). We extend this line of empirical inquiry to a setting in which proprietary data about catastrophic risk generates asymmetric information across private property insurers.

Lastly, we contribute to the literature that investigates the economic regulation of insurance markets. Past work has explored supply-side implications of capital requirements and dynamic pricing regulations across a range of insurance market contexts (Ge 2022; Koijen and Yogo 2015; Aizawa and Ko 2023). Our paper is closely related to work that investigates how private property insurers respond to economic regulation (Born and Klimaszewski-Blettner 2013; Oh, Sen, and Tenekedjieva 2022; Taylor, Turland, and Weill 2023). Whereas prior work has frequently used aggregated data to study the effects of regulation on market outcomes, we are able to leverage parcel-level pricing data to show how economic regulations interact with asymmetries in risk information across insurers.

The remainder of this paper is organized as follows. Section 2 provides background and institutional detail on wildfire risk and homeowners insurance regulation. Section 3 introduces data and documents important descriptive trends in homeowners insurance and risk pricing. Section 4 introduces a theoretical benchmark for the fair price of wildfire risk, which guides the empirical analysis. Section 5 estimates the empirical relationship between offered premiums and assessed wildfire risk. Section 6 explains these price-risk gradients using empirical evidence on adverse selection and regulation. Section 7 introduces an equilibrium model of a regulated insurance market where access to more sophisticated risk information is costly.

Section 8 concludes.

2 Institutional Background

2.1 Homeowners insurance in the United States

We study the market for homeowners' (HO) multi-peril insurance. Under standard HO insurance contracts, coverage for wildfire losses is bundled with other perils. HO multi-peril premiums exceed $125 billion annually in the United States, with California representing 9.4 percent of the market.[9]

Most mortgage lenders require HO insurance coverage as a mortgage precondition. If a homeowner neglects to purchase and hold HO insurance, their lender will purchase "force-placed insurance" on their behalf, which is typically more expensive and only provides coverage for the bank's interest in the house. Given these economic incentives, a large majority of U.S. homeowners purchase HO insurance each year.[10] Multi-peril HO policy terms typically last for one year. Holders receive annual renewal statements which include information about any changes to rates or policy terms. Contracts are automatically renewed unless they are canceled by insurers or homeowners.

2.2 Insurance market regulation

State regulators exercise considerable authority over insurers' entry, exit, insurance premium setting, underwriting, and claims settlement choices. Regulations fall under two broad categories. *Prudential* regulations are designed to ensure that insurers can meet their financial obligations. *Market conduct* regulations aim to ensure that consumers are charged fair insurance prices and have access to beneficial and compliant insurance products.

Regulatory intervention in insurance markets is partly rationalized based on market failures. Given the complexity of property insurance contracts, households face significant challenges in judging the financial risk of insurers and in understanding contract terms. In addition to these information-related market failures, there is also the possibility that insurers could acquire sufficient market power to restrict competition and earn excess profits.

9. See: National Association of Insurance Commissioners (NAIC). (2023). 2022 Market Share Reports For Property/Casualty Groups and Companies by State and Countrywide. https://content.naic.org/sites/default/files/publication-msr-pb-property-casualty.pdf.

10. In a 2023 survey conducted by the Insurance Information Institute (III), it was estimated that 88 percent of U.S. homeowners purchased multi-peril homeowners insurance. This is down from 92-95 percent reported in past years. https://www.iii.org/sites/default/files/docs/pdf/2023_q2_ho_perception_of_weather_risks.pdf.

There are also features of the market that are not failures in the economic sense, but rather undesirable market outcomes that motivate regulatory intervention. Unequal bargaining power between homeowners and insurance companies, together with the complexity of insurance underwriting, can result in HO premiums that are higher than necessary.[11] Although high consumer prices will not generate deadweight loss in a market where the purchase of insurance is effectively mandatory, they can lead to undesirable transfers from consumers to producers. High prices are a leading concern that motivates regulatory oversight of firms' underwriting practices.

The stated objective of California's Department of Insurance (CDI) is to promote solvency, affordability, and availability. Under the provisions of Proposition 103, CDI is required to review and approve rates for most property and casualty lines of insurance to ensure that they are "fair" (i.e. not excessive, inadequate, or unfairly discriminatory).[12] These market conduct regulations constrain the overall rate of increase that an insurer can implement within a rate case. Requests for overall rate increases that exceed 6.9 percent are subject to costly public rate hearings.[13] In addition, insurers are limited in their use of simulation-based stochastic risk models. Insurers can – and do – use these models to segment risks or adjust prices on the basis of assessed wildfire risk exposure.[14] But they cannot use these models to justify an overall rate of increase in earned premiums. Instead, they must appeal to the historical record of their past catastrophe claims. This catastrophe load is assessed based on loss history and then used to calculate the actuarially justified rate, which may be greater than the 6.9 percent threshold.[15]

2.3 Wildfire risk modeling

As wildfire damages escalate, more resources have been allocated to the modeling and analysis of wildfire risk. Catastrophe ("CAT") models have increasingly been used to simulate

11. Insurance contracts are generally recognized to be "contracts of adhesion" in which the consumer must either accept the terms of the policy as written or reject the terms and accept similar terms from another insurance company.

12. California's underwriting regulations apply to the "admitted market" insurers who comprise the majority of the California insurance market. If an admitted insurer fails financially, the state will make payments on claims as necessary. A relatively small group of insurers operates outside the admitted market who are not subject to the same regulations and are not backed by state guaranty funds. These "surplus line" carriers cover risks that are too high or too complex for standard home insurance providers to cover.

13. For example, if a company earns $100 million statewide and would like to increase its revenue, it could increase it to $106.9 million without a public hearing.

14. One possible complication is that information used to design and run catastrophe models may be considered trade secret or proprietary. This can limit an insurance company's ability to utilize catastrophe models in a rate filing.

15. Section 6.2 presents evidence of bunching at this constraint.

catastrophic event probabilities using factors that predict wildfire damages, factors which include meteorology, topography, vegetation type, dwelling characteristics, or other information.

A relatively small number of CAT modeling firms cater to the insurance sector, offering modeling tools and analytics that are well-suited to underwriting and risk exposure assessment. These models can generate dollar-denominated predictions of annual expected losses, probabilistic measures of maximum expected losses, and simulated probability distributions of insured losses associated with a given property or an entire book of business. In addition to licensing costs, it can be costly to develop and maintain the resources required to use these models internally, and negotiate the extensive regulatory and validation requirements.

3 Data and Descriptive Facts

We leverage several sources of data in our analysis. Datasets are described in detail in Appendix A. In what follows, we use these data to highlight some empirical facts and market developments.

3.1 Annual insurer profits are variable

In states that are affected by high-severity, low-frequency weather events, property insurers must build up surplus capital during uneventful years so as to be able to cover losses incurred during a catastrophe. The National Association of Insurance Commissioners (NAIC) tracks industry profits by state and by insurance line.[16] Figure 1 summarizes state-level data on insurer profits in the U.S. homeowners' insurance market over the period 1985 to 2021. California's homeowners insurance line profits are shown in red. The figure shows how California's catastrophic wildfires in 2017 and 2018 erased several years of insurer profits. It also demonstrates the extent of the losses insurers have realized in some parts of the country due to other natural catastrophes, such as hurricanes.

3.2 Insurance premiums are rising

We use zip code-level data collected by the California Department of Insurance (CDI) to summarize trends in homeowners' insurance premiums, admitted market participation, and policy cancellations over time. Beginning in 2018, insurers writing more than $10 million

16. Because most insurers are multi-line and multi-state operations, the allocation of profits to a single line or state is approximate at best. This caveat notwithstanding, these data provide a useful measure of insurer profits across states and time.

in premiums were required to report zip code-level information about the assessed wildfire risk exposure of the properties they insure. Using these data, we group California zip codes according to their average reported level of wildfire risk. This allows us to analyze outcomes separately, albeit coarsely, by wildfire risk category.

Figure 2 summarizes average increases in HO insurance premiums over time. To construct this figure, we use zip code-level average annual HO premiums reported by CDI, data which have complete coverage for insurers in the admitted market in California. Across all wildfire risk quantiles, real premiums increased noticeably after the destructive 2017 and 2018 wildfire seasons. Statewide, premiums rose 16.4 percent from 2017 to 2020; in the lowest-risk zip codes, premia grew only 13.2 percent, while premia in the two highest-risk quintiles grew 20.0 percent and 13.6 percent over the same period.

3.3 Insurance availability is declining

CDI collects information on the number of housing units insured by the admitted market. The second panel of Figure 2 shows that the size of the admitted market had been increasing in all but the highest-hazard zip codes over the period 2009 to 2016. Policy counts fell across all categories during the 2017 and 2018 fire seasons. Reductions in admitted market participation were particularly significant in the highest-risk zip codes.

The third panel of Figure 2 tracks participation in the California FAIR Plan, which provides basic backstop coverage for properties that struggle to find coverage in the admitted market.[17] Growth in FAIR Plan participation has been increasing since 2018. Increases are most pronounced in the highest risk areas.

The bottom panels of Figure 2 summarize trends in insurance policy cancellations. Prior to 2019, insurer-initiated cancellations averaged around 2 to 3 percent.Since 2019, insurers have been canceling policies at higher rates in high-hazard areas. The right-hand panel shows customer-initiated cancellations. These rates have increased noticeably in the highest-hazard areas since 2018. This increase could be driven in part by rising premiums which induce homeowners to search for lower-cost options.

17. While the FAIR Plan is instituted at the state level, it is financially backed by all private insurers licensed to write insurance in California. Each company shares in FAIR Plan profits, losses, and expenses in an amount proportionate to its market share in the state.

3.4 Risk pricing strategies vary across insurers

The regulatory filings submitted to CDI provide detailed documentation of the information insurers use to assess and price wildfire risk.[18] Table 1 summarizes some of this information for the ten largest insurance groups and the FAIR Plan. Column (1) reports insurer market shares across the state of California, while column (2) focuses on market share in the highest quintile of zip code-level wildfire risk. The three insurers with the largest market presence in California – State Farm, Farmers, and the CSAA Insurance Group – are also the firms with the largest market presence in high-risk areas.

Column (3) of Table 1 provides a rough summary measure of the level of granularity or complexity in wildfire risk pricing strategies. To build this measure, we count the number of risk-rating variables that each insurer uses to assess the likelihood of wildfire damages.[19] The wildfire risk pricing strategies we observe in these rate filings broadly fall into three types. Some insurers price wildfire risk at the zip code level. Other insurers use parcel-level categorical wildfire risk scores which come from gridded products based on qualitative factors such as slope, vegetation, fuel load, and road access. Finally, some insurers use more granular measures generated using relatively sophisticated, probabilistic CAT models based on simulations.

Column (3) shows the wide variation in the granularity of firms' wildfire risk measurement. In general, the firms with the largest market share in high hazard zip codes also have the most granular risk rating regimes.

Why do all firms not use probabilistic CAT Models to inform their risk-based pricing? Firms likely make a cost-based decision. First, there are direct costs; purchasing a license to use a state-of-the-art CAT model has been reported to cost millions of dollars per year.[20] Second, there are regulatory costs. Once licensed, an insurer needs to have professional staff to use the model effectively within the context of a state's particular regulatory environment. Firms must also secure regulatory approval to use these models for pricing.[21] Taken together, these costs could deter firms which serve relatively small shares of the high-hazard market.

18. All rate filings are publicly available through CDI's website. California Department of Insurance (CDI). Web Access to Rate and Form Filings (WARFF). http://www.insurance.ca.gov/0250-insurers/0800-rate-filings/0050-viewing-room.

19. More information on the measurement of risk-rating variables is available in Appendix A.

20. Jergler, Don. (2021). Grim California Wildfire Outlook Has Insurers Forking Over Big Bucks for Modeling. The Insurance Journal. https://www.insurancejournal.com/magazines/mag-features/2021/07/05/621088.htm.

21. To simplify a complicated body of regulation, use of catastrophe models for setting relative prices across customer classes is generally allowable in California, but firms must demonstrate that the resulting relativities are actuarially sound. Use of catastrophe models is not allowed when justifying the requested overall increase in revenue from the book of business.

Table 1 also shows that insurers differ in the amount of variation that their wildfire risk rating captures. Column (4) reports the R^2 in a regression of parcel-level expected wildfire losses on risk rating factors for a subset of insurance groups. Firms with more risk rating variables capture more of the variation in expected losses than firms with fewer risk rating variables.

3.5 Assessed risk exposure varies across homes

A fourth source of data is a leading provider of property information and risk-based analytics. Through a data-sharing agreement with CoreLogic, Inc., we obtained proprietary information for a sample of 100,000 single-family homes. To draw this sample, we identified 400 California zip codes with high variation in parcel-level wildfire risk exposure and received a sample of 250 houses from each of these zip codes. Details are provided in Appendix A.

We purchased three related but distinct sets of data from CoreLogic. The first includes detailed information about property characteristics and reconstruction costs. The second contains CoreLogic's proprietary, parcel-level Wildfire Risk Scores (WRS) that are used by some "Type 2" insurers in California. The WRS is a 5-100 score that incorporates factors influencing wildfire hazard, such as slope, aspect, fuel, surface composition, drought and wind, at a 30-meter resolution. Third, we obtained risk metrics generated by CoreLogic's 2021 probabilistic CAT model. For each property, we have probabilistic measures of the annual average loss, the standard deviation of losses, and aggregate exceedance probability (AEP) losses over return periods of 50, 100, 250, and 500 years.

Our preferred summary measure of assessed parcel-level risk exposure will be the CoreLogic measure of average annual loss (AAL). This estimates the average yearly losses from wildfire in dollars across thousands of simulated realizations for each property in the dataset. In ancillary analyses, we replicate empirical analysis using an alternative measure of assessed risk exposure, the 1-in-500 year loss. We observe significant variation in these average loss measures across parcels. Regressing CoreLogic AAL measures on zip code fixed effects and categorical WRS scores explains 46 percent of the total variation in assessed AAL. One implication of this variance decomposition is that firms that assess wildfire risk on the basis of zip code or categorical scores will capture only a subset of the underlying variation in risk exposure.

4 Theoretical Benchmark

Fair, adequate, and affordable insurance prices are guiding principles for insurance market regulation. In this section, we formulate a wildfire risk price benchmark that is consistent with these principles. We present a model of insurance costs that incorporates not only expected damage claims, but also administrative costs, fixed costs, and risk load. We first consider a full-information scenario wherein all premiums are set to reflect parcel-level insurance costs. We then consider a more realistic scenario in which firms assess wildfire risk using segment-level proxies for risk exposure, such as categorical risk scores or zip codes. In both cases, we define the "fair" price to be that which reflects insurers' expected costs. We show how this cost should rise with expected wildfire losses. For now, we ignore the potential for adverse selection; we assume all firms have access to the same information. In Section 7, we extend our modeling framework to accommodate asymmetric information across firms and binding market conduct regulation.

4.1 Cost-based insurance pricing under full information

We consider an insurance market in which firms offer a single insurance contract that covers property damages. In the spirit of Akerlof (1970), insurers compete on prices but do not compete on contract features. Households indexed by i must buy insurance for disaster losses from insurers indexed by j.

Households vary in terms of how costly they are to insure. The random variable L_i gives i's disaster losses during the contract period, with mean l_i and variance σ_i^2. In the baseline model, insurers have complete information about households' wildfire risk profiles. In contrast, households are relatively uninformed about their risk exposure.

When purchasing a home, we assume that households must purchase insurance to qualify for a mortgage. We assume that households choose a single contract to maximize indirect utility u_{ij}, where $u_{ij} = -p_{ij} + \delta_j$. The price charged by insurer j to insure property i is p_{ij}. The δ_j term represents average brand preferences for insurer j and, once the household has selected an insurer, switching costs.[22]

We define i's choice set Ψ_i to include all firms that will sell to i. The value associated with choosing a firm other than j is given by $\bar{u}_{ij} = \max_{k \in \Psi_i, k \neq j} (\delta_k - p_{ik})$. Demand for firm j is thus:

22. When two firms yield identical utility, the household randomizes which to buy.

$$Q_j = \sum_{i|j \in \psi_i} 1[\delta_j - p_{ij} \geq \bar{u}_{ij}]. \tag{1}$$

Insurer j's book of business is comprised of the group of customers who purchase its insurance: $\Omega_j = i_{\delta_j - p_{ij} > \bar{u}_{ij}}$.

When thinking about the costs to insure customer i, the expected value of insurance payouts provides a useful point of departure. However, setting insurance prices at expected payouts will not in general be economically sustainable because insurers must also cover operating expenses and the costs of holding sufficient capital reserves to pay out claims with an acceptably low probability of default. The amount of surplus capital or reinsurance that a firm needs to hold will depend on the risk characteristics of its book of business Ω.[23]

The cost of holding the required capital surplus or reinsurance is often referred to as "catastrophe load" or "risk load" in the insurance literature (Jaffee and Russell 1997; Kunreuther and Michel-Kerjan 2011). Let $\phi(\Omega_j)$ denote risk load, and define the firm's total annual cost function as:

$$C_j = \sum_{i|j \in \psi_i} (l_i + a_i) 1[\delta_j - p_{ij} \geq \bar{u}_{ij}] + \phi(\Omega_j) + F_j, \tag{2}$$

where l_i is expected annual value of disaster claims by household i and a_i captures a customer's administrative costs plus the expected costs for non-catastrophe losses such as burst pipes or liability claims. F_j represents any fixed costs, such as the costs to license more granular risk analytics.

A cost-based insurance price ρ_i reflects the expected marginal cost to insurer j from adding customer i to its portfolio plus a cost component f_i that allows the firm to prudently recovery fixed costs:

$$\rho_i(\Omega_j) = l_i + a_i + \phi'_{ij}(\Omega_j) + f_i. \tag{3}$$

In the empirical analysis that follows, we will estimate the empirical relationship between insurance premiums and assessed wildfire risk. To fix ideas, consider the difference in insurance costs for a home with zero risk ($l_0 = 0; a_0 = a$) and an otherwise identical home with strictly positive risk exposure ($l_i > 0; a_i = a$).

23. As an example, solvency regulations may require firms to hold sufficient reserves or reinsurance to cover their full losses in a 1-in-200 loss year (that is, a 99.5th percentile realization of total losses).

$$\frac{l_i + a + f_i + \phi'_{ij}(\Omega_j) - (l_0 + a + f)}{l_i - l_0} = 1 + \frac{\phi'_{ij}(\Omega_j)}{l_i} \equiv \beta_{ij}. \tag{4}$$

The β_{ij} parameter measures the increase in the insurance costs associated with a unit increase in expected loss. We will refer to this subsequently as the risk price *gradient*. If we assume that the fixed cost component does not vary across otherwise similar homes, $f_i = f$, and if we further assume that all California wildfire-exposed homes have the same covariance with the firm's remaining book of business, this cost-based risk price gradient has a slope of 1 plus the average marginal surplus term $\frac{\phi'_{ij}(\Omega_j)}{l_i}$.

4.2 Cost-based pricing under incomplete information

In practice, the true value of future parcel-level disaster claims cannot be directly observed by insurers. Due to modeling limitations and feasibility constraints, insurers use risk proxies, such as categorical wildfire risk scores, to price wildfire risk.

Consider a symmetric limited-information case in which all insurers observe a discrete signal $\gamma(l_i) \in \{\gamma_0, \gamma_1, ..., \gamma_K\}$. If insurers cannot differentiate customer-level risk costs beyond this discrete signal, they must charge a single price to all customers with signal k (hereafter, risk segment k). Let $\bar{L}_k$ denote the mean of l_i in group γ_k. The expected cost associated with parcel i in segment k is now given by:

$$\rho_k(\Omega_j) = \bar{L}_k + a_i + f + \phi'_{ij}(\Omega_j). \tag{5}$$

If insurers set prices to reflect segment-specific average costs, parcel-level risk exposure will be priced with error $\epsilon_i = L_i - \bar{L}_k$. A parcel that is exposed to lower (higher) risk than the segment-average level of risk will thus pay a higher (lower) premium vis-à-vis the full information pricing regime summarized by Equation 3.

If we compare prices across units that differ in terms of risk segment but are otherwise identical, the cost-based price gradient β_{jk} can be formulated as:

$$\frac{\bar{L}_{k(i)} + a + \phi'_{ij}(\Omega_j) - (\bar{L}_0 + a)}{\bar{L}_{k(i)} - \bar{L}_0} = 1 + \frac{\phi'_{ij}(\Omega_j)}{\bar{L}_{k(i)}} \equiv \beta_{jk}. \tag{6}$$

In the empirical analysis that follows, we will observe the pricing formulas and risk segmentation strategies used by different insurers in California. Econometric comparisons of insurance prices charged to similar parcels assigned to different risk segments will allow us

to estimate these β_{jk} parameters.

4.3 Marginal surplus calculations

To calibrate Equations 4 and 6, we must estimate marginal surplus costs. Following Kreps (1990), we formulate this cost component as the product of the insurer's costs of capital, a "distribution statistic" z, and the change in the standard deviation of the firm's loss distribution after adding parcel i to the risk portfolio:

$$\phi'_{ij}(\Omega_j) = \underbrace{\frac{y}{1+y}}_{\text{capital cost}} \times \underbrace{z}_{\text{"distribution statistic"}} \times \underbrace{\frac{(2SC+\sigma)\sigma}{S+S'}}_{\text{change in s.d. of firm's losses}} . \tag{7}$$

The y parameter denotes the market cost of capital and z is a distribution statistic that indicates the number of standard deviations above a mean loss year that the firm can survive. The change in the standard deviation of the firm's annual total losses after adding parcel i to the portfolio is expressed in terms of the standard deviation of losses from the existing book of business S, the standard deviation of losses from the combined book of business S' with the addition of parcel i, the standard deviation of annual losses associated with parcel i, σ, and the correlation of losses between the new parcel and the existing book of business, C (Kreps 1990).

We approximate the risk load associated with covering successively larger portfolios of HO policies in high wildfire hazard areas of California using CoreLogic's parcel-specific AAL distributions. Appendix C describes how we build a statewide pseudosample to explore the relationship between risk load and market share. We calibrate measures of marginal surplus under a range of assumptions about the correlation in risks across homes and the risk profile of an insurer's country-wide book of business.

Table 2 shows how the calibrated marginal catastrophe load costs per dollar of assessed AAL increase with market share. Intuitively, firms with a higher concentration of customers in high-hazard areas have higher surplus requirements due to spatially correlated risks. We estimate that a representative 5 percent market share in high-hazard zip codes is associated with $30 million in expected annual losses. At this 5 percent share, taking on an additional dollar of California wildfire risk exposure increases surplus requirements by about $0.03. At a market share of 30 percent, this marginal risk load increases to $0.18.[24]

24. Kunreuther and Michel-Kerjan (2011) calibrate loading factors for insurance pricing in areas at high risk for hurricanes that include both risk load and administrative costs. They calibrate a "loading factor" of $0.50 which serves as a useful point of comparison. We should expect that risk loads for hurricane risk

The marginal change in risk load associated with adding a high-hazard parcel to a firm's book of business depends not only on the riskiness of the property, but also its covariance with other properties in the firm's risk portfolio. Firms with a larger share of business outside of California will have lower surplus requirements because the correlation between a high-hazard property in California and insured risks outside of California is lower.

Panel B of Table 2 illustrates how the marginal surplus measures vary with exposure to other catastrophe perils. To generate these results, we focus on hurricanes and assume a high-hazard market share of 10 percent. If an insurer has no exposure to hurricane risk (such that the variability of non-wildfire losses is driven exclusively by non-catastrophe homeowners and auto losses), the variability of wildfire losses dominates the overall portfolio and the risk load can reach 48 cents per dollar of AAL. Adding hurricane exposure significantly decreases this risk load. Given the larger magnitude of hurricane risk compared to wildfire risk across the United States, an insurer that is adequately capitalized against hurricane losses is well-positioned to manage wildfire risk. More generally, these calculations help to illustrate how variation in insurers' overall risk profile can generate meaningful variation in marginal surplus costs.

4.4 An illustrative example

We can use the estimated marginal surplus numbers, together with parcel-level AAL metrics and categorical risk scores, to calibrate the relationship between wildfire risk and cost-based insurance pricing under different market segmentation strategies. We start with Equation 4, which defines the gradient parameter β_{ij} under a stylized full and symmetric information scenario. Our marginal surplus calculations imply that an additional dollar of wildfire risk exposure should increase insurance costs by no more than \$1.18 with a conservatively large high-hazard market share of 30 percent. The largest HO insurer in California claims less than a 20 percent share according to Table 1. We thus define an upper bound on the gradient parameter β_{ij} of 1.18 and a lower bound of 1.00.

In practice, insurers pool customers into risk groups or segments to price wildfire risk. Figure 3 illustrates a hypothetical pricing strategy for a "Type 2" insurer that uses CoreLogic's categorical risk scores to price wildfire risk. The horizontal box plots show the mean, interquartile range, and 10th and 90th percentiles of parcel-level predicted losses (expressed in terms of expected losses per \$1,000 of insurance coverage) within each risk segment. Average losses increase with the risk score values, making these categorical scores a valuable

should be significantly higher than wildfire risks given the magnitude of damages and high degree of spatial correlation in these risks.

proxy for expected losses. The box plots show the extent to which these individual predicted losses vary within a risk score segment or category. This variation is more significant in the higher-risk segments.

Suppose that this hypothetical insurer sets the segment-specific prices equal to segment-specific average losses plus an 18 percent risk load. This pricing rule is a "fair" risk pricing strategy insofar as it reflects the insurer's best estimates of wildfire risk-related costs. The vertical axis measures the price per $1,000 of insurance coverage. The black fitted line shows a locally-weighted regression of risk prices on segment-mean expected losses. The slope of this segment average price gradient is $\beta_{jk} = 1.18$.

The dashed line in Figure 3 shows a locally-weighted regression of these risk segment-based prices on *parcel*-level AAL values. This non-linear relationship between segment-based pricing and parcel-level risk exposure deviates significantly from the full-information, segment-based price gradient β_{ik}. On average, higher-risk (lower-risk) households pay insurance prices that are lower (higher) than what it actually costs to insure them. These parcel-level pricing differences result from using segment-average AAL to proxy for parcel-level risk exposure.

Before turning to empirical estimation, some aspects of this conceptual framework merit further discussion. The first point of discussion is the benchmark price gradient. In what follows, we will compare empirical estimates of risk price gradients against the "cost-based" benchmarks calibrated in this section. Although the full-information cost-based price gradient in Equation 4 provides a useful point of departure, the "segment-based" price gradient parameters defined in Equation 6 serve as a more meaningful basis for comparison. Absent selection concerns, segment-level average costs provide a reasonable proxy for an insurer's expected costs. We later extend our analysis to consider the potential cost implications of risk information asymmetries.

A second point of discussion is the distributional implications of segment-based pricing. Figure 3 graphically illustrates some distributional implications of pricing wildfire risk based on segment-level average risk measures. If this insurer were to use more granular information to price wildfire risk, pricing "errors" would be reduced. More granular risk pricing would lower (increase) prices on average for low-risk (high-risk) customers. In other words, using more granular information alters the distributional burden of wildfire property risk.

The third point of discussion pertains to the ramifications of segment-based pricing for efficiency. The efficiency implications of errors in segment-based wildfire risk pricing will depend on the elasticity of HO insurance demand and the exogeneity of wildfire risk exposure.

Because the purchase of insurance is required by mortgage lenders, insurance demand is highly price-inelastic. If we further assume that wildfire risk exposure is independent of insurance pricing, pricing errors will not generate deadweight loss.

Alternatively, if insurance pricing plays a significant role in determining households' location choices or investments in self-protection, pricing errors could undermine efficiency along these dimensions. Recent empirical work fails to detect an effect of insurance price variation on homeowners' location or self-protection choices (Ostriker 2023). These results suggest that the efficiency implications of insurance pricing errors have been limited to date.

5 Empirical Analysis of Wildfire Risk Pricing

In this section, we analyze the empirical relationship between insurance prices and assessed wildfire risk exposure using data from California's HO insurance market. We first describe how we recover the parcel-level premiums charged by insurers in this market. Next, we establish the risk segmentation strategy used by each insurer in our data. Finally, we estimate empirical risk price gradients for each insurer and compare these against corresponding, cost-based benchmarks.

5.1 Parcel-level insurance premiums

Insurers in California's admitted market must submit detailed documentation of the data sources, formulas, and risk factors they use to set insurance premiums.[25] We extract the pricing formulas used by the six major California insurance groups that price wildfire risk using data we can access.[26] We use these formulas to construct the prices that each insurer would charge each of the homes in our data. This generated dataset is unique in that it includes complete sets of offered prices, versus the subset of transaction-based prices paid by existing customers.[27]

The six insurers we analyze include examples from the three risk pricing strategy types introduced in Section 3.4:

25. This information is publicly available from: California Department of Insurance (CDI). (2024). Web Access to Rate and Form Filings (WARFF). http://www.insurance.ca.gov/0250-insurers/0800-rate-filings/0050-viewing-room.

26. Because our parcel-level wildfire risk data correspond to modeling and risk analytics generated for 2021, we focus on rate cases that leverage 2021 risk information.

27. Not all of the prices we construct will be offered to customers in the market. As we discuss below, over the time period we study, some insurers had stopped offering insurance in some market segments. Thus, some of the prices we calibrate would be available to existing customers, but not offered to new customers.

- **Type 1 firms** are AAA of Southern California and Liberty Mutual. These insurers use relatively coarse, zip code-level rating factors to calibrate their insurance premiums.
- **Type 2 firms** are Allstate and Nationwide. Both insurance groups rank in the top ten largest property insurance companies in the United States, and both use CoreLogic wildfire risk scores to segment the market, price insurance, and define eligibility criteria.
- **Type 3 firms** include USAA, which uses wildfire-specific zip code factors that are calibrated using granular, probabilistic wildfire catastrophe model predictions. State Farm is the most sophisticated user of catastrophe model-based risk analytics. State Farm assesses wildfire risk at a 1 square km resolution using wildfire CAT model predictions.

These six large insurers collectively represent approximately 45 percent of the homeowners insurance market. We are unable to replicate the pricing formulas for other large insurers because they use wildfire analytics from other providers such as Verisk FireLine scores.

HO insurance prices depend on parcel-level characteristics we can observe, such as the age of the home, construction materials, roof type, distance to vegetation, and other factors. The a component of insurance premiums (see Equation 2) also depends on *occupant* characteristics and coverage choices that we cannot observe. To construct insurer-level premiums, we assume constant values for these occupant characteristics.[28] Appendix A describes how we construct these insurance prices in more detail.

5.2 Variance decomposition

We use a regression-based variance decomposition exercise to elucidate how different insurers segment the market for the purpose of wildfire risk pricing. Let i index properties or parcels. For each insurer j, we regress insurance premiums p_{ijk} on a set of control variables and an increasingly granular set of risk segment indicators indexed by k:

$$p_{ijk} = f(L_i; \beta_j) + g_j(R_i) + X_i\psi_j + \sum_k \gamma_{jk} D_k + \eta_{ijk}. \tag{8}$$

We parameterize a flexible function of parcel-specific CoreLogic AAL values $f(L_i)$ using

28. For example, we assume that a homeowner purchases coverage equal to the reconstruction cost of the home (which is generally advised by insurers), chooses a $1,000 deductible, has not had a recent claim, and bundles their homeowners and automobile insurance policies. As of 2015, 78 percent of consumers bundled their homeowners and auto policies. See: J.D. Power. 2015 US Household Insurance Study.https://www.jdpower.com/business/press-releases/2015-us-household-insurance-study.

a step-wise function of L_i with bin widths of \$25. The variable β_j is an insurer-specific vector of coefficients. To isolate the effects of variation in assessed wildfire risk as opposed to reconstruction costs, we include a polynomial function $g_j(R_i)$, where R_i is demeaned reconstruction cost. The vector X_i includes additional controls such as 5 year bins for the age of the home (with single bins for homes built before 1950 or after 2015), categorical variables for roof type, and categorical variables for public protection class. We define D to be a vector of $k-1$ market segment dummies.

We estimate Equation 8 using increasingly granular sets of risk segmenting variables D_k. Note that the relationship between a firm's insurance prices and assessed wildfire risk L_i will be completely absorbed by the segmenting variables used by the firm to price wildfire risk.

Figure 4 summarizes this variance decomposition graphically. The top panel corresponds to the Type 2 insurers that segment the market using CoreLogic's categorical scores, in addition to adjustments for fire protection class. The red lines in these figures summarize the average relationship between insurance premiums and assessed AAL, controlling only for the reconstruction cost polynomial. Intuitively, higher levels of wildfire risk exposure are associated with higher insurance premiums. The blue lines add controls for structure characteristics, including age of home, fire protection class (a measure of fire department quality), and an indicator for Class A roof. The green lines, which add zip code dummies, summarize within-zip code relationships between parcel-level wildfire risk and insurance premiums, conditional on reconstruction costs. Thus, the green lines in these figures are the empirical analog to the dashed line in Figure 3 insofar as they are estimated using variation in insurance prices across otherwise very similar parcels assigned to different wildfire risk segments.

The purple lines in Figure 4 summarize the β_j coefficient estimates from regression specifications that include indicators for the full set of CoreLogic wildfire risk dummies, in addition to protection class and reconstruction costs. For Type 2 firms, Nationwide and Allstate, adding the CoreLogic wildfire risk score indicators absorbs the positive relationship between p_{ij} and L_i because these controls capture all of the risk information that these firms use to price wildfire risk.

Type 1 firms, Liberty Mutual and AAA Southern California, are shown in the second row of Figure 4. Because these firms use relatively coarse market segmentation strategies, the strength of the correlation between insurance prices and CoreLogic's parcel-level AAL is attenuated. Once zip code fixed effects and protection class controls are included, the residual

price variation that remains is uncorrelated with AAL values.

The lower panel of Figure 4 summarizes results for the two firms that use the most sophisticated risk pricing strategies: USAA and State Farm. USAA uses granular CAT modeling to calibrate zip code-level wildfire pricing factors. As compared to the zip code factors used by Liberty Mutual and AAA Southern California, these factors capture more of the variation in parcel-level AAL. Still, controlling for zip code dummies and fire protection class fully absorbs the relationship between L_i and USAA's prices. State Farm uses parcel-specific CAT modeling outputs to calibrate highly granular, 1 square km risk segments. This risk measurement strategy explains why a significant residual relationship between State Farm premiums and L_i remains, even after controlling for wildfire risk scores and zip code dummies. Including dummies for each of the 1 km grid cells used by State Farm to segment the market fully eliminates the relationship between L_i and insurance premiums, as shown by the yellow lines.

Overall, this variance decomposition helps elucidate the risk segmentation strategies used by insurers to price wildfire risk. It also hints at the superior information that informs State Farm's more granular pricing strategy. We will investigate the implications of this information advantage in more detail in Section 6.

5.3 Econometric specifications and identification

Having identified the risk segmentation strategies used by each insurer, we may now estimate the empirical analog of Equation 6, the segment-based gradient for cost-based pricing. Let D^*_{jk} be indicator variables for the k segments (e.g. zip codes, wildfire risk scores, etc.) that firm j uses to price wildfire risk. For each insurer, we estimate the following two equations:

$$L_{ik} = \psi_j + \sum_{k=1}^{K_j} \lambda_{jk} D^*_{jk} + X_i \rho_{1j} + h_j(R_i) + \zeta_{ijk}; \tag{9}$$

$$p_{ijk} = \alpha_j + \sum_{k=1}^{K_j} \gamma_{jk} D^*_{jk} + X_i \rho_{2j} + f_j(R_i) + u_{ijk}, \tag{10}$$

where L_{ik} denotes the CoreLogic parcel-level AAL and p_{ijk} denotes the insurance premium charged by insurer j for parcel i. The $h_j(R_i)$ and $f_j(R_i)$ are flexible polynomial functions of demeaned reconstruction costs. The λ_{jk} parameters estimate the average assessed AAL value in pricing segment k used by firm j, conditional on the reconstruction cost polynomial

values and other factors. The γ_{jk} coefficients recover the average insurance price charged by firm j in segment k, controlling for reconstruction cost and other controls. We choose the lowest-risk wildfire segment as the omitted D^*_{jk} category. Thus, the ψ_j and α_j estimate the average AAL and annual premiums, respectively, in the lowest wildfire risk segment.

We are primarily interested in estimating the empirical relationship between assessed risk and the risk price (i.e. the β_{jk} parameters defined by Equation 6). These β_{jk} parameters can be estimated using the ratio of the γ_{jk} and λ_{jk} provided that our control variables effectively capture the variation in non-catastrophe losses and other price components (e.g. fixed cost recovery) that generate variation in insurance premiums.

Equations 9 and 10 control flexibly for reconstruction costs and other factors we can observe, denoted by X_i, such as the age of the home, the roof type, and public protection class. However, after conditioning on these observables, the residual variation in assessed wildfire risk exposure could still be correlated with unobserved insurance cost drivers such as local crime rates.

We estimate a second set of specifications that include a full set of zip code fixed effects. In the rate filings we analyze, for all insurers but State Farm, wildfire risk is the only peril that is priced at the sub-zip code level. Other perils, such as crime or water pipe failures, are priced at the zip code level or higher. The advantage of this approach is that, with the possible exception of State Farm, this strategy will absorb variation in all cost drivers assessed by the firm that we cannot observe directly. A limitation of this approach is that it cannot be used to analyze prices charged by Type 1 firms because zip code fixed effects absorb all risk price variation.

In addition to Equations 9 and 10 above, we estimate a more parsimonious specification wherein the dependent variable is the parcel-level insurance premium net of assessed parcel-level AAL:

$$(p_{ijk} - L_{ik}) = a_j + \sum_k \omega_{jk} D^*_{jk} + X_i \rho_{3j} + z_j(R_i) + \nu_{ijk}. \tag{11}$$

The estimated ω_{jk} parameters recover the average difference between insurance prices and parcel-level measures of AAL.

5.4 Empirically estimated risk price gradients

This empirical exercise generates a large number of parameter estimates for each of the insurers in the dataset. We are most interested in understanding what the γ_{jk} and λ_{jk} estimates imply for the slope of the risk price gradients across insurer-specific market segments. Figures 5 and 6 illustrate these relationships graphically.

Figure 5 summarizes the γ_{jk} and λ_{jk} coefficient estimates for the Type 2 firms, Allstate and Nationwide. Given the market segmentation strategies used by these firms, the D^*_{jk} denote categorical WRS indicators. For comparison, Figure 5 also presents results from estimating these same equations using State Farm's prices and the WRS indicators. The vertical axis plots the λ_{jk} coefficient estimates and confidence intervals from Equation 10. The horizontal axis plots the γ_{jk} estimates and confidence intervals from Equation 9. Each marker corresponds to a different WRS value.

The top panel in Figure 5 shows results from the specifications of Equations 9 and 10 that omit zip code fixed effects. When zip code indicators are omitted, the average annual premiums charged in the lowest wildfire risk segments provide an estimate of the average per-customer non-catastrophe losses (e.g. theft risk) and administrative costs as well as profit margins and the fixed cost component (f). These average premiums, which are in the range of \$1,500 to \$1,750, define the anchor point for the cost-based risk pricing benchmarks derived in Section 4. The grey wedges in each graph span the upper and lower bounds of the cost-based gradients given the market segmentation strategy used by these Type 2 firms.

To facilitate a comparison of the empirical gradients against the cost-based risk gradients, we run a linear OLS regression of the λ_{jk} estimates on the corresponding γ_{jk} estimates, weighting by the number of homes in each risk segment. The estimated slope parameters are reported, along with standard errors, in Figure 5. Standard errors are estimated by bootstrapping the full estimating procedure using a zip code-level block bootstrap.

In the top panel, we estimate a risk price gradient parameter of 1.18 for State Farm. This is exactly in line with the upper-bound of the cost-based benchmark estimate. In contrast, the linear approximation of the price gradients we estimate for Allstate and Nationwide are much steeper.

The bottom panel of Figure 5 reports the coefficient estimates from the more saturated specifications that include zip code fixed effects. In these figures, the estimated γ_{jk} parameters in very low-risk segments are close to zero because the zip code fixed effects absorb the average costs of insuring homes in these segments. Comparing the risk price gradients from these

more saturated regressions against the cost-based benchmarks, we observe similar qualitative patterns as above.[29] Across all insurers represented in these figures, note that whereas we fit a linear approximation to the segment-level risk price gradient to facilitate comparisons with the benchmark measure, the relationship we observe between segment-level average prices and segment-level average AAL is noticeably concave.

Figure 6 summarizes a similar set of results for the three firms that segment the market at the zip code level, as well as State Farm as a point of comparison. To generate these figures, we ranked zip codes in ascending order of wildfire hazard as reported by the CDI Widlfire Risk Information Report. We then aggregated zip codes into 20 bins to improve statistical precision. The D_k^* in Equations 9 and 10 are calibrated to match this level of market segmentation.[30]

As in Figure 5, we find that the linear approximation of State Farm's zip code based insurance pricing gradient aligns well with the cost-based benchmark. In contrast, the estimated price gradients of the other firms do not. USAA and Liberty Mutual have risk pricing gradients that are significantly steeper. Using premiums charged by AAA Southern California, which uses the least granular risk pricing strategy of all the insurers we study, we find a relatively imprecise relationship between zip code average AAL measures and risk pricing. This result is presumably due to AAA Southern California's inability to price discriminate risk within coarsely defined market segments.

In summary, the risk segment-based risk price gradients we estimate empirically differ from the cost-based benchmarks in notable ways. First, these empirical gradients increase more steeply across moderate-to-high-risk segments for most of the firms that use relatively less granular pricing strategies. Second, we see a concave relationship between segment-level average prices and average AAL measures for some firms. Finally, the empirical gradient associated with the most sophisticated firm, State Farm, tracks the cost-based benchmark very closely over all but the very highest risk segments.

Table 3 reports the results from estimating Equation 11, in which the dependent variable is the difference between price and CoreLogic AAL. For ease of exposition, we aggregate AAL values into eight bins on the right-hand side. The omitted category contains AAL values of 0-50 and includes 39 percent of parcels in the data. In each regression specification, we control for the segmentation strategy used by an insurer.[31] In the first column, the Allstate-

29. The linear approximation to State Farm's gradient parameters is noticeably less steep; the estimated slope coefficient is less than 1. However, this estimated gradient falls within the benchmark range if we omit the highest wildfire risk score bins. See Appendix Table 2

30. Note that D_k^* does not vary by firm for Type 1 pricers.

31. For example, in column (1) of Table 3, Equation 11 conditions on reconstruction costs, the age of the

specific risk segment indicators are identified using within-risk segment variation. Because this insurer fails to capture this within-segment variation with its WRS-based risk pricing strategy, increases in risk exposure within a segment are associated with commensurate decreases in the dependent variable. We see a distinctly different pattern when this same regression is estimated using State Farm premiums in column (3). Because State Farm uses a much more granular risk pricing strategy, a higher AAL value within an Allstate risk segment is associated with a commensurately higher State Farm premium. We see no significant variation in revenues net of assessed AAL across the range of AAL that includes 75 percent of homes in column (3) – that is, the coefficients for AAL bin 50-99 through AAL bin 200-299 are not statistically different from zero. A similar pattern holds for column (7), a comparison of State Farm versus zip code pricers. Notably, we do see a reduction in net revenues for the highest-risk homes. This empirical result is consistent with, but not proof of, binding regulations that constrain premiums charged to the riskiest homes.

6 Empirical Evidence of Adverse Selection and Binding Price Regulation

Thus far, we have documented several ways in which the risk pricing we observe in the California market departs from calibrated cost-based benchmarks. However, the benchmarks we have used assume symmetric information and do not account for any binding market regulation. In what follows, we investigate the empirical evidence on the extent to which these two factors impact insurers' risk pricing strategies.

6.1 Adverse selection

The gradients we have been using as cost-based risk pricing benchmarks, (see, for example, the shaded regions in Figures 5 and 6), are based on risk segment-level average measures of wildfire risk exposure. These average values may underestimate the risk-related costs that a firm will actually face if the firm is at an information disadvantage vis-à-vis its competitors. In other words, adverse selection can have significant implications for an insurer's risk exposure and expected claims costs.

The data we develop are uniquely suited to analyze the cost implications of observed risk information asymmetries within the context of a stylized model in which firms with different risk rating strategies compete in a static, homogeneous product Bertrand pricing game.

home, protection class, roof type, and an indicator for each wildfire risk segment used by Allstate to price wildfire risk.

When there is asymmetric information across firms about risk-related costs, the probability of a relatively uninformed firm winning a customer is correlated with expected disaster claims L_i. Thus, the average expected losses incurred by a relatively less-informed firm in a given market segment s_{jk} will be larger than the average losses associated with all customers in that segment:

$$E[L_i|s_{jk}, p_{ij} < p_{i(-j)}] > E[L_i|s_{jk}], \tag{12}$$

where $p_{i(-j)}$ denotes the price offered by the firm's relatively more informed competitor.

Equation 12 summarizes the insurance market analog of the winner's curse in common value auctions. Intuitively, adverse selection will reduce profits relative to the no-selection scenario and increase profits for the firm with superior information. A static Bertrand duopoly model provides a useful – albeit stylized – framework to explore this idea.

We estimate the winner's curse implied by the pricing strategies we observe under a series of duopoly scenarios that feature State Farm (i.e. the most informed firm) competing with other firms in our data. We begin with a set of homogeneous product duopoly cases in which the δ_j in Equation 1, which capture any switching costs or average brand preferences for insurer j, are uniformly set to zero. In these cases, the insurer offering the lowest price p_{ij} "wins" parcel i. We re-formulate Equations 9 and 11 to explore the implications of the information asymmetries. We add an indicator variable $1[\text{Win}]_{ij}$ that equals 1 if firm j offers a lower insurance premium to parcel i, as compared to State Farm. When log(Wildfire AAL) is used as the left-hand side variable, the coefficient for $1[\text{Win}]_{ij}$ can be interpreted as the percentage increase in assessed AAL for a property won by firm j, relative to the AAL values won by the more sophisticated rival. When $(p_{ijk} - L_{ik})$ is used as the dependent variable, the coefficient on $1[\text{Win}]_{ij}$ is interpreted as the difference in revenue net of expected losses using challenger j's price when it wins a parcel, relative to losing it.

Table 4 summarizes the results. Panel A shows the extent to which adverse selection increases the wildfire risk exposure of relatively less-informed firms in a static duopoly setting. For example, consider Allstate. The households for whom Allstate offers a lower price (in duopoly competition with State Farm) have AAL values that are approximately 50 percent higher, on average, than the properties it loses to State Farm. Although the magnitude of this winner's curse varies across insurers, all estimated values are economically and statistically significant.

Intuitively, in these stylized Bertrand duopoly games, State Farm tends to win the lower-risk homes in each segment. Figure 7 summarizes this result graphically for duopoly scenarios that feature State Farm competing with Allstate and Nationwide, respectively. The figures

show how the average AAL within a segment compares to the average AAL within the selected sample served by each duopolist. The black markers are generated using a regression of wildire AAL measures on wildfire risk score dummies. These coefficients capture the average AAL measure within each WRS segment. The blue markers denote the average AAL associated with parcels won by State Farm. The red markers denote the average AAL associated with parcels won by the relatively less-informed Type 2 firm. For the large majority of WRS segments, the Type 2 firm wins an adversely selected, and thus higher risk, sample.

Panel B of Table 4 summarizes results from estimating empirical specifications that feature net revenue (i.e. annual premium minus wildfire AAL) as the dependent variable. Because the duopolist at an information disadvantage serves an adversely selected sample, the average price *net of AAL* in a given market segment is significantly lower than it would be if firms were serving a representative sample. On average, revenues net of assessed AAL among parcels won by relatively uninformed firms are between 6 and 19 percent lower than the segment average.

The winner's curse shows that adverse selection is costly to relatively less-informed firms. The converse question is, how beneficial is more granular risk information for the most-informed firm? To measure the value of wildfire risk information, we estimate an alternative specification of the net revenue equation:

$$(p_{ij*k} - L_{ik}) = a_j + \sum_k \omega_{jk} D_k^{SF} + \varphi_j 1[\text{Win}^{SF}]_{ij} + X_i \rho_{3j} + z_j(R_i) + \eta_{ijk}. \tag{13}$$

Here, the dependent variable is defined as the price charged by the winning duopolist j^* net of the assessed AAL. We include a binary indicator $1[\text{Win}^{SF}]_{ij}$ that switches to 1 if State Farm offers the lowest price and "wins" parcel i against challenger j. We saturate the model with State Farm's granular segment fixed effects.

Table 5 reports results. The coefficients reported in the first row of this table estimate the average increase in net revenues earned by State Farm relative to the grid-segment average earned by the rival duopolist. This table illustrates the potentially significant value of this information advantage, albeit in a stylized Bertrand setting, measured in terms of higher expected net revenues. On average, State Farm's simulated per-parcel expected profits are 8 to 15 percent higher than those of relatively uninformed rivals.

These estimates surely overestimate the realized value of superior information. Recall that these duopoly simulations have assumed away switching costs or brand preferences; the

δ_j parameters are uniformly set to zero. In fact, we observe very low rates of customer-initiated cancellations in the presence of significant price dispersion, as indicated by Figure 2, which suggests that switching costs could be significant, or that consumers are inattentive and inertial. Presumably, insurers are aware of these market frictions and set their prices accordingly. To explore the implications of non-zero switching costs, Appendix Table 4 extends the duopoly simulations to include positive δ_j values. In these exercises, customers are randomly assigned across duopolists in an initial period. In the second period, customers' perceived price for the firm it is not insured by is increased by a constant δ_j. Intuitively, switching costs increase net revenues for all firms and lower the informed firm's excess profits. Even at high switching costs (e.g. \$1,000), the informed firm continues to enjoy a substantial net revenue advantage. In the limit, when switching costs are infinite, the informed firm actually realizes *lower* net revenues than the uninformed competitor, since eliminating all choice by customers eliminates selection entirely – in which case the higher average price schedules for the uninformed firm generate high profits.

6.2 Market conduct regulation

We have presented evidence to show that asymmetric information, and associated adverse selection, could help rationalize the steep risk price gradients we observe among relatively less-informed insurers. Adverse selection cannot explain why risk pricing gradients becomes noticeably less steep across the very highest risk market segments. We posit that binding regulations could help rationalize these empirical patterns. We provide several pieces of suggestive evidence that price regulation binds in this market.

First, if price regulations are a limiting factor, we should see firms routinely increasing premiums at the regulated threshold rate of 6.9 percent, a level beyond which firms would face costly public rate hearings. Panel (a) of Figure 8 summarizes 636 requested rate increases to CDI from 2008 to 2023 for owner-occupied homeowners' insurance (HO-3) policies. The figure shows that the vast majority of rate increases are bunched at the 6.9 percent threshold. This suggests that, at least historically, the pricing regulation has been a limiting factor in this market. More recently, firms have been requesting increases of 10 percent or more. Presumably, in these cases, the expected costs of constraining the rate of premium increase below 7 percent exceed the cost of a public hearing.

Although firms are limited in the size of the premium increase they can request with a rate case, they are not limited in the number of rate cases they can sequentially file. Thus, firms could serially file rate cases to ratchet up earned premiums over time. Panels (b) and (c) of Figure 8 document evidence that is consistent with this kind of behavior. To construct

these figures, we build price schedules from sequential rate cases filed over time by the same insurer. We regress these prices on binned parcel-level AAL values.[32] These figures should be interpreted carefully as some of the price variation in rates across years could be due to increases in assessed AAL over time. This caveat notwithstanding, these data show how firms serially increase premiums over time.

Binding price regulation is consistent with firms' observed risk pricing strategies. Rational firms which correctly anticipate adverse selection adjust their prices up to compensate, which is the analog of shading down one's auction bids. However, when price regulations limit firms' ability to shade up premiums, it could force these firms out of high-risk market segments.

Empirically, we observe that firms are exiting high-risk market segments. First, Figure 2 showed reduced availability of insurance in high-risk zip codes. Second, for a subset of insurers in the analysis, we are able to observe eligibility for new policies at a parcel level. Figure 9 plots the fraction of homes in the dataset by wildfire risk score that would be eligible for a new policy. Allstate and Nationwide, which are relatively less-informed than State Farm, generally do not offer new policies above risk scores of 30 out of 100, whereas State Farm offers high levels of new policy eligibility up to risk scores of about 86 out of 100.

In sum, the risk pricing behavior we observe suggests that adverse selection, together with binding market regulation, are important forces shaping pricing strategies. In what follows, we formalize this reasoning with an equilibrium model of a regulated insurance market.

7 An Equilibrium Model of Asymmetric Information and Binding Regulation

We analyze a single risk segment, such as a geographic area (e.g. a zip code) or a set of properties with wildfire risk scores in a given range, and assume that risk, measured by AAL, is uniformly distributed across properties. The key features of the model are costly investment by firms in risk information, consumers who face costs of switching insurers (alternatively, have brand loyalty), and regulatory constraints on pricing. Initially, we assume that firms' prices are unconstrained by regulation. We derive the market equilibrium and the value of information associated with the adoption of risk information. Our results rationalize many of the empirical results presented above. We then extend the model by incorporating

32. These cross-sectional regressions do not condition on wildfire risk segments.

regulatory constraints and consider the implications for policy prices and availability of increases in risk, as has been observed recently in California.

7.1 Setup

Firms provide insurance to a group of property owners within a risk segment. Structure values are assumed to be identical, but risk varies among properties. Property risk is defined as the expected loss l and uniformly distributed according to $U(0, l^*)$, with mean risk $\bar{l}$ and variance σ^2. A firm charges P for a homeowners policy and makes expected profits $\pi = P - l$. Because the relevant variation in costs for our model comes from differences in risk, we normalize a, ϕ', and f in Equation 3 to zero. We assume that firms can charge different prices to different consumers, but that regulation requires a given firm to charge the same price to all consumers with the same risk.[33]

Consumers buy one unit of insurance to maximize utility $u = -P + I(0, \delta)$. Once consumers have had a policy with a particular firm, they face costs of switching to other firms: $I(0, \delta)$ is an indicator function equal to $-\delta$ if the consumer switches insurers, 0 otherwise. Switching costs are plausible in this setting because homeowners policies are complex contracts between the firm and consumer that are infrequently purchased.[34] Specifically, after time t, consumers need to be offered a price more than δ below another firm's price to induce them to switch. Alternatively, switching costs could be interpreted as brand loyalty. A consumer may have had a positive experience with an insurer and need to compensated by δ to switch to another firm. The total number of consumers within the risk segment is normalized to 1.

Prior to time t, firms are assumed to know the risk distribution but not the specific risk of any individual property. In time t, a risk modeling technology (e.g., a probabilistic catastrophe model) becomes available at cost F that provides perfect information about the risk of properties.[35] We characterize the decision by a firm to adopt the technology in terms of the additional profits it can earn (i.e., the value of information).

7.2 Initial conditions

In time 0, consumers have not yet purchased a policy and competitive firms compete in prices knowing only the risk distribution $U(0, l^*)$. In equilibrium firms make zero expected profits,

33. This is consistent with California's insurance regulations. Insurers must propose rate structures that amount to an algorithm mapping risk of a given property to a price for a homeowner's policy.

34. Switching costs have been documented in the cases of automobile and medical insurance (Honka 2014; Ho, Hogan, and Scott Morton 2017).

35. The assumption of perfect information allows us to derive pure-strategy equilibria, which accord with the rate filings by insurers in California that map house characteristics to a single price.

which occurs at the price $P_0 = \bar{l}$. Between time 0 and t, consumers buy from the same firm and have no incentive to switch firms because there is a single price for insurance.

In the spirit of the "dominant firm-competitive fringe" model, we assume that one firm captures a relatively large share α of the market and that other firms share the rest of the market. The dominant firm may have "brand recognition" due to past advertising investments. Brand recognition does not give the firm a pricing advantage, but consumers may be more likely to select them when indifferent on the price dimension.[36] We assume that the dominant firm's customers are distributed over risk according to $\alpha U(0, l^*)$, implying that the fringe's customers are distributed according to $(1-\alpha)U(0, l^*)$.

7.3 The value of information

In time t, the dominant firm decides whether to adopt the information technology, accounting for the cost of adoption and expected equilibrium profits. In this section, we assume no regulatory constraints on pricing.

7.3.1 Pricing by the dominant firm at the initial equilibrium

If the dominant firm adopts the technology, it can distinguish customers by risk and charge them different prices. At the initial equilibrium, the dominant firm will either set a price at $P^D = \bar{l} + \delta$ to earn positive expected profits on its existing customers or a price at $P^D = \bar{l} - \delta$ to capture the whole market. The latter strategy is more profitable for low-risk customers provided δ is not too large. In particular, at $l = 0$, profits from selling to all customers, $\pi^D = \frac{1}{l^*}(\bar{l} - \delta)$, are larger than those from selling only to its original customers, $\pi^D = \frac{\alpha}{l^*}(\bar{l}+\delta)$, provided that $\bar{l} > \delta\frac{1+\alpha}{1-\alpha}$, an assumption we adopt hereafter.[37] As risk rises, the difference in profits shrinks until at $\tilde{l} = \bar{l} - \delta\frac{1+\alpha}{1-\alpha}$, the dominant firm earns equal profits with the two pricing strategies. As shown by the red line in Figure 10, below $\tilde{l}$ the dominant firm prices at $P^D = \bar{l} - \delta$ and captures both types of consumers. Above $\tilde{l}$, it prices at $P^D = \bar{l} + \delta$ and sells only to its existing consumers. However, the strategy $P^D = \bar{l} + \delta$ is only profitable up to $l_1 = P^D + \delta$ and so the dominant firm elects not to sell to any consumers with risk above l_1.

36. In the classic dominant firm-competitive fringe model, the dominant firm has a cost advantage. In our model, we will allow the dominant firm to have an information advantage relative to the competitive fringe.

37. We expect prices for insurance policies to be large relative to switching costs, suggesting $P_0 = \bar{l} \gg \delta$. As well, for market share values in Table 1, the term $\frac{1+\alpha}{1-\alpha}$ is at most 1.44.

The dominant firm's pricing strategy yields profits given by:

$$\pi^D = \frac{1}{2}\left\{\bar{l}^2 - 2\delta\bar{l} + \frac{\delta^2}{(1-\alpha)^2}[1 + 2\alpha - 3\alpha^2]\right\}. \tag{14}$$

Given the dominant firm's pricing, the competitive fringe earns positive expected profits on the interval $[\tilde{l}, \bar{l}]$ and negative profits on the interval $(\bar{l}, l^*]$. Because the fringe firms cannot distinguish risks, they cannot avoid losing money on high-risk customers. In the aggregate, the fringe's profits are given by:

$$\pi^F = \frac{1}{2}\left\{\delta^2\frac{1+3\alpha}{1-\alpha} - \bar{l}^2\right\}. \tag{15}$$

Given the assumption $\bar{l} > \delta\frac{1+\alpha}{1-\alpha}$, the fringe's profits are negative. Thus, once the dominant firm has adopted the technology, the initial equilibrium cannot be supported.

7.3.2 Equilibrium and the value of information

We define market equilibrium in a risk segment as the set of prices that yield zero profits for the competitive fringe and maximum profits for the dominant firm conditional on the fringe's price. Formally, market equilibrium is given by:

Definition I: Market equilibrium is the set of prices P^F and $\boldsymbol{P}^D(P^F)$ such that 1) the competitive fringe earns zero profits at P^F and 2) $\boldsymbol{P}^D(P^F)$ is the best response by the dominant firm to the price P^F.

Because the competitive fringe cannot distinguish customers by risk, it charges a single price P^F. However, given its information advantage, the dominant firm can charge different prices to different customers and decline coverage to a subset of customers. At a given risk level l, the dominant firm ensures it will have no customers with a price $P^D(l) > P^F + \delta$.[38] The fringe firms have no such ability to limit coverage and so accept all customers willing to buy policies at the price P^F.

For the uniform risk distribution, the following proposition defines the market equilibrium:

Proposition I: If a) $l \sim U(0, l^*)$ and b) $\bar{l} > \delta\frac{1+\alpha}{1-\alpha}$, then market equilibrium is given by: 1) $P^F = l^* - \delta\sqrt{\frac{1+3\alpha}{1-\alpha}}$ and 2) $P^D = P^F - \delta$ for $l \in [0, \tilde{l})$, $P^D = P^F + \delta$ for $l \in [\tilde{l}, l_1)$, and $P^D > P^F + \delta$ for $l \in [l_1, l^*]$ where $\tilde{l} = P^F - \delta\frac{1+\alpha}{1-\alpha}$ and $l_1 = P^F + \delta$.
Proof: See Appendix.

38. In practice, an insurer would simply decline coverage to given customers.

Condition b) ensures that the dominant firm can set a low enough price on the interval $[0, \tilde{l})$ to take the whole market. This requires that δ and/or α not be too large.[39] On the interval $[l_1, l^*]$, the dominant firm ensures it gets no customers by charging any price above $P^D + \delta$.

The equilibrium prices are represented in Figure 10. It can be shown that $P^F > \bar{l}$, indicating that the competitive fringe must raise it price in order to break even in a risk segment with a better-informed dominant firm. The dominant firm exploits its information advantage by serving low-risk customers[40] and declining coverage to high-risk customers. It earns positive profits given by:

$$\pi^D = \frac{1}{2}\left\{\tilde{l}(2P^F - 2\delta - \tilde{l}) + \alpha(P^F + \delta - \tilde{l})^2\right\}. \tag{16}$$

The competitive fringe, on the other hand, sells money-losing policies to the high-risk portion of the segment and only breaks even with profitable policies sold to medium-risk customers. Its profits are given by:

$$\pi^F = \frac{1}{2}\left\{(1-\alpha)(P^F - \tilde{l})^2 - (l^* - P^F)^2 + \alpha\delta^2\right\}. \tag{17}$$

Since the dominant firm makes zero profits when it does not adopt the technology, the value of information (VOI) is given by the equilibrium profits in (16). Although the VOI is always positive, it is only profitable for the dominant firm to adopt the technology when $VOI > F$. Since VOI is a function of market share, we consider how it varies with α. It may seem intuitive that a larger firm has more to gain from adopting the technology, but it turns out to depend on particular parameter values, as stated in the following proposition:

Proposition II: The value of information is increasing in market share ($\frac{\partial VOI}{\partial \alpha} > 0$) if and only if:

$$\frac{1+3\alpha}{1-\alpha} > \left(\gamma - \frac{1}{2}\right)^2, \tag{18}$$

where $\gamma = \frac{\bar{l}}{\delta}$.

39. The competitive fringe can only earn non-negative profits at a price $P^F > \bar{l}$. Together with condition b), this implies $\tilde{l} > 0$ and that a two-tiered pricing strategy is optimal for the dominant firm.

40. Although the lowest-risk consumers pay the lowest prices, the dominant firm faces no competition for these consumers as long as its price is at or below $P^F - \delta$. In practice, a firm like State Farm is likely to face competition from other large, well-informed firms (e.g., Farmers) operating in a given market segment. Although we do not formally consider this extension, we would expect competition among well-informed firms to drive down prices closer to expected cost (l in our model), yielding a positive relationship between price and risk at low prices. This is consistent with Radner (2003), who finds in a model with sticky adjustment of consumers among firms ("viscous demand") that duopoly equilibria tend to be more competitive than the monopoly outcome.

Proof: Differentiate 16 with respect to α and rearrange, making use of the definitions $P^F = l^* - \delta\sqrt{\frac{1+3\alpha}{1-\alpha}}$ and $\tilde{l} = P^F - \delta\frac{1+\alpha}{1-\alpha}$.

γ measures the relative magnitude of switching costs, specifically the size of δ compared to the average AAL ($\bar{l}$) in the segment. For the parameter values $\alpha = 0.2$ and $\gamma = 7$, the condition in (18) holds and $\frac{\partial VOI}{\partial \alpha} > 0$. However, if α is lowered to 0.1, $\frac{\partial VOI}{\partial \alpha} < 0$. For $\alpha < 1$, the left-hand side of (18) is increasing in α and, thus, we find that VOI is more likely to increase in market share when the market share is relatively large to begin with.

The model generates the following predictions that are consistent with empirical findings presented above: 1) the high-information firm uses a more granular pricing strategy than low-information firms, 2) the high-information firm uses its superior information to take the low-risk customers within a risk segment, 3) the high-information firm only sells profitable policies, 4) low-information firms set high prices to avoid selling money-losing policies to high-risk consumers, 5) for some parameter values, the value of adopting the information technology is increasing in market share.

7.4 Equilibrium with price regulation

In California, insurance prices are constrained by the historical loss experience of firms. In this section, we approximate price regulation with an upper bound on the average price of the dominant firm and the competitive fringe. We continue to examine a single risk segment and assume a uniform risk distribution.

The dominant firm and the competitive fringe may have different historical losses due simply to the randomness of wildfire events. If the fringe firms have a tight constraint on their prices, then the adoption of the new information technology by the dominant firm may result in them dropping out of a risk segment. As shown above, once the dominant firm has superior information, the fringe firms must raise their price in order to remain profitable. If they cannot raise it sufficiently, their profits will be negative and they will elect to not sell any policies in the risk segment.

We consider formally the effect of a price constraint on the dominant firm. The average price of the dominant firm is given by:

$$\bar{P}^D = \eta(P^F - \delta) + (1 - \eta)(P^F + \delta), \tag{19}$$

where $\eta = \frac{\tilde{l}}{\tilde{l}+\alpha(P^F+\delta-\tilde{l})}$. Suppose that the firm's average price cannot exceed $\bar{P}^R$ under the

regulation. Then the maximization problem for the dominant firm is:

$$\max_{\tilde{l}} \pi^D \quad s.t. \quad \bar{P}^D \leq \bar{P}^R, \tag{20}$$

where π^D and $\bar{P}^D$ are given in (16) and (19), respectively. The maximization is over $\tilde{l}$, the risk level at which the dominant firm switches from selling to the whole market at $P^F - \delta$ and selling to the share α of the market at $P^F + \delta$. When the constraint is binding, we can use (19) to derive the chosen value of $\tilde{l}$ as:

$$\tilde{l} = \frac{\bar{P}^R\alpha(P^F + \delta) - \alpha(P^F + \delta)^2}{P^F(1-\alpha) - \delta(1+\alpha) - \bar{P}^R(1-\alpha)}. \tag{21}$$

The regulation forces the dominant firm to depart from the unconstrained pricing rule under which the low and high prices earn the same profits at $\tilde{l}$.

The fringe's profits change when the dominant firm adjusts $\tilde{l}$. Thus, to define the market equilibrium we need a new value of P^F that makes the fringe's profits equal to zero. In general, this is given by[41]:

$$P^F = \frac{l^* - \tilde{l}(1-\alpha)}{\alpha} - \frac{1}{\alpha}\sqrt{(1-\alpha)(l^* - \tilde{l})^2 + \alpha^2\delta^2}. \tag{22}$$

For a given value of $\bar{P}^R$, the constrained market equilibrium is given by the values $\{P^{F*}, \tilde{l}^*\}$ that satisfy (21) and (22). The equilibrium can be illustrated with isoclines in $\{P^F, \tilde{l}\}$ space corresponding to the zero profit and average price conditions (Figure 11). We show in the Appendix that at the unconstrained equilibrium[42] the isoclines are upward sloping and that the relative magnitude of the average price and zero profit isocline slopes is indeterminate. Numerical analysis shows that except for small values of γ, requiring large values of δ relative to $\bar{l}$, the zero profit isocline has a steeper slope than the average price isocline (Figure 11). We adopt this as the empirically relevant case, although we also consider the alternative.

An admitted market insurer in California who experiences losses can raise its prices through the rate filing process. We represent this in our model as an increase in $\bar{P}^R$, which shifts up the $\bar{P}^D$ isocline (see Appendix). As shown in Figure 11, when the constraint on the dominant firm's average price is relaxed ($\bar{P}_1^R > \bar{P}_0^R$), the equilibrium values of P^F and $\tilde{l}$ increase. This has important implications for insurance availability. Profits for the fringe are increasing

41. In (22), P^F is the solution to a quadratic equation. We can rule out one of the solutions because it implies a value of P^F that exceeds l^*.

42. The unconstrained equilibrium is the values $\{P^{F*}, \tilde{l}^*\}$ such that $\tilde{l}^*$ is freely chosen in (20). Associated with this value of $\tilde{l}^*$ is an average price $\bar{P}^D$ according to (19).

in the fringe's price P^F (see Equation 17), implying that a regulatory constraint on the fringe's price can be at most weakly binding, because otherwise fringe profits are negative and fringe firms will exit the risk segment. Thus, as long as fringe firms cannot raise their own prices, relaxing the regulatory constraint on the dominant firm will have the effect of lowering availability as fringe firms decline coverage to their current customers. After the exit of the fringe, the dominant firm would want to pick up some, but not all, of the fringe's customers if its price remains constrained at $\bar{P}_1^R$.

There is abundant evidence that wildfire risk has increased recently in California. In our model, we can represent this by a shift in the risk distribution from $U(0, l^*)$ to $U(a, l^* + a)$, which raises the mean risk within the segment while holding constant the variance. We assume that the constraint on the dominant firm's average price ($\bar{P}^D = \bar{P}^R$) is unchanged. As shown in Figure (12), the increase in risk shifts up both the zero profit and the average price isoclines (see Appendix). When the zero profit isocline is steeper than the average price isocline (top figure), the equilibrium values of P^F and $\tilde{l}$ decline. Nevertheless, we find that the overall average price can increase even though P^F declines and $\bar{P}^D$ remains the same.[43] The reason is that the decline in $\tilde{l}$ lowers the share of the market that had been served exclusively by the dominant firm at a relatively low price of $P^F - \delta$. Under the new equilibrium, the fringe firms capture some of these customers at a higher price.

When the magnitude of the relative slopes is reversed (Figure 12, bottom), equilibrium values of P^F and $\tilde{l}$ increase. Numerical analysis shows that the overall average price can increase in this case as well.[44] The two sets of results illustrated in Figure (12) indicate that in insurance markets with asymmetric information, price caps may be ineffective at controlling prices in the face of increasing risk. Moreover, in this second case shown in the bottom figure, rising risk may result in the fringe firms exiting the segment if regulatory constraints prevent their prices from increasing.

As an alternative to price constraints, the government could instead provide public risk information, as is done for hurricanes in Florida.[45] We consider how the market equilibrium changes when information provision allows fringe firms to distinguish properties with risk distributed as $U(0, \bar{l}$ or $U(\bar{l}, l^*)$, compared to the original case in which they know only that risk is distributed $U(0, l^*)$. There are two cases according to whether a) $\tilde{l} > \bar{l}$ or b) $\tilde{l} < \bar{l}$ under the original equilibrium (Figure 13). In case a), the overall average price unambiguously

43. For example, for parameter values $\alpha = 0.2$, $\delta = 10$, and $l^* = 100$, the overall average price increases when the risk distribution shifts by $a = 5$.

44. For example, for parameter values $\alpha = 0.2$, $\delta = 30$, and $l^* = 100$, the overall average price increases when the risk distribution shifts by $a = 5$.

45. Florida Public Hurricane Loss Model: https://fphlm.cs.fiu.edu.

declines. Prices do not change on the interval $[\tilde{l}, l^*]$ and they are lower on the interval $[0, \tilde{l})$.[46] In case b), the effect on the overall average price is unclear, however, we provide numerical results showing that average price falls for a large range of parameter values (see Appendix). Although the cost of information provision would need to be considered, our results show that this may be a more effective way to address affordability and availability objectives than price caps.

8 Conclusion

In the face of mounting climate risk, well-functioning property insurance markets can provide households and businesses with crucial protection from losses as well as appropriate incentives to reduce those losses. However, there are signs that property insurance markets may not currently be adapting well to climate change pressures. This study asks why private insurance markets appear to be struggling to manage climate change risk, with a focus on wildfire risk and homeowners insurance in California.

To answer this question, we developed a selection market model of natural hazard insurance that embeds solvency standards, asymmetric information between insurers, and price regulation. This theoretical exercise brings together the existing theoretical literature on catastrophe insurance and a largely separate literature on selection markets from public economics and industrial organization. This model generates empirical predictions that can help to untangle the root causes of observed insurance market outcomes.

The empirical analysis combines CoreLogic proprietary parcel-level wildfire risk scores with information in insurers' public rate filings to exactly reconstruct price and eligibility schedules at the individual home level. We then compare these premiums to variation in predicted mean wildfire losses from a state-of-the-art catastrophe model to measure the implied pricing of wildfire risk across firms.

For most homes, our findings suggest a central role for asymmetric information between firms about wildfire risk. Given large disparities in the granularity of wildfire pricing across insurers, less-informed firms face a substantial winner's curse when participating in high-wildfire risk market segments. This winner's curse means that a rational insurer will either charge prices substantially higher than the losses implied by their own coarse model, or will refuse to participate in these market segments. A critical policy question for future

46. On the interval $[0, \tilde{l})$, the fringe price is $P^F = \bar{l} - \delta\sqrt{\frac{1+3\alpha}{1-\alpha}}$. Since the original fringe price is greater than $\bar{l}$, we know that all prices are lower on $[0, \tilde{l})$, which lowers the overall average price.

research is to understand why there is such wide dispersion of wildfire risk model quality across insurers.

For a smaller group of homes with the most extreme wildfire risk, we also identify a role for price regulation in suppressing rate increases. Given that firms may be able to overcome these regulatory barriers over time by serially filing rate requests just below the maximum regulatory threshold, our results imply that the price regulation channel may have temporary effects on the pricing and availability of insurance.

Our findings are directly relevant to current policy discussions about insurance regulation in California. More broadly, these results highlight the underappreciated importance of the winner's curse as a barrier to participation in insurance markets for large, hard-to-model risks. This will be less of an issue in markets for flood or earthquake insurance where high-risk homes are publicly insured and parcel-level risks are less dynamic and easier to assess. Further investigating the generality and implications of these findings to other forms of climate risk will be critical to designing efficient insurance markets in an era of climate change.

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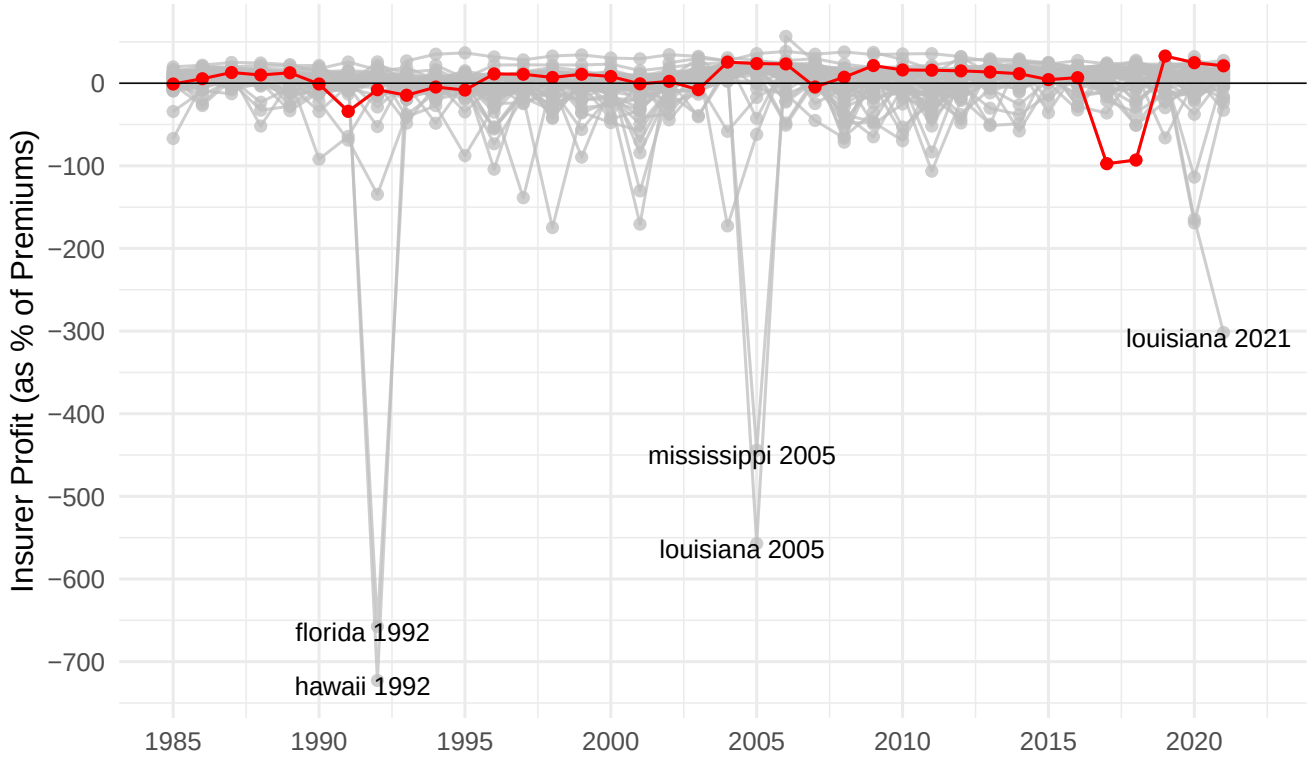
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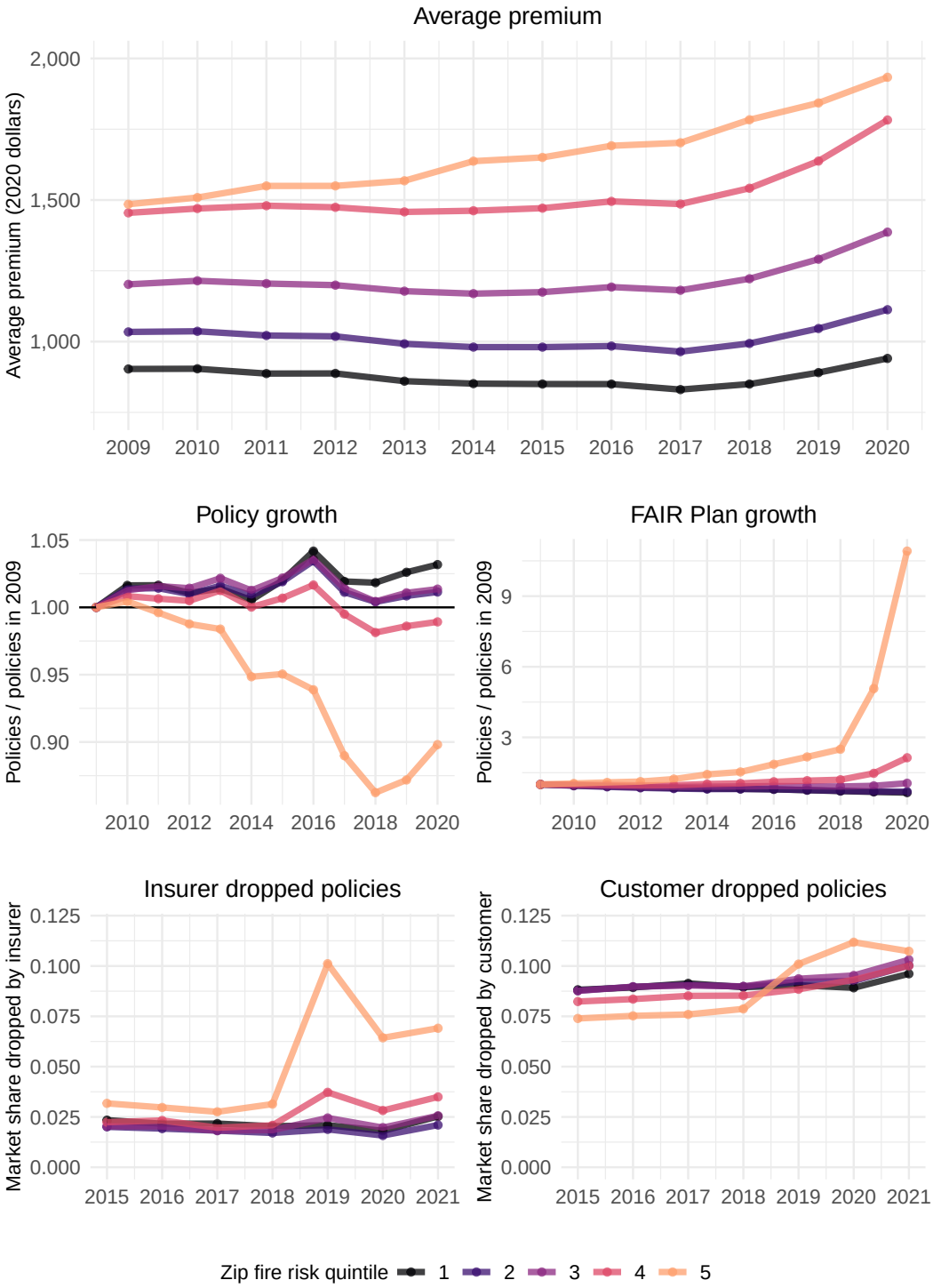
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Figure 1: Profitability of homeowners' insurers by state and year



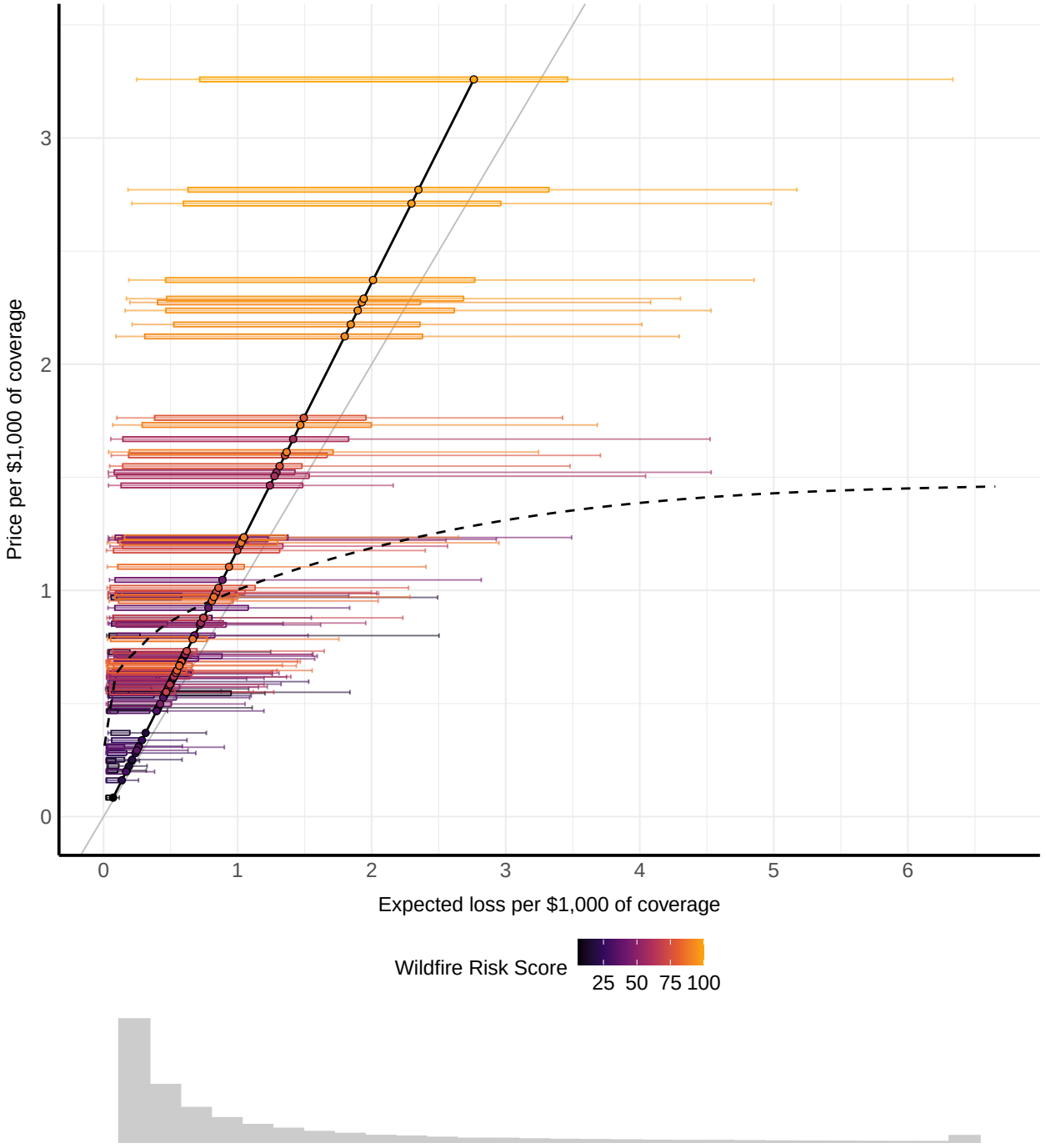
Notes: Figure reports state-level summaries of insurer profitability in homeowners' insurance. California is in red; all other states are in gray. The data represent profit on insurance transactions, which accounts for underwriting profit, investment gains, and federal taxes. Data are from National Association of Insurance Commissioners "Report on Profitability by Line by State" for the years 1985 to 2021. See Appendix A for a data description.

Figure 2: California homeowners insurance by year



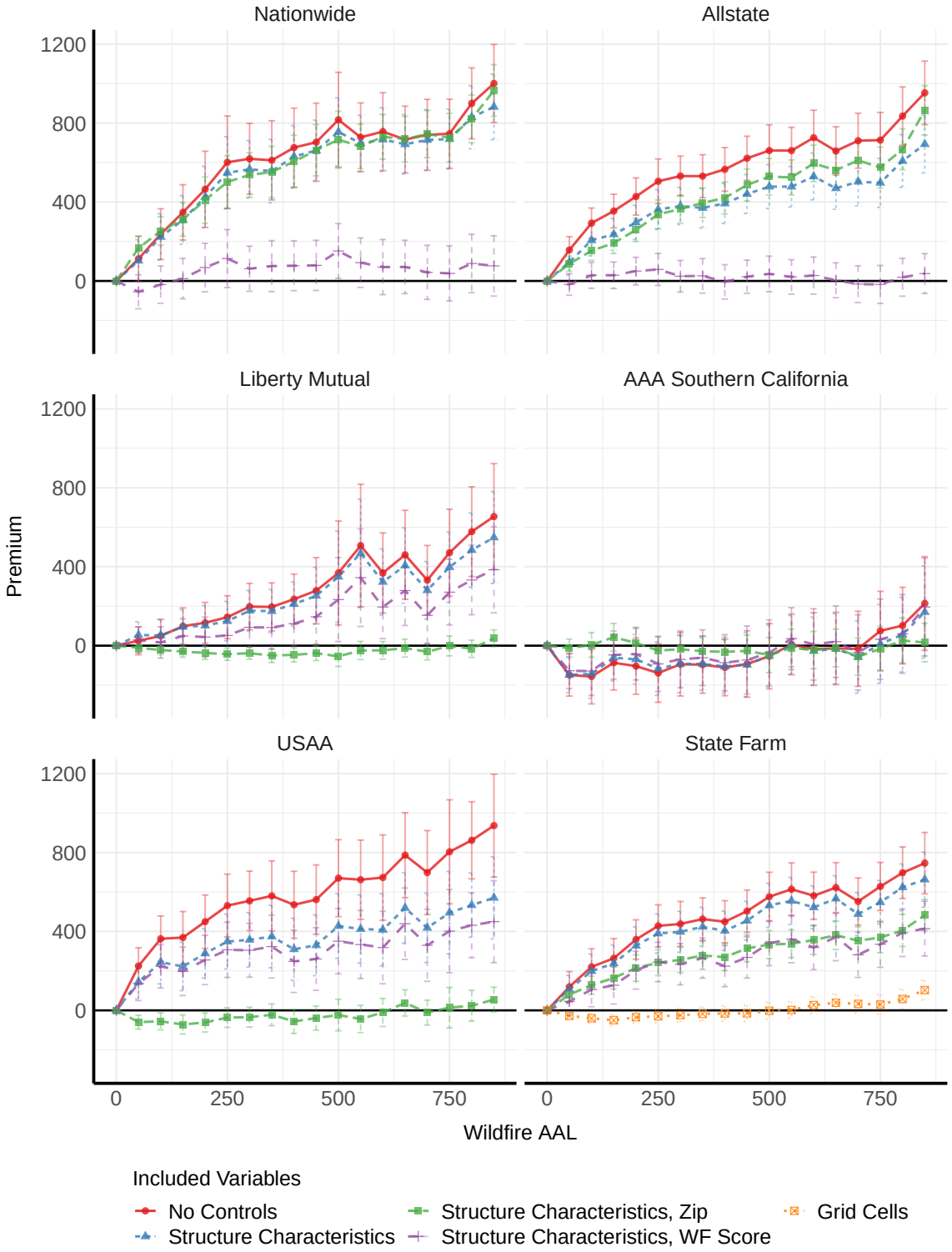
Notes: Figure summarizes zip code-level outcomes over time. Zip codes are classified into wildfire risk quintiles on the basis of zip code average risk. Risk scores are derived from California Department of Insurance Wildfire Risk Information Reporting, which lists proportions of insurance policies in various hazard categories (Negligible = 0, Low = 1, Moderate = 2, High = 3, Very High = 4). Annual zip code-level premiums, policy growth, and dropped policies are reported by the California Department of Insurance.

Figure 3: Regression of a cost-based, segment-level price on segment expected loss versus on parcel expected loss



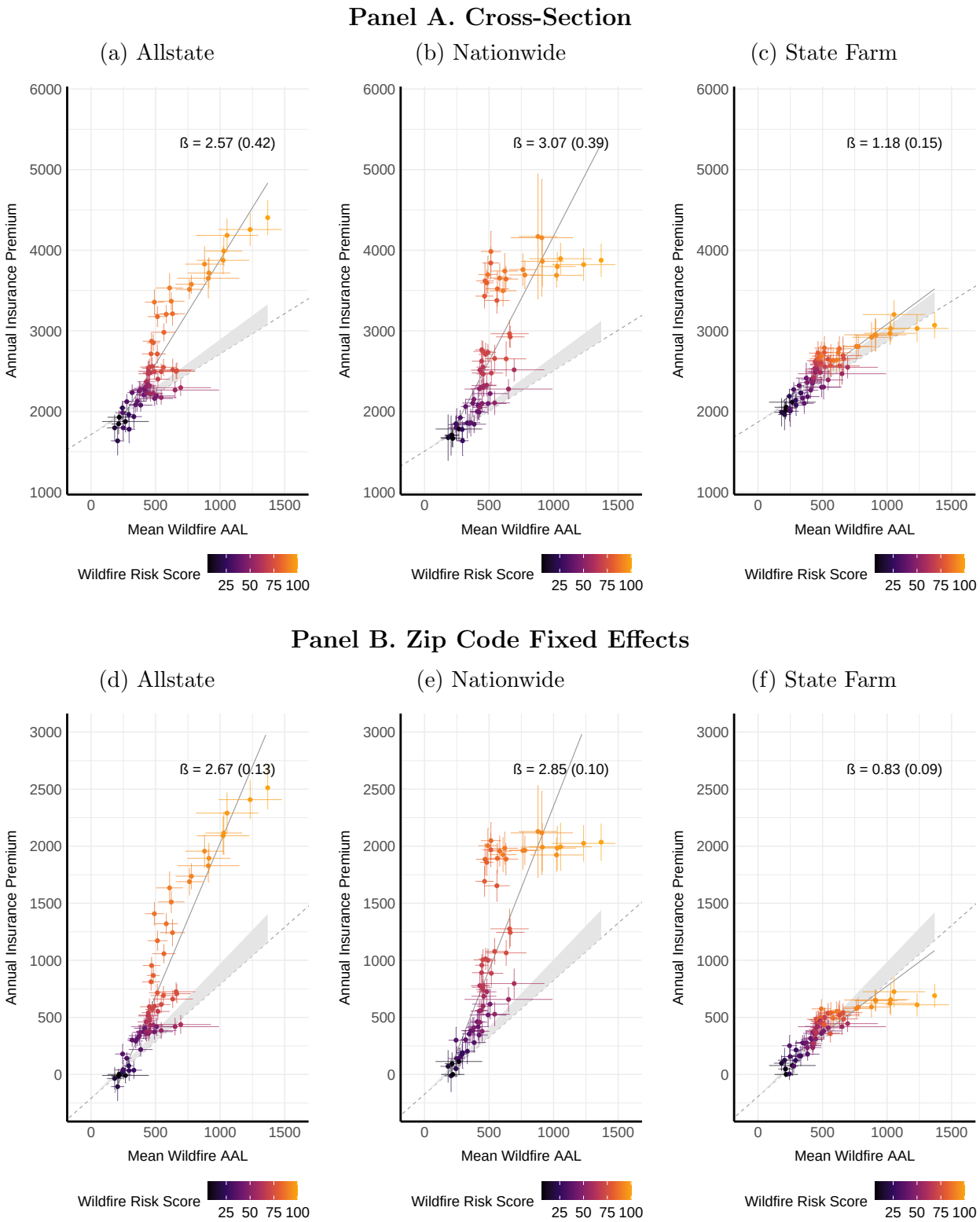
Notes: Horizontal box plots show the distribution of individual expected losses within each wildfire risk score. Whiskers show the 10th and 90th percentiles; notches show the interquartile range; circular markers are means. The vertical axis shows prices for a hypothetical firm that pools customers by wildfire score and prices at segment-mean expected loss plus 18 percent risk load. The solid line is a locally-weighted regression of these prices on segment-mean expected loss. The dashed black line is a locally-weighted regression of prices on individual expected loss. The gray line has a slope of 1. The histogram at bottom shows the overall distribution of expected losses for homes in the data. The contrast between the solid line and the dotted line shows that, under a segment pricing regime, parcels with high risk pay less than expected losses.

Figure 4: Validating firms' reported pricing variables



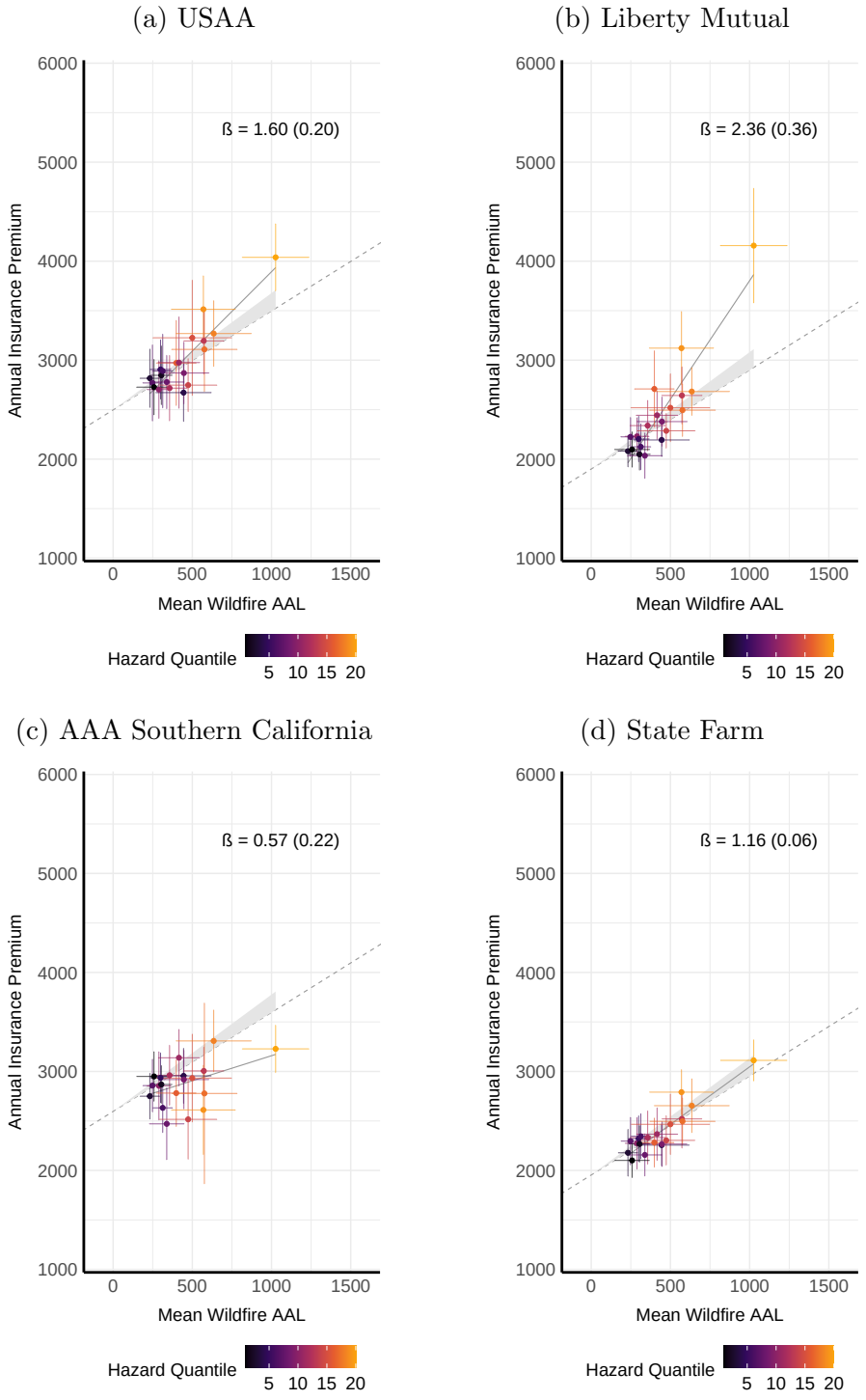
Notes: Each panel shows coefficients from multiple separate regressions of annual premium on a binned specification of wildfire AAL. All regressions (including "no controls") include a polynomial in demeaned reconstruction cost. Structure characteristics include age of home, protection class (a measure of fire department quality), and an indicator for Class A roof. Standard errors are clustered by zip code.

Figure 5: Wildfire price gradients for Allstate and Nationwide



Notes: Each panel shows a separate regression of annual premium on wildfire score dummies, with additional controls for fire protection class and reconstruction cost. Panel B regressions also include zip code fixed effects in the price regression. Vertical bars represent confidence intervals for prices; horizontal bars represent confidence intervals for mean AAL. Standard errors are clustered by zip code to allow for arbitrary within-zip code shocks to residuals. The gray shaded regions show slopes between 1 and 1.18, the cost-based benchmark.

Figure 6: Wildfire price gradients for firms using geographic segmentation

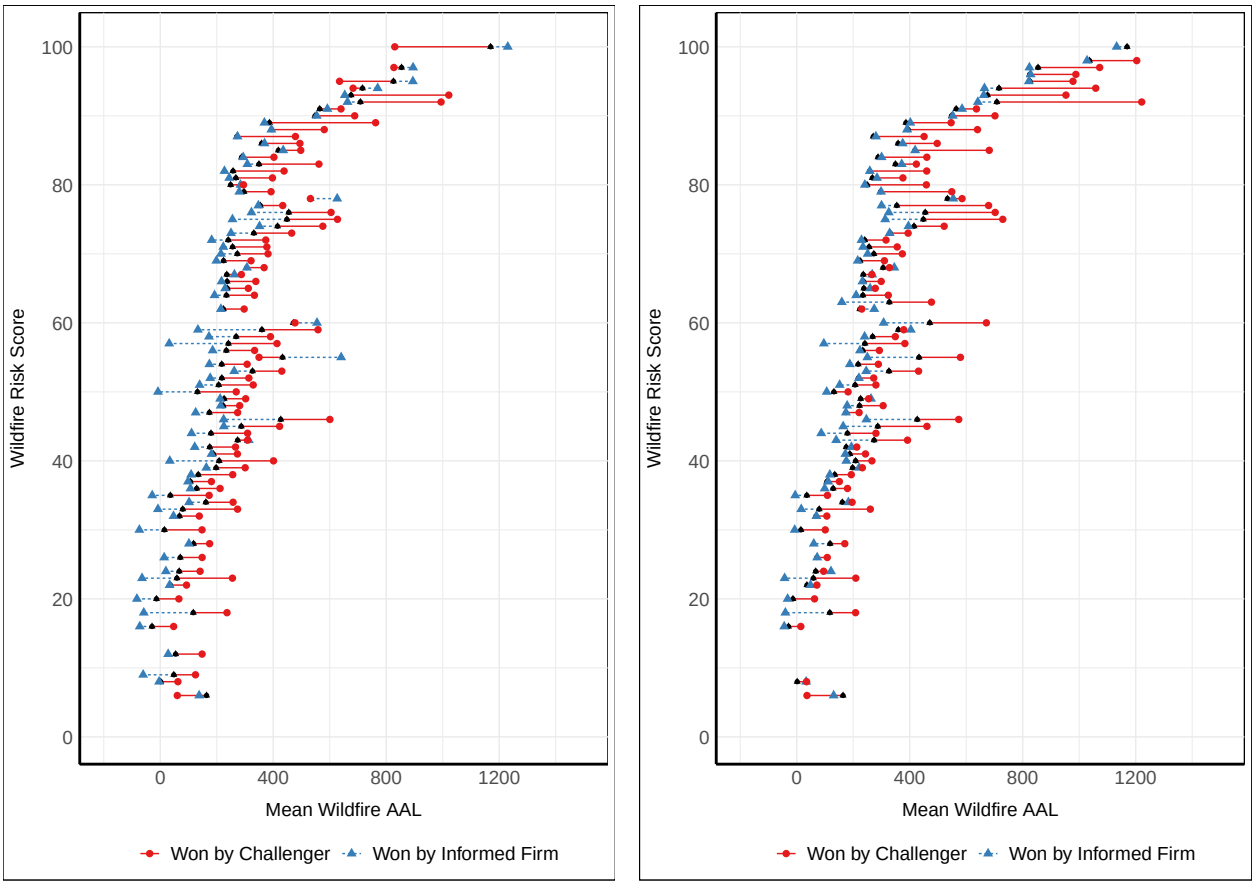


Notes: Each panel shows a separate regression of annual premium on 20 bins of zip code-level wildfire hazard, as defined by the CDI Widlfire Risk Information Report and described in the text. Regressions also include additional controls for fire protection class and reconstruction cost. Vertical bars represent confidence intervals for prices; horizontal bars represent confidence intervals for mean AAL. Standard errors clustered by zip code. Gray shaded region shows slopes between 1 and 1.18, the cost-based benchmark.

Figure 7: Selection on Wildfire Risk under Bertrand Duopoly

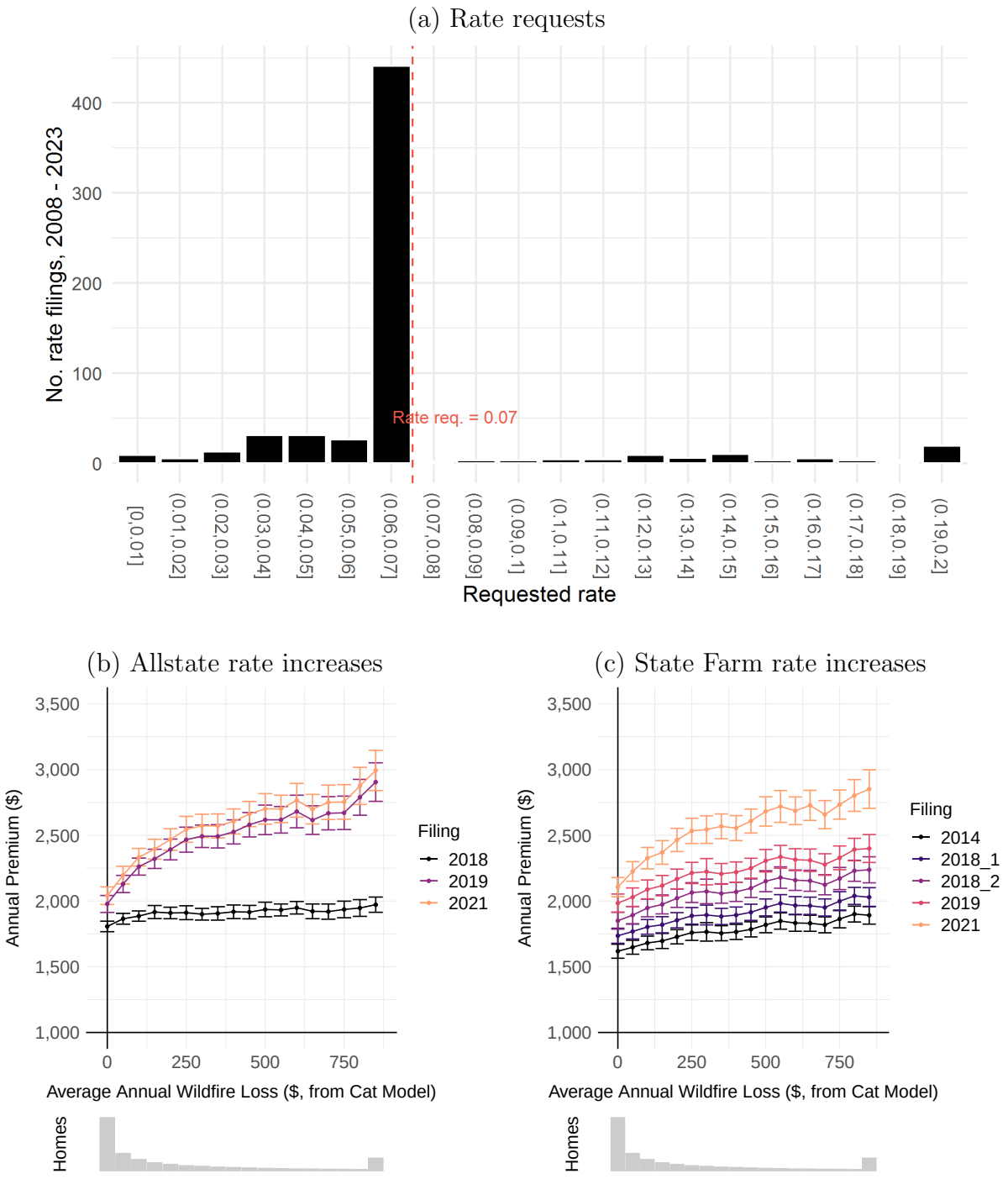
(a) Allstate-State Farm Duopoly

(b) Nationwide-State Farm Duopoly



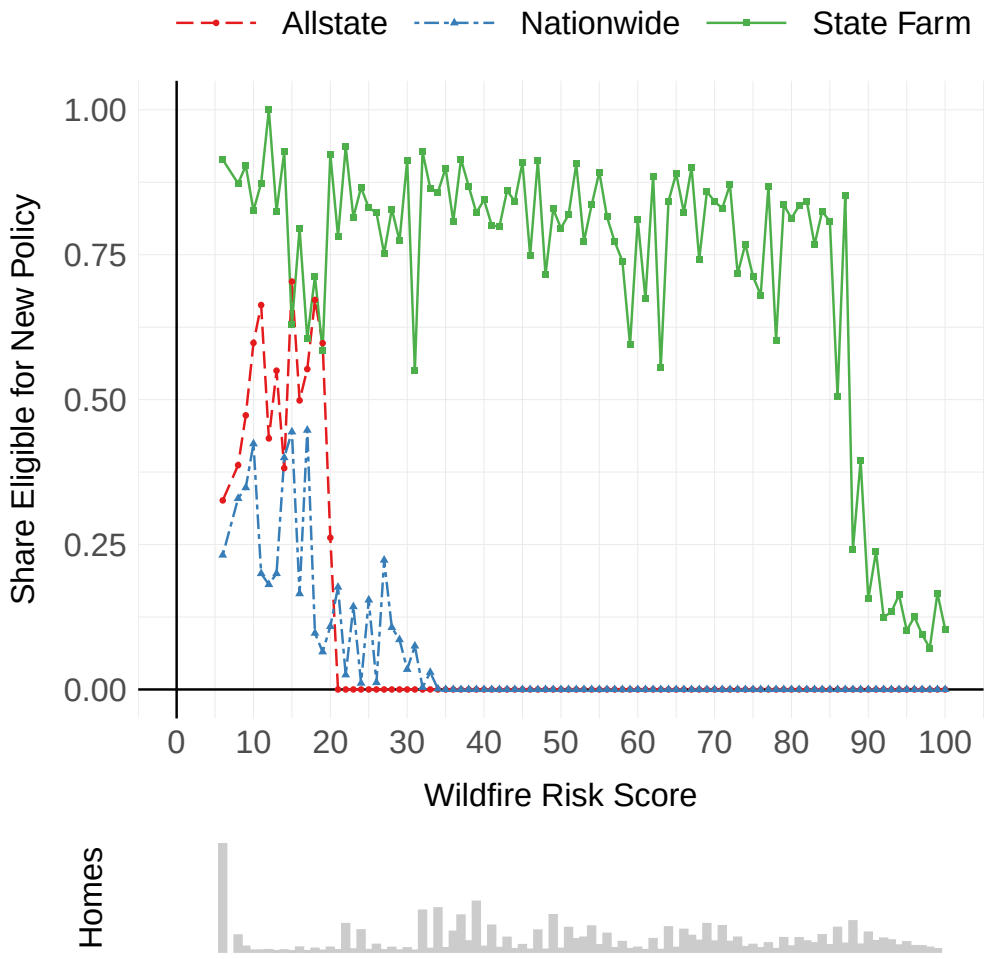
Notes: Figures show estimates from two versions of Equation 10. The black markers are from a regression of wildfire AAL on wildfire risk score dummies. The red and blue markers are from a regression of wildfire AAL on wildfire risk score dummies interacted with the firm that wins the home under duopoly price competition between State Farm and the challenger firm (Allstate in panel A and Nationwide in panel B). Risk scores where one of the duopoly competitors wins fewer than 50 homes are not plotted.

Figure 8: Rate filing behavior



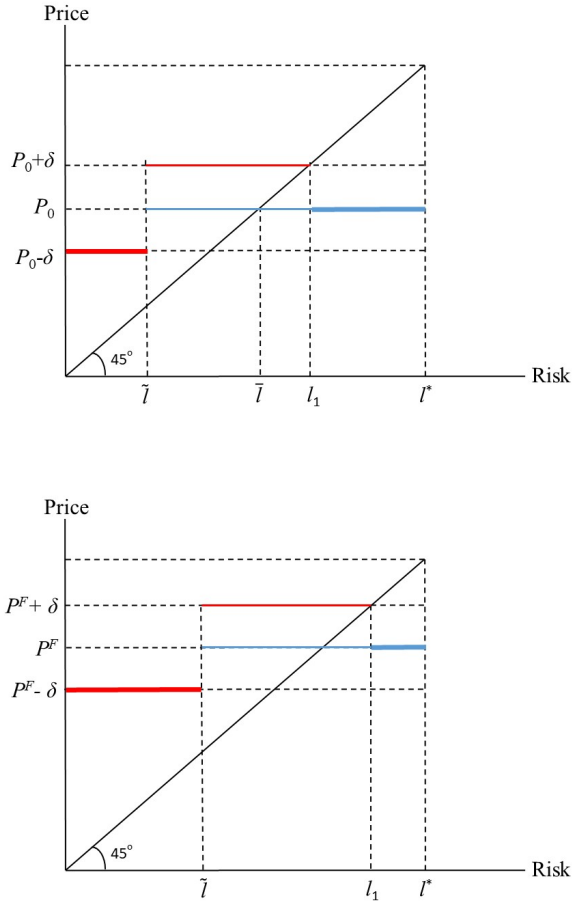
Notes: Panel (a) of this figure displays the distribution of all 636 requested rate increases to CDI from 2008 to 2023 for owner-occupied homeowners' insurance (HO-3) policies. These data cover rate requests from companies belonging to all the insurers in California. Firms tend to request rate increases just below 7 percent, a threshold above which firms may face costly public rate hearings. Panels (b) and (c) plot the results of two separate sets of regressions. The dependent variable is annual premium and the independent variable is binned AAL, not conditioned on wildfire risk segment. Each regression corresponds to a different rate case submitted by Allstate and State Farm. These regressions show, in the cross section, price increases by each of the companies over several years.

Figure 9: New policy eligibility versus parcel wildfire scores



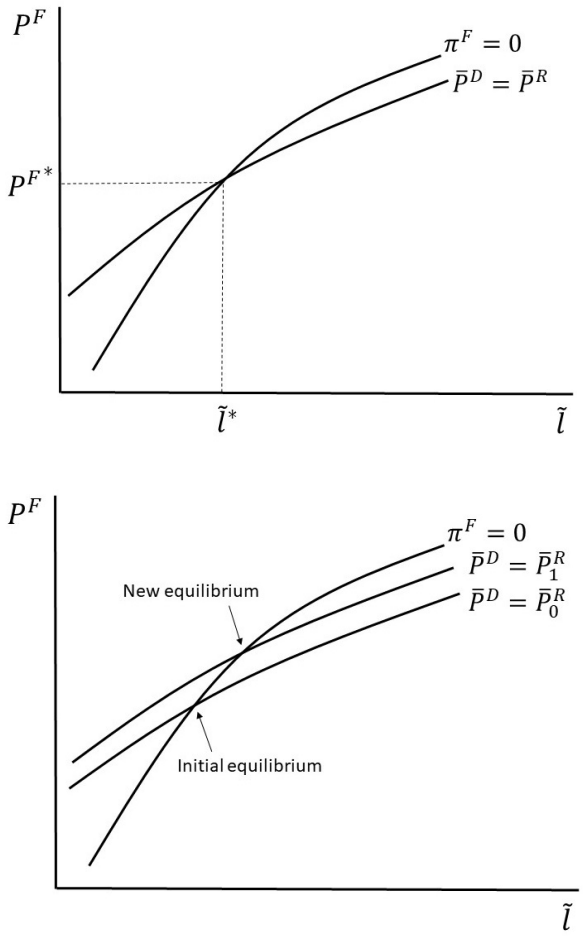
Notes: Figure reports the fraction of homes in each risk score bin that would have been eligible for a new homeowners policy in 2021 from each firm.

Figure 10: Equilibrium pricing by dominant firm and competitive fringe



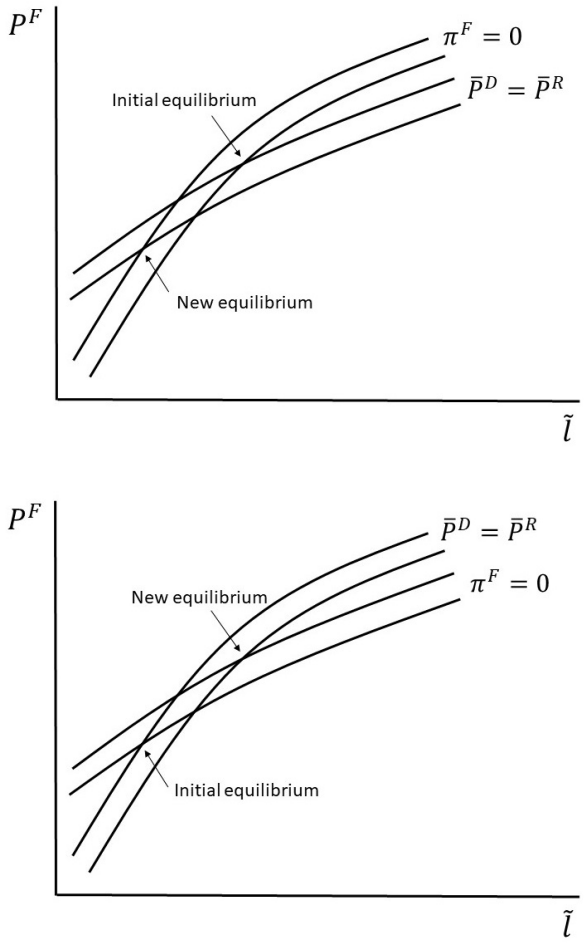
Notes: The top figure shows the dominant firm's best response at the initial equilibrium price P_0. The price charged by the dominant firm at each risk level l is shown in red, where the width of the line indicates the firm's market share (the widest line corresponds to a share of one). The competitive fringe's price and market shares are shown in blue. The lower figure shows the market equilibrium prices at which the profits of the competitive fringe are zero.

Figure 11: Market equilibrium with regulatory price constraints



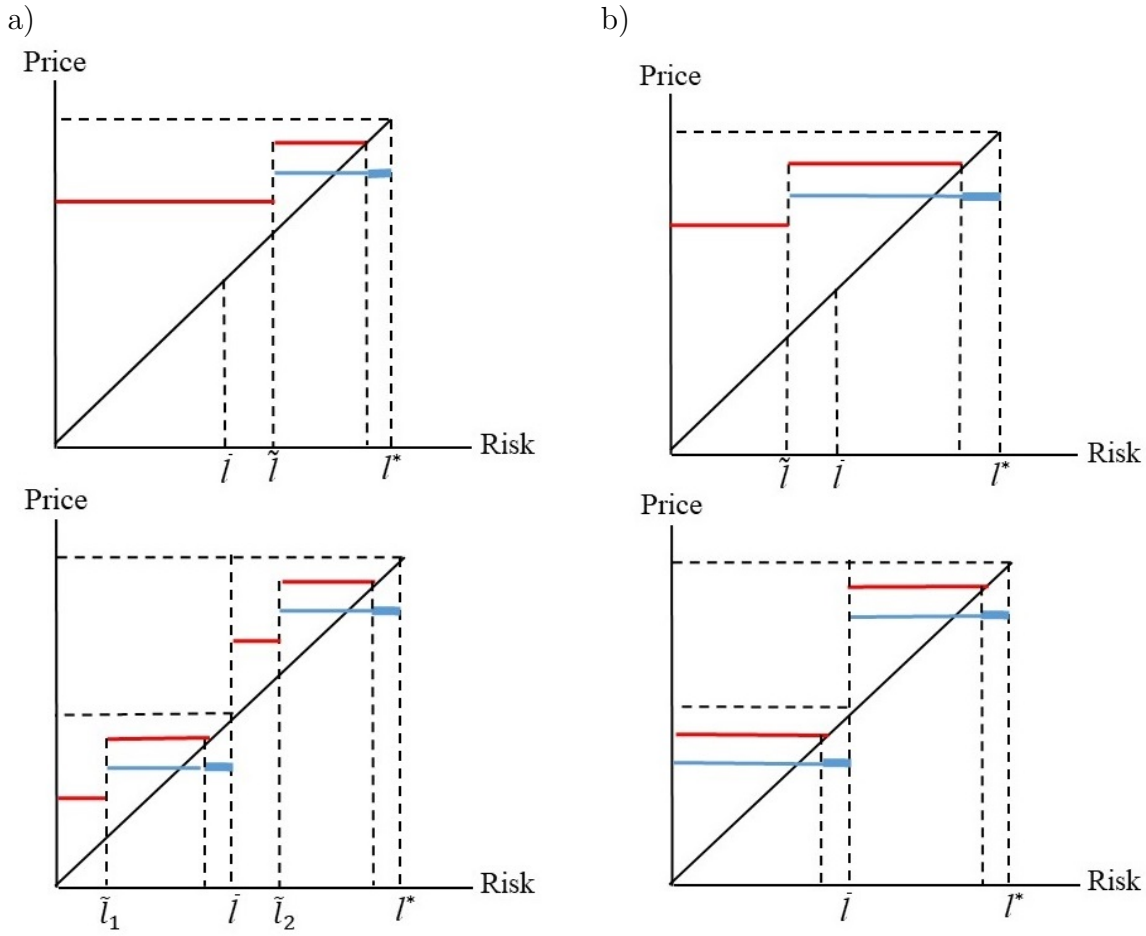
Notes: The top figure shows the isoclines corresponding to the zero profit and average price conditions in Equations (21) and (22). The intersection of the isoclines defines the equilibrium for $\bar{P}^D = \bar{P}^R$. The bottom figure shows how the equilibrium changes when the average price constraint on the dominant firm is relaxed ($\bar{P}_1^R > \bar{P}_0^R$).

Figure 12: Effects of risk increases on market equilibrium with regulatory price constraints



Notes: The two figures show how the market equilibrium changes when the risk distribution shifts from $U(0, l^*)$ to $U(a, l^* + a)$ and the constraint on the dominant firm's average price remains at $\bar{P}^D = \bar{P}^R$. The top figure corresponds to the case in which the zero profit isocline is steeper than average price isocline. In this case, the increase in risk results in lower P^F and $\tilde{l}$. This result is reversed in the bottom figure for the case in which the slope of the average price isocline exceeds that of the zero profit isocline.

Figure 13: Effects of information provision on market equilibrium



Notes: The two panels show how equilibrium prices change when new information is provided to the competitive fringe firms. In the top figures, the fringe firms know only that properties are distributed according to $U(0, l^*)$. In the bottom figures, the firms can distinguish whether properties are distributed according to $U(0, \bar{l})$ or $U(\bar{l}, l^*)$. There are two cases. Case (a) on the left corresponds to $\tilde{l} > \bar{l}$ in the initial equilibrium and (b) on the right corresponds to $\tilde{l} < \bar{l}$ in the initial equilibrium.

Table 1: Insurer market shares and granularity of wildfire rating

Insurer	Market Share (Percent)		Wildfire Hazard Variables	Hypothetical Best Fit
	Statewide	High-Risk Zip Codes		
State Farm	18.0	18.4	434,252	0.82
Farmers	15.5	14.7	2,304	nd
CSAA	7.6	8.6	26,055	0.67
Mercury	7.1	0.9	2,248	nd
Auto Club Enterprises	6.9	0.2	22	0.13
Liberty Mutual	6.5	3.4	1,698	0.47
Allstate	5.8	3.3	111	0.18
USAA	5.3	5.9	838	0.43
Travelers	3.2	4.8	1,572	nd
Nationwide	2.5	2.5	59	0.16
FAIR Plan	2.5	20.4	736	nd
All Others	19.2	16.9		

Notes: Market shares are based on CDI CSS exposures data for 2020 at the insurer group level for the HO insurance line plus FAIR Plan. High-hazard zip codes are those falling into the highest quintile of average wildfire risk as reported in the CDI Wildfire Risk Information Report for 2021. Wildfire hazard variables count the number of factors an insurer uses to capture the likelihood of wildfire occurrence; more information on wildfire hazard variables is available in Appendix A. Hypothetical best fit is the R^2 from a regression of catastrophe model wildfire risk (average annual loss or AAL) on rating variable indicator variables using the 100,000 homes in the dataset. Firms with no data ('nd') use proprietary information such as Verisk FireLine scores or Zesty AI ratings, which were unavailable for regression.

Table 2: Approximate risk load from marginal surplus

Panel A: Risk load versus market share in California wildfire zip codes

Market Share (%)	Policies	Wildfire AAL ($M)	σ ($M)	S ($M)	S' ($M)	Risk Load ($M)	Average Risk Load per AAL ($)	Marginal Risk Load per AAL ($)
1	27,825	6	8.9	550.1	550.1	0.0	0.00	NA
5	139,722	30	44.0	550.1	551.8	0.6	0.02	0.03
10	279,612	61	88.2	550.1	557.1	2.4	0.04	0.06
20	559,379	120	174.8	550.1	577.2	9.1	0.08	0.11
30	839,123	181	262.5	550.1	609.5	20.0	0.11	0.18
50	1,398,690	302	438.0	550.1	703.2	51.4	0.17	0.28
100	2,797,560	604	876.3	550.1	1,034.7	162.8	0.27	0.41

Panel B: Sensitivity of risk load to other catastrophe perils

Hurricane AAL ($M)	Policies	Wildfire AAL ($M)	σ ($M)	S ($M)	S' ($M)	Risk Load ($M)	Average Risk Load per AAL ($)	Marginal Risk Load per AAL ($)
0	279,612	60	87.59	8.54	88.01	26.70	0.44	0.48
50	279,612	60	87.66	137.76	163.29	8.57	0.14	0.21
100	279,612	60	87.55	275.13	288.73	4.57	0.08	0.11
200	279,612	61	88.15	550.07	557.08	2.36	0.04	0.06
300	279,612	60	87.82	825.04	829.71	1.57	0.03	0.04
500	279,612	60	87.76	1,375.03	1,377.82	0.94	0.02	0.02

Notes: The table reports the marginal surplus and associated risk load required to cover various shares of homes in wildfire areas of California for a hypothetical countrywide property insurer.

Table 3: Revenue net of expected wildfire losses within rate segments

	Within Risk Score Segments			Zip code-based territories				Grid
	Allstate	Nationwide	State Farm	USAA	Liberty Mutual	AAA SoCal	State Farm	State Farm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AAL 50-99 (13% of Homes)	-62**	-101**	0	-84***	-35***	-172***	49***	-41***
	(27)	(44)	(35)	(17)	(11)	(41)	(18)	(10)
AAL 100-199 (14% of Homes)	-86***	-113**	-1	-141***	-108***	-200***	51**	-109***
	(32)	(48)	(43)	(22)	(12)	(51)	(25)	(13)
AAL 200-299 (8% of Homes)	-159***	-118*	8	-217***	-214***	-282***	46	-176***
	(37)	(69)	(48)	(23)	(15)	(60)	(33)	(15)
AAL 300-499 (10% of Homes)	-334***	-269***	-105**	-341***	-352***	-418***	-40	-289***
	(41)	(61)	(50)	(25)	(16)	(66)	(32)	(18)
AAL 500-749 (6% of Homes)	-550***	-465***	-230***	-532***	-545***	-551***	-172***	-456***
	(43)	(60)	(56)	(30)	(21)	(75)	(35)	(21)
AAL 750-999 (3% of Homes)	-797***	-743***	-452***	-746***	-761***	-774***	-370***	-649***
	(46)	(69)	(58)	(38)	(25)	(94)	(40)	(25)
AAL 1000+ (7% of Homes)	-1,842***	-1,781***	-1,453***	-1,703***	-1,675***	-1,367***	-1,296***	-1,302***
	(80)	(99)	(94)	(54)	(49)	(150)	(59)	(49)
Structure Characteristics	✓	✓	✓	✓	✓	✓	✓	✓
Allstate Segments FE	✓		✓					
Nationwide Segments FE		✓						
USAA Segments FE				✓			✓	
Liberty Segments FE					✓			
AAA SoCal Segments FE						✓		
State Farm Segments FE								✓
Observations	95,352	95,351	95,351	95,297	94,025	55,641	95,296	95,351
Dependent variable mean	2,059	2,163	2,014	2,168	2,090	2,520	2,014	2,014

Notes: Table reports eight separate regressions. The omitted AAL range is 0 to 50, which contains 39 percent of homes. Structure characteristics include reconstruction cost, age of home, class A roof indicator, and public protection class. Standard errors are clustered by zip code.

Table 4: The winner's curse in Bertrand duopoly

Panel A: Expected wildfire losses

	log(Wildfire AAL)				
	Allstate	Nationwide	USAA	Liberty Mutual	AAA SoCal
	(1)	(2)	(3)	(4)	(5)
1[Win]	0.51***	0.33***	0.44***	0.39***	0.56***
	(0.08)	(0.08)	(0.03)	(0.04)	(0.09)
Structure Characteristics	✓	✓	✓	✓	✓
Allstate Segments FE	✓				
Nationwide Segments FE		✓			
USAA Segments FE			✓		
Liberty Segments FE				✓	
AAA SoCal Segments FE					✓
Observations	95,295	95,295	95,295	93,976	55,606
R^2	0.36	0.32	0.74	0.77	0.28
Dependent variable mean	4.54	4.54	4.54	4.53	4.40
Fraction Won	0.54	0.56	0.50	0.44	0.50

Panel B: Revenue net of expected wildfire losses

	Price - Wildfire AAL				
	Allstate	Nationwide	USAA	Liberty Mutual	AAA SoCal
	(1)	(2)	(3)	(4)	(5)
1[Win]	-257.75***	-136.45***	-194.84***	-176.11***	-470.65***
	(37.73)	(46.21)	(27.95)	(16.06)	(37.63)
Structure Characteristics	✓	✓	✓	✓	✓
Allstate Segments FE	✓				
Nationwide Segments FE		✓			
USAA Segments FE			✓		
Liberty Segments FE				✓	
AAA SoCal Segments FE					✓
Observations	95,295	95,295	95,295	93,976	55,606
R^2	0.75	0.72	0.87	0.84	0.85
Dependent variable mean	2,059.49	2,162.46	2,168.25	2,089.15	2,521.27
Fraction Won	0.54	0.56	0.50	0.44	0.50

Notes: 1[Win] is an indicator for the firm's price being less than or equal to State Farm's price for that customer. Dependent variable in Panel A regressions is wildfire AAL. Dependent variable in Panel B regressions is (Price - Wildfire AAL) using the challenger firm's price. Structure characteristics include reconstruction cost, age of home, class A roof indicator, and public protection class. Standard errors are clustered by zip code.

Table 5: Value of information for the informed firm in Bertrand duopoly

	Price - Wildfire AAL				
	Allstate	Nationwide	USAA	Liberty Mutual	AAA SoCal
	(1)	(2)	(3)	(4)	(5)
State Farm	150.14***	260.76***	181.80***	250.35***	210.60***
	(14.61)	(12.70)	(15.94)	(17.27)	(28.92)
Rebuild Cost	✓	✓	✓	✓	✓
GRIDID FE	✓	✓	✓	✓	✓
Observations	95,295	95,295	95,295	94,241	55,606
R^2	0.94	0.93	0.93	0.92	0.96
Dependent variable mean	1,787.04	1,767.89	1,808.48	1,777.79	2,072.88
Fraction Won by Challenger	0.54	0.56	0.50	0.44	0.50
Homes With Useful Variation	0.40	0.43	0.44	0.36	0.44

Notes: Table reports results of five separate regressions. Each regression corresponds to a duopoly between State Farm and the indicated firm. An observation is a home-firm pair, and the sample is limited to the winning firm for each home. The dependent variable is (Price - Wildfire AAL) using the winning firm's price. The variable of interest is an indicator variable equal to one if State Farm wins the parcel in Bertrand competition. "Fraction won" is the share of customers for whom the challenger firm's price is lower than State Farm. "Homes with useful variation" is the share of observations located in GRID ID cells where we observe multiple insurers in the duopoly outcome.

Online Appendix to: How Are Insurance Markets Adapting to Climate Change? Risk Selection and Regulation in the Market for Homeowners Insurance

Judson Boomhower, Meredith Fowlie,
Jacob Gellman, Andrew Plantinga

A Data Documentation **A2**

A.1 National Association of Insurance Commissioners statewide data A2

A.2 California Department of Insurance zip code data A2

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A.4 Insurer rate filings A4

B Additional Results **A6**

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D Proofs and Results for Equilibrium Model **A18**

A Data Documentation

We compile several sources of data. The first data source, taken from the National Association of Insurance Commissioners (NAIC), provides state-level insurance company market shares and earned premia for the United States. The second data source was obtained from the California Department of Insurance (CDI) and contains zip code-level information on annual insurance premiums, coverage, dropped policies, and company market share. Next, we use a dataset on property-level information on house characteristics, categorical wildfire risk scores, and probabilistic wildfire risk distributions. Lastly, we use public insurer rate requests made to CDI to develop price and eligibility schedules for the property-level dataset.

A.1 National Association of Insurance Commissioners statewide data

Since 1974, NAIC has produced annual reports on the profitability of insurance lines by state.[47] Specifically, these data report profit on insurance transactions, which accounts for underwriting profit, investment gains, and federal taxes. We gather these reports for years representing 1985 through 2021. The data are used to produce Figure 1, which shows the profitability of HO insurance lines by state. The figure sheds light on losses incurred by natural disasters.

A.2 California Department of Insurance zip code data

We obtained three datasets from CDI in a Public Records Act request.[48] These data report zip code-level information on insurer market share, premia, number of policies, total coverage, deductible, insurer-initiated non-renewals, and customer-initiated non-renewals, for the years 2009 through 2020. In addition, we used a publicly available CDI dataset, Wildfire Risk Information Reporting, which breaks down the distribution of wildfire risk within California zip codes. Although these datasets do not capture sub-zip code variation in premium and exposure, they can provide broader assessments of company behavior, market concentration, competition, and industry trends.

The first dataset is the Community Service Statement (CSS) data, which reports company by year by zip code information on total premium and number of policies, segmented by policy type. All insurance companies licensed to operate in California in the admitted market respond to this data collection survey. We use these data to impute zip code-level, company-specific market shares, such as in Table 1.

The second dataset is the Personal Property Experience (PPE) data, which gives zip code-level information on number of policies, total coverage, and deductibles, separated by policy

47. National Association of Insurance Commissioners (NAIC). (2021). Report on Profitability by Line and by State. https://naic.soutronglobal.net/Portal/Public/en-US/RecordView/Index/7008.

48. The request numbers were PRA-2022-00204 and PRA-2023-00342.

type. Insurers that wrote more than $5 million in premium for either dwelling fire or homeowners insurance report this information. While most CDI data are reported for all years from 2009 to 2020, the coverage and deductible data in PPE were linearly interpolated for the years 2010, 2012, 2014, and 2016.

The third dataset is the Residential Property Experience Data (RPE). Beginning in 2015, insurers with combined total written premiums of $5 million or more for dwelling fire or homeowners lines of business were required to respond to an annual RPE data call. These data report, at the zip code level, the number of new residential policies written, the number renewed, the number of non-renewed policies, and the number of cancelled policies. These data are used to show the cancellation panels of Figure 2.

The last zip code-level dataset from CDI is the Wildfire Risk Information Report. Starting in 2018, all admitted insurers with at least 10 million dollars or more in written California premium in dwelling fire or homeowners lines of business have submitted reports to CDI on wildfire risk exposure. The dataset reports, at a zip code level, fire- or wildfire-incurred losses, as well as the distribution of insured parcels across wildfire risk categories. We use these data to coarsely classify zip codes into quantiles of risk, which are used in Table 1 and Figure 2.

A.3 Wildfire risk and home characteristics

We obtained proprietary data from CoreLogic, LLC on parcel-level house characteristics and wildfire risk. The parcel-level sample consists of 100,000 single family homes in California. These data include standard assessor's information such as the home address, geolocated coordinates, reconstruction cost, and the year of construction. They also provide relevant information related to wildfire risk, such as the construction material, the presence of fire resistive siding or roofing, distance to high hazard vegetation, distance to a responding fire station, and a public protection classification that rates community fire protection services.

A key feature of these data is a set of deterministic categorical wildfire risk scores (WRS) which are used by many insurers in the pricing and underwriting process. The main WRS is a rating that ranges from 5 to 100. This measure is based on factors such as slope, aspect, fuel, past burns, and distance to vegetation. Other risk scores are included, such as a brushfire risk rating and a set of crime indices. None of these factors are derived from probabilistic models but are commonly used by insurers in decision-making.

Separately, the data report a set of probabilistic catastrophe loss measures which are derived from simulations. For each property we observe probabilistic measures of the annual average loss (AAL), the standard deviation of losses, and aggregate exceedance probability (AEP) losses over return periods of 50, 100, 250, and 500 years. The AAL is the average yearly loss in dollars, which is roughly the probability of destruction times the reconstruction cost of the home. The AEP describes the probability distribution of the sum of losses over various return periods; for example, for a 250 year return period we might observe that a house has a $1/250 = 0.4\%$ chance of $\$k$ in total losses, where k is reported for each parcel.

To develop the sample of 100,000 homes, we drew on zip code-level data from CoreLogic. These data report the total number of single family homes in a zip code falling into categorical wildfire risk scores of 1 to 50, 51 to 60, 61 to 80, and 81 to 100. We used this dataset to identify 400 California zip codes with high variation in wildfire hazard; then, we received a sample of 250 houses per zip code with the aforementioned parcel-level characteristics, giving us 100,000 properties for the analysis.

A.4 Insurer rate filings

To determine insurance pricing and eligibility we developed data from public insurance rate filings. Because California is a prior approval state, any company in the admitted market must submit rate increase requests for approval by CDI. As part of the rate request, insurers must provide complete copies of their rate manuals which they use to set premiums and eligibility for customers. All rate filings are publicly available through CDI's website.[49]

We reviewed rate filings for dozens of large insurance companies. Rate requests can range from several hundred pages to more than 10,000 pages. A typical rate request takes between six months and two years from submission to approval and involves several rounds of correspondence and objection letters from state rate specialists. There is no limit on how often an insurer may file a new request, although an insurer cannot submit a new request for an insurance line while another is pending.

Using the property and risk data, we develop the full insurance pricing and eligibility schedule of the 100,000 home sample for six large insurers listed in Appendix Table 1. As a result of this exercise we are able to observe the price a company would offer to any house, even if the house is ineligible for a policy. For each company, we use the most recent rate filing as of 2021; correspondingly, the premia are priced in 2021 dollars.

Several parcel-level characteristics affect the insurance premium or eligibility, such as the age of the home, zip code, geocoordinates, construction, roof, proprietary wildfire risk score, public protection class of the community, or distance to vegetation. To derive full prices, we must make several assumptions about the policy. First, we assume that a homeowner purchases coverage equal to the reconstruction cost of the home, which is generally advised by insurers. In addition, we assume a $1,000 deductible. For all other coverages, such as liability or loss of use, we assume default coverage for each insurer, which is summarized in Appendix Table 1. We do not assume any additional coverages, such as for scheduled items like furs and jewelry. Lastly, we assume the most standard homeowners policy, i.e. not a deluxe or premium plan.

We must also make assumptions about the homeowner characteristics. We assume that the customer has not had a recent claim, that they have been with the insurer for fewer than two years, and that they bundle their homeowners and automobile insurance policies.[50]

49. California Department of Insurance (CDI). (2024). Web Access to Rate and Form Filings (WARFF). http://www.insurance.ca.gov/0250-insurers/0800-rate-filings/0050-viewing-room.

50. As of 2015, 78 percent of consumers bundled their homeowners and auto policies. See: J.D. Power. 2015 US Household Insurance Study. https://www.jdpower.com/business/press-releases/2015-us-household-insurance-study.

Appendix Table 1: Standard coverage levels for rate filings

Company filing	Coverage A - Dwelling	Coverage B - Other Structures	Coverage C - Personal Property	Coverage D - Loss of Use	Coverage E - Personal Liability	Coverage F - Medical Payments	Deductible
AAA SoCal 15-6084	Repl. cost	10% of Cov. A	75% of Cov. A	20% of Cov. A	$100,000	$1,000	$1,000
Allstate 21-1436	Repl. cost	10% of Cov. A	50% of Cov. A	20% of Cov. A	$100,000	$1,000	$1,000
Liberty Mutual 19-1562	Repl. cost	10% of Cov. A	50% of Cov. A	20% of Cov. A	$100,000	$1,000	$1,000
Nationwide 20-612	Repl. cost	10% of Cov. A	55% of Cov. A	No limit (24 months)	$100,000	$1,000	$1,000
State Farm 21-1404	Repl. cost	10% of Cov. A	75% of Cov. A	30% of Cov. A	$100,000	$1,000	$1,000
USAA 21-809	Repl. cost	10% of Cov. A	50% of Cov. A	20% of Cov. A	$300,000	$5,000	$1,000

Notes: Coverage A is assumed as the structure replacement cost, which is recommended by insurers. Deductible is assumed as $1,000. All other values are standard for each rate filing. Rate filing identifiers correspond to California Department of Insurance filing numbers, accessible through Web Access to Rate and Form Filings (WARFF).

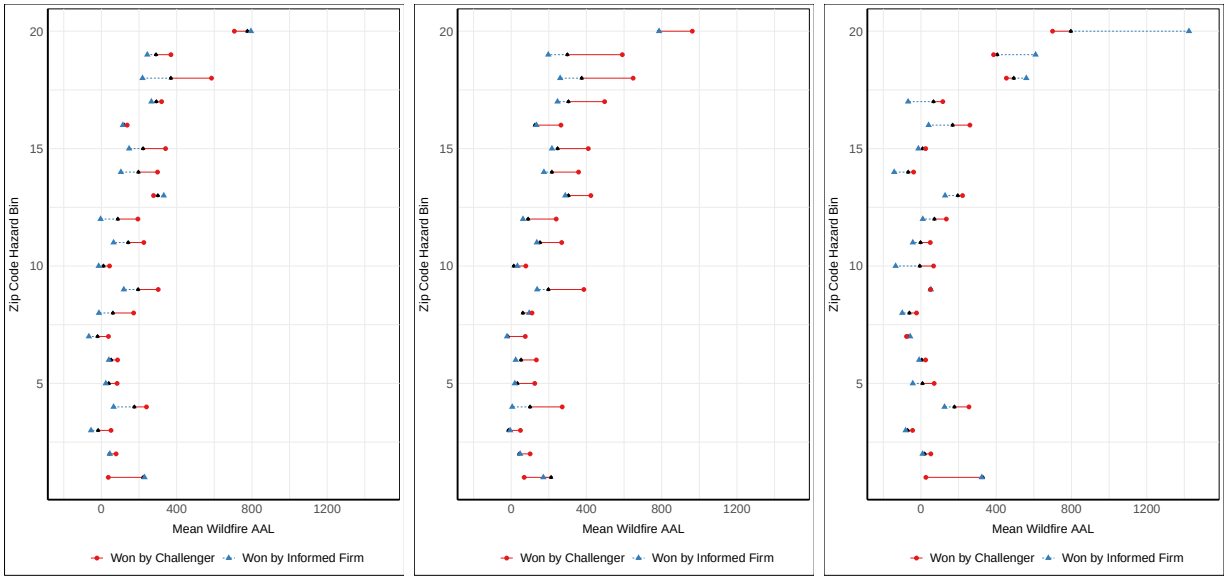
Protective devices also typically factor in to homeowners insurance; we assume the customer has smoke detectors, dead bolt locks, and fire extinguishers, but no burglar alarm (local or central-reporting), no central-reporting fire alarms, and no sprinklers. The homeowner is assumed to be 45 years old and married without children. Importantly, these characteristics are assumed constant when pricing every company's premia.

Besides constructing premia, we also use the rate filings to assess the granularity of each firm's wildfire risk measurement. The count of each firm's rating variables is reported in Table 1. The following variables were counted as wildfire variables: (i) Numeric wildfire hazard scores from firms such as CoreLogic or Verisk; (ii) Any custom territory, such as State Farm's grid ID, AAA Southern California's brush fire territories, or a territory that aggregates several zip codes; (iii) An administrative territory such as a zip code if there is wildfire-specific information; if there is only a general zip code factor which is not explicitly related to wildfire, it is not counted; (iv) Public protection class or any variable interacted with it, such as construction type $\times$ protection class. Table 1 is constructed using the following rate filings, which reflect the most recent filings as of 2021: State Farm 21-1404, Farmers 21-2410, CSAA/AAA NorCal 20-4189, Mercury 20-3267, Auto Club Enterprises/AAA SoCal 15-6084, Liberty Mutual 19-1562, Allstate 21-1436, USAA 21-809, Nationwide 20-612, Travelers 20-887, FAIR Plan 21-2452.

B Additional Results

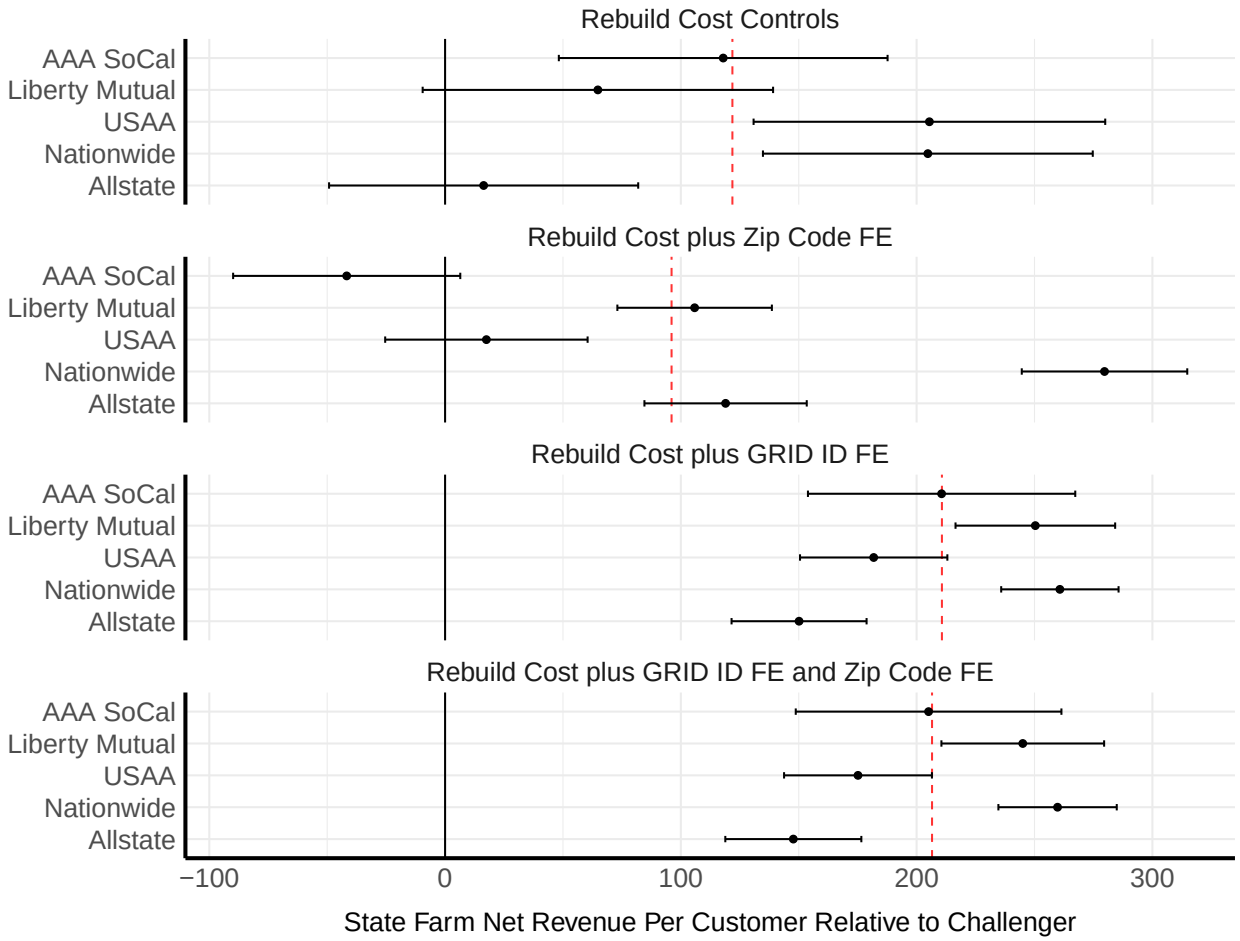
Appendix Figure 1: Duopoly Selection on wildfire risk, firms segmenting on geography

(a) USAA-State Farm (b) Liberty Mutual-State Farm (c) AAA SoCal-State Farm



Notes: Figures show estimates from two versions of Equation 10. The black markers are from a regression of wildfire AAL on dummies for 20 bins of zip code-level wildfire hazard, as defined by the CDI Widlfire Risk Information Report and described in the text. The red and blue markers are from a regression of wildfire AAL on zip bin dummies interacted with the firm that wins the home under duopoly price competition between State Farm and the indicated challenger firm. Zip code bins where one of the duopoly competitors wins fewer than 50 homes are not plotted.

Appendix Figure 2: Difference in net revenue per customer in duopoly, alternative regressions



Notes: Each marker represents regression estimates and 95 percent confidence intervals for the difference in net revenue per customer served between the two duopoly competitors in a duopoly with State Farm and the indicated firm. The three figure panels represent different sets of control variables. Red dashed lines are means for each panel.

Appendix Table 2: Price gradients by firm and wildfire score range

Insurer	Price Gradient 0–60	Price Gradient 0–80	Price Gradient 0–90	Price Gradient 0–100
Allstate	1.47 (0.20)	1.74 (0.17)	2.74 (0.26)	2.67 (0.13)
Nationwide	1.66 (0.31)	2.80 (0.20)	3.94 (0.29)	2.85 (0.10)
State Farm	1.24 (0.29)	1.31 (0.10)	1.26 (0.16)	0.83 (0.09)
N	57272	76479	88776	95350

Notes: Table reports results of twelve separate regressions. Each table cell reports estimate and standard error from the two-step price gradient estimation. Column (4) is identical to Figure 5. The other three columns show price gradients for lower wildfire score ranges. All price regressions include zip code fixed effects. Standard errors are calculated using block bootstrap by zip code.

Appendix Table 3: Wildfire risk pricing within rate segments

	Within Risk Score Segments			Zip code-based territories				Grid
	Allstate	Nationwide	State Farm	USAA	Liberty Mutual	AAA SoCal	State Farm	State Farm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AAL 50-99 (13% of Homes)	-17	-55	45	-57***	-10	-128***	75***	-27***
	(27)	(44)	(35)	(17)	(11)	(41)	(18)	(9)
AAL 100-199 (14% of Homes)	28	2	114**	-56**	-24**	-86*	136***	-43***
	(32)	(48)	(44)	(22)	(12)	(52)	(25)	(12)
AAL 200-299 (8% of Homes)	53	94	221***	-40*	-38**	-68	222***	-30**
	(37)	(68)	(48)	(23)	(15)	(60)	(32)	(15)
AAL 300-499 (10% of Homes)	17	84	246***	-26	-41***	-62	274***	-17
	(41)	(60)	(50)	(25)	(15)	(67)	(31)	(17)
AAL 500-749 (6% of Homes)	17	106*	337***	-8	-29	20	351***	16
	(42)	(60)	(55)	(29)	(20)	(75)	(33)	(20)
AAL 750-999 (3% of Homes)	19	79	363***	15	-13	47	391***	51**
	(45)	(68)	(58)	(37)	(20)	(94)	(38)	(23)
AAL 1000+ (7% of Homes)	37	109	426***	62*	57**	280*	469***	122***
	(54)	(80)	(75)	(33)	(24)	(143)	(40)	(27)
Structure Characteristics	✓	✓	✓	✓	✓	✓	✓	✓
Allstate Segments FE	✓		✓					
Nationwide Segments FE		✓						
USAA Segments FE				✓			✓	
Liberty Segments FE					✓			
AAA SoCal Segments FE						✓		
State Farm Segments FE								✓
Observations	95,352	95,351	95,351	95,297	94,025	55,641	95,296	95,351
Dependent variable mean	2,362	2,466	2,317	2,470	2,389	2,756	2,316	2,317

Notes: Table reports eight separate regressions. The omitted AAL range is 0 to 50, which contains 39 percent of homes. Structure characteristics include reconstruction cost, age of home, class A roof indicator, and public protection class. Standard errors are clustered by zip code.

Appendix Table 4: Value of information under duopoly, alternative switching costs

	$\delta = 0$	$\delta = 100$	$\delta = 500$	$\delta = 1000$	$\delta = \infty$
Allstate vs. State Farm					
Average Net Revenue Per Customer	1787	1792	1855	1932	2036
State Farm - Challenger Net Revenue Difference	150 (15)	101 (11)	53 (12)	44 (17)	-29 (26)
Market Share of Challenger	0.54	0.53	0.50	0.48	0.50
Share of Customers Switching Insurers	0.50	0.41	0.17	0.06	0.00
Nationwide vs. State Farm					
Average Net Revenue Per Customer	1768	1771	1835	1916	2086
State Farm - Challenger Net Revenue Difference	261 (13)	222 (11)	131 (12)	86 (17)	-138 (37)
Market Share of Challenger	0.56	0.55	0.48	0.46	0.50
Share of Customers Switching Insurers	0.50	0.43	0.20	0.09	0.00
USAA vs. State Farm					
Average Net Revenue Per Customer	1808	1813	1874	1955	2094
State Farm - Challenger Net Revenue Difference	182 (16)	146 (14)	57 (11)	20 (18)	-134 (37)
Market Share of Challenger	0.50	0.50	0.47	0.47	0.50
Share of Customers Switching Insurers	0.50	0.41	0.19	0.07	0.00
Liberty Mutual vs. State Farm					
Average Net Revenue Per Customer	1778	1781	1847	1938	2058
State Farm - Challenger Net Revenue Difference	250 (17)	188 (13)	26 (12)	-36 (20)	-65 (35)
Market Share of Challenger	0.44	0.45	0.48	0.50	0.50
Share of Customers Switching Insurers	0.50	0.43	0.20	0.07	0.00
AAA SoCal vs. State Farm					
Average Net Revenue Per Customer	2073	2076	2140	2221	2421
State Farm - Challenger Net Revenue Difference	211 (29)	163 (23)	54 (17)	35 (24)	-215 (51)
Market Share of Challenger	0.50	0.50	0.49	0.47	0.50
Share of Customers Switching Insurers	0.50	0.43	0.20	0.09	0.00

Notes: Table summarizes twenty-five duopoly scenarios with alternative switching costs and challenger firms competing against State Farm. Each home is randomly assigned to the Challenger or State Farm in period 0. The price for the non-period 0 firm for each home is then incremented by the indicated switching cost. State Farm - Challenger net revenue difference and standard errors are calculated with a GRID ID fixed effects regressions as in Table 5.

Appendix Table 5: The duopoly winner's curse in 1-in-500-year wildfire losses

	log(500-year loss)				
	Allstate	Nationwide	USAA	Liberty Mutual	AAA SoCal
	(1)	(2)	(3)	(4)	(5)
1[Win]	0.67***	0.38***	0.43***	0.35***	0.43***
	(0.10)	(0.11)	(0.05)	(0.05)	(0.11)
Structure Characteristics	✓	✓	✓	✓	✓
Allstate Segments FE	✓				
Nationwide Segments FE		✓			
USAA Segments FE			✓		
Liberty Segments FE				✓	
AAA SoCal Segments FE					✓
Observations	95,295	95,295	95,295	93,976	55,606
R^2	0.27	0.24	0.71	0.75	0.25
Dependent variable mean	7.87	7.87	7.87	7.86	7.53
Fraction Won	0.54	0.56	0.50	0.44	0.50

Notes: 1[Win] is an indicator for the firm's price being less than or equal to State Farm's price for that customer. Dependent variable is the property-level 1-in-500 year wildfire loss from the wildfire catastrophe model. Structure characteristics controls include reconstruction cost, age of home, class A roof indicator, and public protection class. Standard errors are clustered by zip code.

C Risk Load

This section describes how we approximate the risk load associated with covering the high wildfire hazard homes in our dataset. Our approach uses catastrophe model estimates of the variance of property-level losses. We use this information to calibrate an analytical "marginal surplus" risk load calculation (Kreps 1990). We first describe how we create a statewide pseudosample that allows us to explore the relationship between risk load and market share. We then present details on the marginal surplus calculation.

C.1 Constructing a statewide pseudosample

We calculate the risk load associated with successively larger portfolios of homeowners policies in high wildfire hazard areas of California. The following process generates a pseudosample that approximately replicates the full population of wildfire-threatened homes in California.

We start from our sample of 100,000 homes in 400 high-hazard zip codes. We augment these data with summary counts of total homes and high-hazard (score > 50) homes for all California zip codes from our data provider. In the course of this merge, we calculate that the 400 zip codes in our detailed sample account for about 75 percent of the total homes in California with wildfire scores above 50. We then define 800 zip code $\times$ hazard (score above/below 50) bins. In each of these bins, we draw homes from that bin with replacement until we reach the total number of homes reported for that bin in the zip code totals data. This "builds up" a sample that approximately matches the wildfire risk distribution for the true population of homes in these zip codes.[51] We can then study the relationship between risk load and market share by calculating risk loads associated with covering various fractions of these homes (10 percent, 20 percent, etc.). This exercise assumes that insurers equalize their market shares across zip codes, which is a reasonable approximation given the diversification benefits of such a strategy.

C.2 Marginal surplus calibration

Our wildfire catastrophe model data report the mean (AAL), standard deviation, and 99th, 99.6th, and 99.8th percentiles of annual wildfire losses for each property in our dataset. We do not observe information about the covariance of losses across properties. We assume a conservatively high degree of correlation given our interest in benchmarking approximate upper bounds on risk loads. Define each home i's probability of being exposed to a wildfire in a given year as f_i. Define the probability of destruction, conditional on exposure, as d_i, so home i's annual probability of destruction is $f_i d_i$. Let λ_{ij} be the correlation in annual wildfire experience between homes i and j. Assume d is independent across homes. One can

51. The need to stratify by high/low instead of simply resampling at the zip level arises because the process originally used to select these 100,000 homes was not a simple random sample.

show that the correlation in annual losses across homes i and j is

$$\rho_{ij} = \frac{d_i d_j \sqrt{f_i(1-f_i)}\sqrt{f_j(1-f_j)}}{\nu_i \nu_j},$$

where

$$\nu_i = \sqrt{f_i d_i(1-d_i) + d_i^2 f_i(1-f_i) + f_i(1-f_i)(d_i)(1-d_i)}.$$

See Section C.3 for the proof. We take d_i to be 0.5 for all i based on destruction probabilities conditional on exposure reported in Baylis and Boomhower (2022). We assume conservatively high annual exposure probabilities of 1 percent for all homes.[52] We define a 20-by-20 km grid over the state of California and assume that the correlation in annual wildfire occurrence for two homes in the same grid cell is 0.5, and that this correlation is zero across grid cells. These assumptions imply that ρ_{ij}, the correlation in realized losses, is 0.25 for homes in the same grid cell and 0 for homes in different grid cells.

Kreps (1990) derives the minimum necessary premium to add a portfolio of risks to an existing book of insurance contracts as

$$p = \mu + \mathbb{R}\sigma + E,$$

where μ is the average annual loss of the contracts being added, σ is the standard deviation of annual losses on the contracts being added, and E is a constant that captures administrative costs. Let S be the standard deviation of losses from the existing book of business, S' the standard deviation of losses from the combined book of business, C the correlation of losses on the new contracts with the existinb book of business, y a market cost of capital, and z a distribution statistic that reflects the firm's "acceptable probability of ruin". For example, if annual losses are distributed normally, setting $z = 2.65$ implies the firm will cover losses in 99.6 percent of years, enough for a 1-in-250 year event. Kreps shows that

$$\mathbb{R} \times \sigma = \underbrace{\frac{y}{1+y}}_{\text{capital cost}} \times \underbrace{z}_{\text{"distribution statistic"}} \times \underbrace{\frac{(2SC+\sigma)\sigma}{S+S'}}_{\text{change in s.d. of firm's losses}}.$$

The final term is the change in the standard deviation of the firm's losses after adding the new contracts to the portfolio. It can be derived by starting from the identity $Var(X+Y) = Var(X) + Var(Y) + 2Csd(X)sd(Y)$.

$$(S')^2 = S^2 + \sigma^2 + 2CS\sigma$$

$$(S')^2 - S^2 = \sigma(\sigma + 2CS)$$

52. Based on data in Buechi et al. (2021), we estimate that the average annual share of acres in California that experience a wildfire was 0.3 percent to 0.7 percent in each decade between 1979 and 2018.

$$(S' + S)(S' - S) = \sigma(\sigma + 2CS)$$
$$(S' - S) = \frac{\sigma(\sigma + 2CS)}{(S' + S)}.$$

Given an assumed correlation structure across homes, the data allow us to calculate σ for our portfolio of high wildfire hazard homes by summing standard deviations within and then across grid cells, again using the variance sum rule. We calibrate S to match the distribution of losses for an insurer with a countrywide portfolio of homeowners and automobile insurance policies using aggregate loss statistics from the Insurance Information Institute (III).[53] We assume that this insurer faces another catastrophe peril (e.g., hurricane, fire following earthquake) with expected annual losses of $200 million and coefficient of variation of 2.5.[54] We see these assumed hurricane/earthquake exposures as conservative for several reasons (1) we only assume one other peril type; (2) the hurricane AAL values we can observe in 10K filings are net of reinsurance (and so do not represent the full AAL); (3) we choose a coefficient of variation on the small side of reported values. We assume that wildfire losses are independent of all other types of losses. We set z equal to 2.65, so that the firm is required to meet its obligations up to a 1-in-250-year loss total. We assume the market return y on capital is 0.15.

Appendix Figure 3 shows the relationship between risk load $\mathbb{R}\sigma$ and market share. There is a clear convex relationship, reflecting the shrinking diversification benefit as the portfolio becomes relatively more concentrated in wildfire risk.

Table 2 in the paper reports details of the marginal surplus calculations. A 1 percent market share in the 400 high-hazard zip codes would represent about 28,000 insurance policies and $6 million in expected losses. The standard deviation of wildfire losses (σ) would be $15.7 million. The standard deviation of losses on the rest of the portfolio (S) is $500.1 million, and the addition of these 28,000 wildfire risks to the portfolio has only a small effect on the overall standard deviation (S'). The resulting risk load is about $100,000 dollars. This equals about 1 cent per dollar of wildfire AAL, or $3 per wildfire policy. The size of this risk load increases quickly with the number of wildfire policies. At a 20 percent market share, the risk load is 25 cents per dollar of AAL, or $54 per policy. The rate of increase in risk load with market share eventually slows as the variance of the portfolio becomes dominated by wildfire losses.

53. Our hypothetical insurer has 4.5 million U.S. homeowners policies and 4.5 million U.S. auto insurance policies. Based on III data on claims frequency and severity, homeowners insurance claims are an iid binomial process with annual claim probability of 5.92 percent and loss amount per claim of $15,091, while auto insurance claims are an iid binomial process with annual claim probability of 1.1 percent and loss amount per claim of $18,204. See https://www.iii.org/table-archive/21296 and https://www.iii.org/fact-statistic/facts-statistics-auto-insurance.

54. These numbers are calibrated to financial statements from real firms: Zurich Insurance Group (Farmers) reports an AAL of $192 million for North America hurricane losses (see Zurich Insurance Group, Annual Report 2022, page 136). The coefficient of variation is informed by publicly available catastrophe model predictions for hurricane wind losses from insurer filings with the Florida Commission on Hurricane Loss Projection Methodology. See page 205 of the RMS filing "North Atlantic Hurricane Models: Version 23.0 (Build 2250), May 19 2023" and page 191 of the CoreLogic filing "Florida Hurricane Model 2023, April 24, 2023 Version."

Appendix Table 6 illustrates the importance of other catastrophe exposures in this calculation. Our baseline scenario assumes an insurer with expected hurricane losses of $200 million and a coefficient of variation of hurricane losses of 2.5. The rows of Appendix Table 6 hold market share constant at 10 percent and vary the insurer's expected hurricane losses (maintaining the 2.5 hurricane coefficient of variation). If hurricane risk is zero, so that variability of non-wildfire losses is driven only by non-catastrophe homeowners and auto losses, the variability of wildfire losses dominates the overall portfolio and the risk load reaches 85 cents per dollar of AAL. Adding even a small amount of hurricane exposure quickly decreases this risk load. One interpretation of this pattern is that, given the larger magnitude of hurricane risk compared to wildfire risk in the United States, an insurer that is adequately capitalized against hurricane losses is well-positioned to handle wildfire risk.

Appendix Table 6: Sensitivity of risk load to other catastrophe perils

Hurricane AAL ($M)	Policies	Wildfire AAL ($M)	σ ($M)	S ($M)	S' ($M)	Risk Load ($M)	Average Risk Load per AAL ($)	Marginal Risk Load per AAL ($)
0	279,612	60	87.59	8.54	88.01	26.70	0.44	0.48
50	279,612	60	87.66	137.76	163.29	8.57	0.14	0.21
100	279,612	60	87.55	275.13	288.73	4.57	0.08	0.11
200	279,612	61	88.15	550.07	557.08	2.36	0.04	0.06
300	279,612	60	87.82	825.04	829.71	1.57	0.03	0.04
500	279,612	60	87.76	1,375.03	1,377.82	0.94	0.02	0.02

Notes: Table shows the sensitivity of marginal surplus calculations to an insurer's exposure to hurricane or other catastrophe perils, holding constant California wildfire market share at 10 percent. See text and appendix for details and assumptions.

C.3 Derivation of correlation in losses

F_i and F_j are Bernoulli random variables with success probabilities f_i and f_j and correlation λ_{ij}. D_i and D_j are independent Bernoulli random variables with success probabilities d_i and d_j. The correlation of realized losses F_iD_i and F_jD_j is, by definition,

$$\rho_{ij} = \frac{COV(F_iD_i, F_jD_j)}{\sqrt{VAR(F_iD_i)}\sqrt{VAR(F_jD_j)}}.$$

Bohrnstedt and Goldberger (1969) shows that the covariance term in the numerator has an asymptotic approximation as

$$\begin{aligned} COV^*(F_iD_i, F_jD_j) = {} & E[F_i]E[F_j]COV(D_i, D_j) + E[F_i]E[D_j]COV(F_j, D_i) \\ & + E[F_i]E[D_j]COV(F_j, D_i) + E[D_i]E[D_j]COV(F_i, F_j). \end{aligned}$$

The Ds are independent, so this simplifies to:

$$\begin{aligned} &= E[D_i]E[D_j]COV(F_i, F_j) \\ &= d_i d_j \lambda_{ij} sd(F_i) sd(F_j) \\ &= d_i d_j \lambda_{ij} \sqrt{f_i(1-f_i)} \sqrt{f_j(1-f_j)}. \end{aligned}$$

Goodman (1960) derives an exact formula for the variances in the denominator,

$$\begin{aligned} VAR(F_i D_i) &= E[F_i]^2 VAR(D_i) + E[D_i]^2 VAR(F_i) + VAR(F_i)VAR(D_i) \\ &= f_i^2 d_i(1-d_i) + d_i^2 f_i(1-f_i) + f_i(1-f_i)d_i(1-d_i). \end{aligned}$$

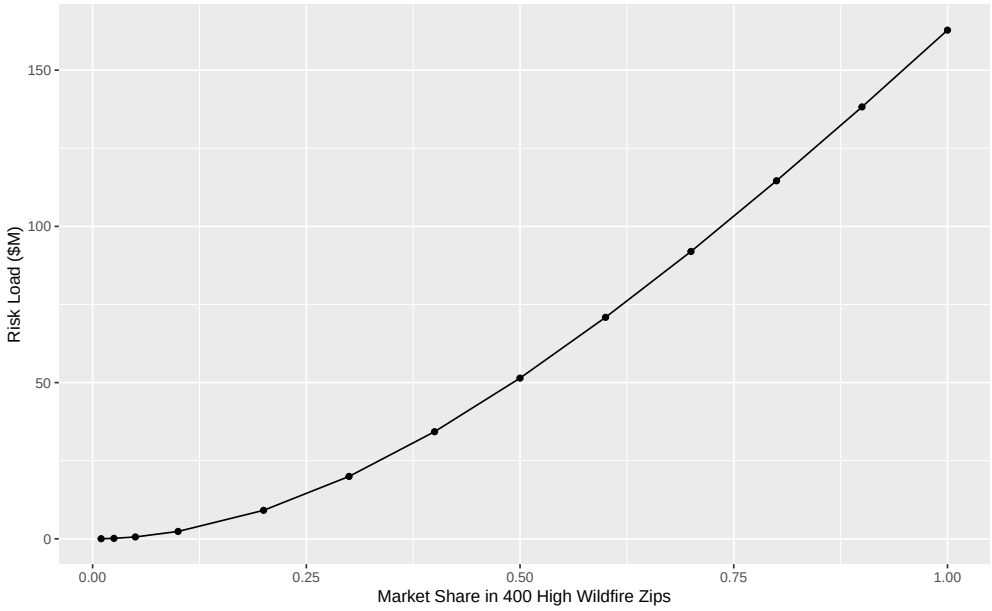
Putting things together yields

$$\rho_{ij} = \frac{d_i d_j \sqrt{f_i(1-f_i)} \sqrt{f_j(1-f_j)}}{\nu_i \nu_j},$$

where

$$\nu_i = \sqrt{f_i d_i(1-d_i) + d_i^2 f_i(1-f_i) + f_i(1-f_i)(d_i)(1-d_i)}.$$

Appendix Figure 3: Risk load versus market share in wildfire areas



Notes: Figure shows total risk load expenses due to the addition of a portfolio of California wildfire risks to a national property insurance portfolio. Horizontal axis shows fraction of total homes that the insurer covers in 400 zip codes that represent most high-hazard California homes. Vertical axis is risk load in millions of dollars. See text for details and assumptions.

D Proofs and Results for Equilibrium Model

1. Proof of Proposition I

The best-response of the dominant firm to a price P^F set by the fringe firms is the set of prices that maximize profits. For a given risk level l, the dominant firm can take all customers at a maximum price of $P^F - \delta$ or sell only to its current customers (a share α of the market) at a maximum price of $P^F + \delta$. Any price below $P^F - \delta$ reduces profits and any price above $P^F + \delta$ loses all customers. The low and high prices yield identical profits at $\tilde{l}$, defined by:

$$\pi^D = P^F - \delta - \tilde{l} = \alpha(P^F + \delta - \tilde{l}) \tag{23}$$

(23) is rearranged as $\tilde{l} = P^F - \delta\frac{1+\alpha}{1-\alpha}$. For $0 < \alpha < 1$, $|\frac{d\pi^D}{dl}|$ is greater for the low price than the high price strategy and, therefore, the low price (high price) strategy yield higher profits for $l < \tilde{l}$ ($l > \tilde{l}$). We next show that $\tilde{l} > 0$, which implies that $P^D = P^F - \delta$ is the best response for $l \in [0, \tilde{l})$. To establish this, we will a) solve for P^F, the price that makes fringe profits zero, and b) show that the condition $\bar{l} > \delta\frac{1+\alpha}{1-\alpha}$ implies $\tilde{l} > 0$. P^F satisfies:

$$\pi^F = \frac{1-\alpha}{2}(P^F - \tilde{l})^2 - \frac{1}{2}(l^* - P^F)^2 + \frac{\alpha}{2}\delta^2 = 0 \tag{24}$$

Solving for P^F yields $P^F = l^* - \delta\sqrt{\frac{1+3\alpha}{1-\alpha}}$, which is result 1 of the Proposition. If $P^F > \bar{l}$, then

$$l^* - \delta\sqrt{\frac{1+3\alpha}{1-\alpha}} > \bar{l} \tag{25}$$

$$\bar{l} > \delta\sqrt{\frac{1+3\alpha}{1-\alpha}} \tag{26}$$

where $l^* - \bar{l} = \bar{l}$. The second inequality is established by showing that $\frac{1+\alpha}{1-\alpha} > \sqrt{\frac{1+3\alpha}{1-\alpha}}$ and combining this with the condition $\bar{l} > \delta\frac{1+\alpha}{1-\alpha}$. Having established that $P^F > \bar{l}$, we have from the definition of $\tilde{l}$:

$$P^F = \tilde{l} + \delta\frac{1+\alpha}{1-\alpha} > \bar{l} \tag{27}$$

$$\tilde{l} > \bar{l} - \delta\frac{1+\alpha}{1-\alpha} > 0 \tag{28}$$

where the last inequality uses $\bar{l} > \delta\frac{1+\alpha}{1-\alpha}$. We have shown the first part of result 2: $P^D = P^F - \delta$ is the dominant firm's best response for $l \in [0, \tilde{l})$. The second part of result 2 is established from (23), where it was shown that $P^D = P^F + \delta$ yields the highest profits for $l > \tilde{l}$. $P^D = P^F + \delta$ maximizes profits for values of $l > \tilde{l}$ yielding positive profits. Dominant firm profits, $\pi^D = P^F + \delta - l$, are decreasing in l and equal zero at $l_1 = P^F + \delta$. Therefore, $P^D = P^F + \delta$ is a dominant firm's best response for $l \in [\tilde{l}, l_1)$, the second part of result 2. Finally, for values of $l > l_1$, dominant firm profits are negative and it maximizes profits

by not selling any insurance policies. It achieves this by setting a sufficiently high price, $P^D > P^F + \delta$, so that all customers are served by the competitive fringe. Thus, we have established the third part of result 2: $P^D > P^F + \delta$ is the dominant firm's best response for $l \in [l_1, l^*]$.

2. Results for the Equilibrium Model with Regulation

We show that the zero profit and average price isoclines in (21) and (22), respectively, are upward sloping at the unconstrained equilibrium. From (17), equilibrium profits for the fringe firms are given by:

$$\pi^F = \frac{1}{2}\left\{(1-\alpha)(P^F - \tilde{l})^2 - (l^* - P^F)^2 + \alpha\delta^2\right\} = 0 \tag{29}$$

Applying the Implicit Function Theorem, we obtain:

$$\frac{dP^F}{d\tilde{l}} = -\frac{\pi^F_{\tilde{l}}}{\pi^F_{P^F}} = \frac{(1-\alpha)(P^F - \tilde{l})}{(1-\alpha)(P^F - \tilde{l}) + l^* - P^F} > 0 \tag{30}$$

where $P^F - \tilde{l} > 0$ and $l^* - P^F > 0$ from the results $\tilde{l} = P^F - \delta\frac{1+\alpha}{1-\alpha}$ and $P^F = l^* - \delta\sqrt{\frac{1+3\alpha}{1-\alpha}}$. From (19), we have:

$$M = \bar{P} - \eta(P^F - \delta) - (1-\eta)(P^F + \delta) = 0 \tag{31}$$

where $\eta = \frac{\tilde{l}}{P^F - \delta}$ at the unconstrained equilibrium. Applying the Implicit Function Theorem, we obtain:

$$\frac{dP^F}{d\tilde{l}} = -\frac{M_{\tilde{l}}}{M_{P^F}} = \frac{2\delta(P^F - \delta)}{2\delta\tilde{l} + (P^F - \delta)^2} > 0 \tag{32}$$

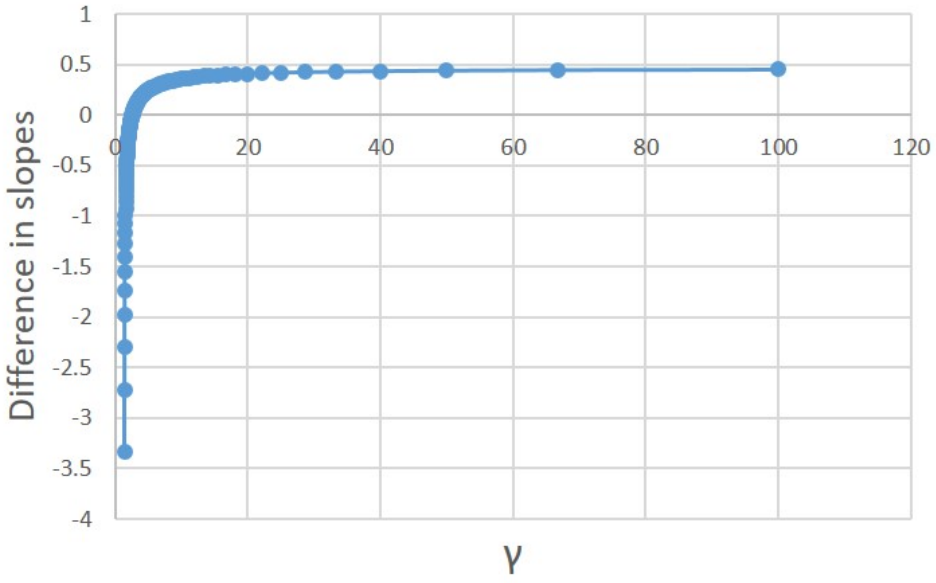
Numerical analysis is used to show that at the unconstrained equilibrium the relative magnitudes of the isocline slopes in (30) and (36) is indeterminate. It can be shown that scaling δ and l^* by a constant factor leaves the slopes in (30) and (36) unchanged. Therefore, we need only consider how the slopes vary with the ratio $\frac{l^*}{\delta}$ or, equivalently, $\gamma = \frac{\bar{l}}{\delta}$. Appendix Figure (4) shows that for $\alpha = 0.2$, the difference in slopes can be positive or negative. Except for small values of γ, the slope of the zero profit isocline is greater than that of the average price isocline.

An increase in $\bar{P}$ shifts up the average price isocline in (19). Fixing P^F and applying the Implicit Function Theorem to (31), we obtain:

$$\frac{d\tilde{l}}{d\bar{P}} = -\frac{M_{\bar{P}}}{M_{\tilde{l}}} = -\frac{[\tilde{l} + \alpha(P^F + \delta - \tilde{l})]^2}{2\delta\alpha(P^F + \delta)} < 0 \tag{33}$$

The decline in $\tilde{l}$ for fixed P^F gives the upward shift in the average price isocline depicted in Figure (11).

Appendix Figure 4: Difference in isocline slopes for different values of γ



Notes: Figure shows the slope of the zero profit isocline in (30) minus the slope of the average price isocline in (36) for $\alpha = 0.2$ and different values of $\gamma = \frac{\bar{l}}{\delta}$. Results show that the zero profit isocline is steeper than the average price isocline at the unconstrained equilibrium for values $\gamma \geq 2.6$.

When we redefine the risk distribution as $U(a, l^* + a)$, the zero profit condition in (29) becomes:

$$\pi^F = \frac{1}{2}\Big\{(1-\alpha)(P^F - \tilde{l})^2 - (l^* + a - P^F)^2 + \alpha\delta^2\Big\} = 0 \tag{34}$$

Holding P^F constant, an increase in a shifts the zero profit isocline up, as shown in Figure (12):

$$\frac{d\tilde{l}}{da} = -\frac{\pi^F_a}{\pi^F_{\tilde{l}}} = -\frac{l^* + a - P^F}{(1-\alpha)(P^F - \tilde{l})} < 0 \tag{35}$$

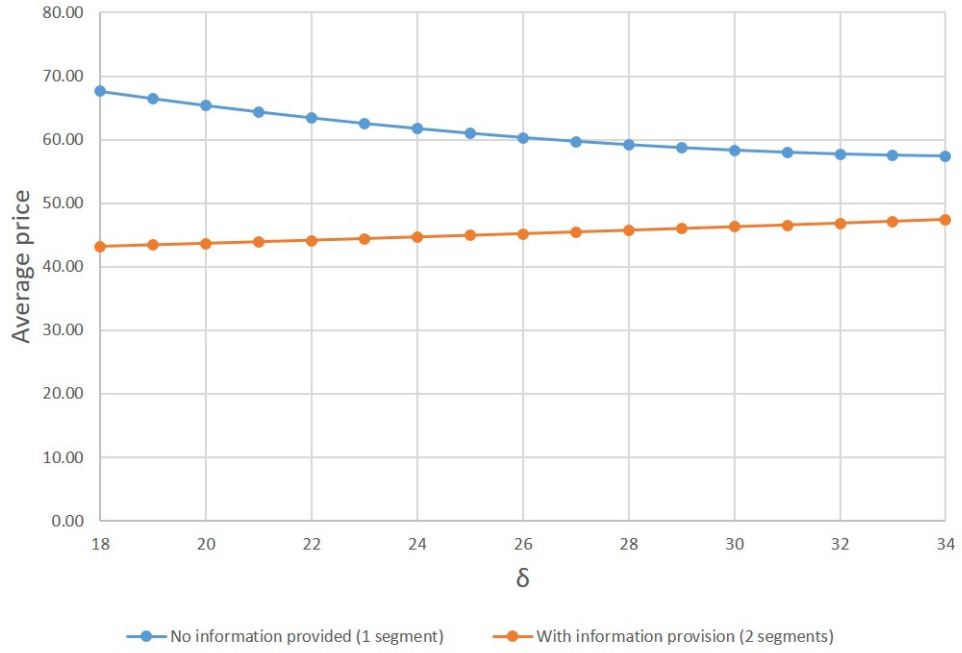
The average price condition is as written in (31) except that, at the unconstrained equilibrium, η is redefined as $\frac{\tilde{l}-a}{P^F-\delta-a}$. Holding P^F constant, an increase in a shifts the average price isocline down, as shown in Figure (12):

$$\frac{d\tilde{l}}{da} = -\frac{M_a}{M_{\tilde{l}}} = P^F - \delta - \tilde{l} > 0 \tag{36}$$

In case b depicted in Figure (13), $\tilde{l} < \bar{l}$. This means that when the segment is divided at $\bar{l}$, there will not exist values of $\tilde{l}$ below which the dominant firm wants to use the low price strategy. Rather, the equilibrium in each segment will be defined by a P^F that makes the fringe profits zero, as before, and a price of $P^F + \delta$ set by the dominant firm that retains its current customers. We use numerical analysis to explore how the overall average price

changes in this case. We set $\alpha = 0.2$ and $\bar{l} = 50$ and calculate the overall average price with and without information provision for δ values ranging from 18 to 34. The lower value of δ yields an $\tilde{l}$ just below $\bar{l}$ and the upper value yields an $\tilde{l}$ just above zero. Appendix Figure (5) shows that information provision reduces average prices for all values of δ.

Appendix Figure 5: Difference in overall average prices with information provision



Notes: Figure shows differences in overall average prices with information provision for case b depicted in Figure (13). Parameters values are $\alpha = 0.2$ and $\bar{l} = 50$. The δ parameter is varied between 18, which yields an $\tilde{l}$ value just below $\bar{l}$, and 34, which yields an $\tilde{l}$ value just above zero. As shown, information provision reduces the overall average price for all δ values.

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