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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

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ABSTRACT

As climate risk escalates, property insurance is critical to reduce the risk exposure of households and firms and to aid recovery when disasters strike. To perform these functions efficiently, insurers need to access high quality information about disaster risk and set prices that accurately reflect the costs of insuring this risk. 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 provided in a large market for homeowners insurance. 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 are consistent with a winner's curse, where firms with less granular pricing strategies face higher expected losses. 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.

Judson Boomhower
Department of Economics
University of California at San Diego
9500 Gilman Drive #0508
La Jolla, CA 92093
and NBER
jboomhower@ucsd.edu

Meredith Fowlie
Department of Agricultural &
Resource Economics
University of California, Berkeley
301 Giannini Hall
Berkeley, CA 94720-3310
and NBER
fowlie@berkeley.edu

Jacob Gellman
Department of Economics
University of Alaska Anchorage
3211 Providence Drive
Rasmuson Hall 205K
Anchorage, AK 99508
jgellman@alaska.edu

Andrew Plantinga
University of California, Santa Barbara
Bren School of Environmental Science
and Management
Rm 3424
Santa Barbara, CA 93106
plantinga@bren.ucsb.edu

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Judson Boomhower Meredith Fowlie
Jacob Gellman Andrew J. Plantinga*

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Keywords: Insurance, adverse selection, natural disasters, climate change, wildfire
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*(Boomhower) Department of Economics, University of California San Diego and NBER; jboomhower@ucsd.edu. (Fowlie) Department of Agricultural and Resource Economics, University of California Berkeley and NBER. (Gellman) Department of Economics, University of Alaska Anchorage. (Plantinga) Bren School of Environmental Science and Management, University of California Santa Barbara. We thank seminar participants at the NBER Summer Institute, NBER Insurance Working Group, the 2023 ASSA meetings, the 2024 AERE Summer Conference, TWEEDS, University of Chicago, Harvard University, MIT, Indiana University, Resources for the Future, the New York Federal Reserve, the San Francisco Federal Reserve, Stanford University, University of Alaska Anchorage, UC Berkeley, UC Davis, UC Santa Barbara, University of Southern California, University of Wisconsin, University of Illinois, University of Calgary, Georgia State University, and Oregon State University. We thank Josh Aarons, Kaleb Javier, and Kendra Marcoux for outstanding research assistance. We thank Benjamin Collier, Chris Costello, Mark Duggan, Penny Liao, Philip Mulder, and Joel Sobel for helpful discussions. This work received generous financial support from the University of California Office of the President Laboratory Fees Program (LFR-20-652467). Boomhower gratefully acknowledges funding via an Andrew Carnegie Fellowship from the Carnegie Corporation of New York.

1 Introduction

As the climate changes, natural disasters are increasing in frequency and intensity (Summers et al. 2022). Annual losses from natural disasters now exceed $120 billion.[1] Property insurance is critical to reduce households' and firms' exposure to the financial impacts of these disasters (Shi and Moser 2021). But there are mounting concerns that 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 the pricing of physical climate risk. 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 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 important 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 better information about climate risk exposure. These information asymmetries subject firms to potentially severe adverse selection, analogous to the winner's curse in the literature on common-value auctions (Engelbrecht-Wiggans, Milgrom, and Weber 1983; Hendricks and Porter 1988; Milgrom and Weber 1982).

We use parcel-level data on insurance premiums and risk analytics to directly measure how insurers are modeling and pricing climate risk. The results elucidate the roles of uncertainty, regulation, and adverse selection in the supply of property insurance. Along the way, we present new insights into how private insurance markets are developing and using catastrophe risk information. Our focus is wildfire risk, which represents the fastest-growing source of catastrophe-related damages in the United States.[2] 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 recognized as a substantial risk capable of threatening the solvency of private property insurers.[3] Despite this significance, wildfire risk remains underexplored in the economic literature addressing insurance market pricing, underwriting, and competition.

Our empirical setting is California's private market for homeowners insurance. California is home

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

2. 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.

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

to an estimated 4.6 million properties with moderate to high wildfire risk exposure, a number that is projected 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.[4] 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. 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. Rising premiums and stricter underwriting practices in high-hazard areas could reflect an efficient industry response to improved assessment of wildfire risk exposure. Alternatively, market or regulatory failures could be contributing to diminishing insurance affordability and availability. Isolating the root causes is critical at a time when industry regulators are under mounting pressure to intervene in insurance markets and reform insurance market regulations.

Our analysis proceeds in three steps. First, we develop a stylized model of cost-based insurance pricing. Canonical work on insurance markets (e.g. Jaffee and Russell 1997; Kreps 1990; Kunreuther 1996; Stone 1973) provides a relatively clear prescription for "fair and adequate" pricing in a competitive market for catastrophic risk insurance.[5] 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 protecting insurer solvency through capital surplus or reinsurance. Within the context of this model, we derive cost-based insurance pricing schedules using probabilistic estimates of expected, parcel-level wildfire losses. These risk price gradients serve as benchmarks in our empirical analysis of the pricing behavior we observe in the market.

Next, we use detailed rate cases filed with California's insurance market regulator, together with the proprietary information firms use to assess risk exposure, to construct parcel-specific insurance premiums charged by several large insurers. We use these rate schedules, which specify a complete mapping between home characteristics and insurers' premiums, to isolate the underlying relationships between firms' risk pricing and assessed wildfire risk exposure. Comparisons between the risk pricing we observe and our cost-based benchmark reveal notable differences. For the insurer with the most granular wildfire risk information, insurance prices increase commensurately with assessed wildfire risk. In contrast, among insurers that use relatively coarse information, prices rise faster than assessed levels of wildfire risk exposure across otherwise similar parcels in higher wildfire risk segments. In the highest-risk segments, we see pricing patterns that are consistent with rate

4. 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).

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

suppression that can manifest under binding rate regulations (Harrington 1992; Jaffee and Russell 1998).

We investigate potential explanations for these empirical patterns, starting with adverse selection. If relatively uninformed firms understand that they serve an adversely selected share of homes in a market segment, they should adjust their prices in response (Hendricks and Porter 1988; Milgrom and Weber 1982). We are uniquely positioned to assess the size of the winner's curse in a pricing game where firms differ in the sophistication of their pricing formulas. We show that the expected wildfire losses associated with customers who purchase from relatively uninformed firms in a stylized model of competition are substantially higher than the average costs among properties that appear identical to the insurer. The insurance pricing patterns we observe are consistent with firms adjusting for this anticipated winner's curse. In addition, conservative pricing behavior could also reflect ambiguity aversion and high capital surplus costs. However, because insurers in our data are similar along key observable dimensions – such as credit rating and loss ratios – it is harder to rationalize the differences in pricing strategies with these explanations.

Motivated by this empirical evidence, we develop an equilibrium model of the property insurance market to analyze interactions between information asymmetries and regulatory constraints. In the model, 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 fixed adoption cost. We show how the value of more sophisticated information increases with a firm's insurance market share. If the costs of adopting and using more sophisticated risk information are sufficiently high, only the firm with the largest market share adopts. The resulting information asymmetries expose less-informed firms to adverse selection. The model predicts that the more-informed firm captures the low-risk customers within a risk segment while the relatively less-informed firms raise their prices to avoid selling unprofitable policies to high-risk customers. The overall effect is an increase in the average price of insurance. The model also elucidates how information asymmetries can exacerbate the effects of price regulation for relatively uninformed firms, and accelerate exit from high-risk segments. Finally, we show how improving access to better risk information could offer an effective approach to ensuring that insurance is fairly priced and available.

This paper's findings are relevant to public conversation about climate risk and insurance regulation (U.S. Department of the Treasury 2023). Across the country, rising insurance premiums are being attributed to escalating climate risk, in addition to other important cost drivers such as construction cost inflation.[6] In California, insurer exit is being ascribed to regulations that restrict prices below the expected costs.[7] We argue that, while important, these explanations are incomplete. Our

6. See, for example: CBS News. (2023). Homes in parts of the U.S. are "essentially uninsurable" due to rising climate change risks. https://www.cbsnews.com/news/insurance-policy-california-florida-uninsurable-climate-change-first-street/

7. See: 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.

results point to a more nuanced story in which imperfect information, together with increasing wildfire risk, puts upward pressure on insurance prices. These 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 may 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 Kunreuther (1996) and Jaffee and Russell (1997) examines the causes of private market failures in catastrophe insurance and the conditions that must be established to make these markets viable. Related work has investigated the response of insurance markets to catastrophic events (Born and Viscusi 2006; Klein and Kleindorfer 1999), the pricing of climate risks (Gourevitch, Kousky, and Liao 2023), and the performance of public markets for catastrophic flood insurance (Bradt, Kousky, and Wing 2021; Gallagher 2014; Hennighausen et al. 2023; Mulder 2021; Wagner 2022a). We extend this literature to consider the market for wildfire risk insurance.

Our work is germane to an expansive literature on adverse selection in insurance markets (Akerlof 1970; Einav, Finkelstein, and Cullen 2010). Innovations in generative artificial intelligence and associated analytics are increasing the sophistication of proprietary assessment tools (Einav, Finkelstein, and Mahoney 2021). Prior work has examined the impacts of proprietary risk information on less-informed competitors who face an adversely selected pool of customers in markets for auto loans (Einav, Jenkins, and Levin 2012) and auto insurance (Jin and Vasserman 2021). We extend this line of inquiry to markets for wildfire risk insurance. Whereas in other settings, asymmetric information can lead to market unraveling (see, for example, Einav and Finkelstein 2011), we show how information asymmetries on the supply side can lead to higher premiums and increased market concentration in markets where the purchase of insurance is effectively mandatory.

Lastly, we contribute to the literature investigating insurance market economic regulation. Past work has explored supply-side implications of capital requirements and dynamic pricing regulations across a range of insurance market contexts (Aizawa and Ko 2023; Ge 2022; Koijen and Yogo 2015). Our paper is closely related to work investigating how private property insurers respond to economic regulation (Born and Klimaszewski-Blettner 2013; Oh, Sen, and Tenekedjieva 2022; Taylor, Turland, and Weill 2023). We leverage parcel-level data to show how economic regulations interact with asymmetries in risk information across insurers. These considerations are crucial in the development of insurance reform.

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 describes 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 investigates possible mechanisms. 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, wildfire losses are 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.[8] Because most mortgage lenders require HO insurance coverage as a mortgage precondition, a large majority of U.S. homeowners hold HO insurance.[9] Multi-peril HO policy terms typically last for one year. Holders receive annual renewal statements that include information about any changes to rates or policy terms. Contracts are automatically renewed unless they are canceled by insurers or homeowners.

2.2 Wildfire risk

Wildfire risk is escalating across the United States. In California, projected annual increases in wildfire risk exceed 1 percent in some of the highest-hazard zip codes (Dixon, Tsang, and Fitts 2018). Multiple factors explain this trend, including climate change, population growth in the wildland-urban interface, and a history of aggressive fire suppression practices.

As wildfire damages increase, more resources are being allocated to the modeling and analysis of wildfire risk. The use of catastrophe ("CAT") models to inform the pricing of catastrophe risk associated with earthquakes and hurricanes dates back to the 1980s. More recently, these models are being used to simulate wildfire damage probabilities based on factors such as meteorology, topography, vegetation type, and dwelling characteristics. 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. Although CAT models have significantly improved insurers' ability to assess wildfire risk, these projections are still inherently uncertain.

2.3 Insurance market regulation

State regulators exercise considerable authority over insurers' entry, exit, insurance premium setting, underwriting, and claims settlement choices. These regulations are partly rationalized on the basis of market failures. Given the complexity of property insurance contracts, households face

8. See: 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.

9. If a homeowner neglects to purchase and hold HO insurance, their lender will purchase "force-placed insurance" which is typically more expensive and only covers the bank's interest in the house. An estimated 88 percent of U.S. homeowners hold HO insurance. See: Insurance Information Institute. (2023). Homeowners Perception of Weather Risks 2023Q2 Consumer Survey. https://www.iii.org/sites/default/files/docs/pdf/2023_q2_ho_perception_of_weather_risks.pdf.

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.

There are other features of the market that motivate regulatory intervention but are not failures in the economic sense. 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.[10] High prices are a leading concern that has motivated regulatory oversight of firms' underwriting practices across the United States. Although high premiums 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.

The stated objective of California's Department of Insurance (CDI) is to promote solvency, affordability, and availability of insurance. 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).[11] Requests to increase premiums earned across a book of business by more than 6.9 percent can be subject to costly public rate hearings. California regulations also limit how insurers use simulation-based stochastic risk models in the pricing of insurance. Insurers cannot use CAT models to justify an overall rate of increase in earned premiums. Instead, they must appeal to the historical record of their past catastrophe claims.[12] Insurers can – and do – use these models to segment risks or price differentiate on the basis of assessed wildfire risk exposure.

3 Data and Descriptive Facts

This section introduces the datasets used in the analysis and highlights some empirical facts. Section 3.1 discusses publicly-available information on aggregate insurance claims, prices, and availability. Section 3.2 introduces the new dataset of insurer-level, structure-specific insurance price schedules that we created for this project. All of these datasets are described in more detail in Appendix A.

3.1 Publicly-available administrative data

Annual insurer profits are variable: The National Association of Insurance Commissioners (NAIC) tracks industry profits by state and by insurance line. Appendix Figure 1 summarizes

10. Insurance contracts are considered "contracts of adhesion" in which the consumer must either accept the terms of the policy or reject the terms and accept similar terms from another company.

11. Rate regulations apply to "admitted market" insurers, which comprise 98 percent of the California insurance market (Dixon, Tsang, and Fitts 2018). "Surplus lines" are not subject to the same regulations.

12. See California Code of Regulations Title 10, § 2644.5 - Catastrophe Adjustment: "The catastrophic losses for any one accident year in the recorded period are replaced by a loading based on a multi-year, long term average of catastrophe claims. The number of years over which the average shall be calculated shall be at least 20 years for homeowners multiple peril fire."

state-level data on insurer profits in the U.S. homeowners insurance market over the period 1985 to 2021. 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. California's catastrophic wildfires in 2017 and 2018 erased several years of modest insurer profit. Similar losses have occurred across the country due to other natural disasters, such as hurricanes.

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 in premiums were required to report zip code-level information about the assessed wildfire risk exposure of the properties they insure. This includes information about the distribution of insured parcels across wildfire risk categories. We use these data to classify zip codes into wildfire risk quantiles, a process which is detailed in Appendix A. We will later show that assessed wildfire risk varies significantly *within* zip codes, so these measures should be interpreted as coarse measures of wildfire risk. Figure 1 summarizes zip code-level average increases in HO insurance premiums over time, in 2020 dollars. 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.

Insurance availability is declining: The CDI also collects information on the number of housing units insured by the admitted market. The second panel of Figure 1 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; these reductions were particularly significant in the highest-risk zip codes. The third graphic in Figure 1 tracks participation in the California FAIR Plan which provides basic backstop coverage for properties that cannot find coverage in the admitted market.[13] Growth in FAIR Plan participation has been increasing since 2018. Increases are most pronounced in the highest risk areas.

Rates of consumer switching are low: The bottom panels of Figure 1 summarize trends in insurance policy cancellations (non-renewals). 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.[14] The right-hand panel shows customer-initiated policy cancellations. These rates have historically hovered around 8 percent. Low rates of switching despite significant variation in premiums across insurers and across time suggests that consumers may be inattentive to insurance pricing. We posit that most households only consider HO insurance choices when purchasing a home. Rates of consumer switching in California align with median homeowner tenure,

13. The FAIR Plan is instituted at a state level but is backed by admitted market insurers. Companies share in FAIR Plan profits, losses, and expenses in an amount proportionate to their statewide market share.

14. This increase coincides with the introduction of Senate Bill 824 which imposed a one-year moratorium on insurance companies canceling insurance policies in or adjacent to wildfire perimeters.

which ranges from 11 to 13 years.[15]

Economic regulation appears binding: In California, the regulatory filings that insurers submit to request rate changes are all in the public domain.[16] Figure 2 summarizes 636 requested rate increases filed with CDI from 2008 to 2023 for owner-occupied homeowners' insurance (HO-3) policies. The figure shows how these rate increase requests are bunched at 6.9 percent, the threshold beyond which insurers may face costly public rate hearings. This suggests that pricing regulations have been a limiting factor in California. More recently, firms have been requesting increases of 20 percent or more and incurring the costs of negotiating public hearings.

3.2 New data on prices and risk from proprietary data

We have created several new datasets that allow us to analyze insurer- and property-specific pricing of wildfire risk. In this section, we summarize several insights.

3.2.1 Wildfire risk pricing strategies vary across insurers

Insurers in California's admitted market must submit detailed documentation of the data sources, formulas, and risk factors they use to set insurance premiums. We extract information from these documents to construct the pricing formulas used by the ten largest California homeowners insurance groups and the FAIR plan. This exercise identifies the precise risk variables used by each insurer to price wildfire risk, as well as changes over time in those pricing methods.

Table 1 summarizes some of this information for 2021 rates. The table reveals a surprising amount of heterogeneity in the granularity and sophistication of wildfire risk pricing methods across major insurers. Column (1) reports insurer market shares across the state of California, while column (2) focuses on market share in the 20 percent of zip codes with the highest average 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. Other private insurers tend to be under-represented in high-hazard zip codes compared to their statewide presence, while the FAIR plan is substantially over-represented.

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 in the location of a given home.[17] Some insurers price wildfire risk using zip code-level territory factors. Other insurers use parcel-level categorical wildfire risk scores based on qualitative factors such as slope, vegetation, fuel load, and road access. Finally, some insurers use more granular measures generated using relatively

15. See: Anderson, Dana. (2022). The Typical U.S. Home Changes Hands Every 13.2 Years. Redfin. https://www.redfin.com/news/2021-homeowner-tenure.

16. Individual filings are publicly available from: CDI. (2024). Web Access to Rate and Form Filings (WARFF). http://www.insurance.ca.gov/0250-insurers/0800-rate-filings/0050-viewing-room.

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

sophisticated approaches, including probabilistic CAT models. In general, it is the firms with the largest market share in high-hazard zip codes that use the most granular risk segmentation.[18]

Why do all firms not use the most advanced and granular pricing methods? We posit that direct and indirect cost considerations are important. Licensing a state-of-the-art wildfire model for insurance use costs millions of dollars per year.[19] The indirect costs of adoption include adapting the firm's internal systems and employing professional staff to use these models. Insurers must also navigate the extensive regulatory approvals required to use these models for pricing. In California, prior approval regulations require each insurer to present evidence that their proposed prices are actuarially justified for their own book of business. These rules also limit firms' ability to mimic the approved premiums charged by other insurers. Thus, for firms with a limited presence in California wildfire areas, the fixed costs of adopting more granular pricing methods may exceed the benefits. We return to this cost-benefit trade-off in the equilibrium model in Section 7.

3.2.2 Assessed wildfire risk varies across homes

We obtain detailed and proprietary wildfire risk and property characteristics data from CoreLogic, Inc., a leading provider of property information and risk analytics. Our sample includes 100,000 single-family homes equally divided across 400 California zip codes that have high average wildfire risk and non-trivial variation in within-zip code wildfire risk. Details on the sampling procedure are in Appendix A. There are three components of these data: property-level characteristics, wildfire risk scores, and state-of-the-art catastrophe model predictions of wildfire loss.

The property characteristics data include estimated reconstruction cost, year of construction, fire department quality, and many other variables commonly used to price insurance. CoreLogic's proprietary, parcel-level Wildfire Risk Score (WRS) is also used by some insurers in California to price insurance. The WRS is a 5-to-100 integer score that incorporates factors influencing wildfire hazard, such as slope, aspect, fuel, surface composition, drought and wind, at a 30-meter resolution. Table 2 summarizes these property characteristics and categorical risk scores. The average home in the dataset was built in 1976, is 2,135 square feet, and would cost about $600,000 to rebuild.

We also obtain parcel-level risk metrics generated by CoreLogic's 2021 probabilistic CAT model. For each property, we observe probabilistic dollar-denominated measures of annual average loss, standard deviation of losses, and aggregate exceedance probability (AEP) losses over return periods of 50, 100, 250, and 500 years. Throughout this paper, our preferred measure of assessed parcel-level risk exposure will be the CoreLogic estimates of average annual loss (AAL) which represents the average of simulated yearly losses from wildfire across thousands of model realizations for each property in the dataset. Table 2 shows that the mean and standard deviation of wildfire AAL from the catastrophe model are $303 and $596. The wildfire AAL varies significantly across parcels.

18. Throughout the paper, we use the shorthand phrases "more-informed" and "less-informed" to refer to firms that price wildfire risk using more or less sophisticated approaches.

19. 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.

Regressing AAL on zip code fixed effects and categorical WRS scores explains 46 percent of the total variation in assessed AAL. Column (4) of Table 1 reports the R^2 in a regression of parcel-level AAL on risk rating factors for a subset of insurance groups. One important implication of this analysis of variation is that firms with more risk rating variables capture more of the variation in expected losses compared to firms using fewer risk rating variables.

AAL metrics are model-generated and uncertain. Validating these AAL estimates is difficult because the ground truth is unknown. In recent work, Wylie et al. (2024) find that CoreLogic AAL estimates compare reasonably well against recorded long-run historical wildfire losses and correlate moderately well with AAL metrics generated by the non-profit First Street Foundation. In what follows, we also conduct auxiliary analyses using publicly provided measures of parcel-level wildfire damage probabilities provided by the US Forest Service.

3.2.3 Parcel-specific insurance prices vary across insurers

We combine the property characteristics and WRS variables with the information assembled from insurer rate filings to reconstruct the exact prices that would be charged to each of the 100,000 homes in our dataset by six of the ten largest California homeowners insurance groups. These six firms price wildfire risk using CoreLogic wildfire risk scores and/or geographic territory factors. They collectively represent 45 percent of the California market.[20] This generated dataset is unique in that it includes complete price menus for each firm, versus the subset of transaction-based prices paid by customers who choose to buy from a given firm.[21]

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. They also depend on *occupant* characteristics and coverage choices. To construct insurer-level premiums, we assume constant reference values for these occupant characteristics.[22] Appendix A describes how we construct these insurance prices in more detail.

The middle panel of Table 2 summarizes these calibrated insurance prices. The average insurance price for the homes in our data is very similar across insurers. The five firms that operate statewide all charge average prices close to $2,400 per year. The sixth firm, AAA Southern California, operates only in the southern part of the state and thus we only observe prices for about half of the homes in the data for that firm. The final panel of Table 2 shows significant dispersion in prices offered by

20. We are unable to calculate parcel-specific prices for the other large insurers because they use wildfire analytics from other data providers, such as Verisk's FireLine scores.

21. 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 to new customers in some market segments. Thus, some of the prices we calibrate would only be available to existing customers. Some firms also engaged in non-renewals of a subset of existing customers in some segments.

22. 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. About 78 percent of consumers bundle their HO and auto policies. See: J.D. Power. 2015 US Household Insurance Study.https://www.jdpower.com/business/press-releases/2015-us-household-insurance-study.

these insurers for a given home. The average standard deviation in premiums offered to a home in our data set is $578. The average range between the minimum and maximum price offered is almost $1,500. In other words, whereas the insurance prices offered to homes in our data are quite similar on average, the prices offered to any particular home differ substantially across insurers.

4 Theoretical Cost-Based Benchmark

Fair, adequate, and affordable insurance prices are guiding principles for insurance market regulation. In this section, we construct 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 extend the model to account for the risk-based market segmentation that insurers use to price risk in the California market. We define the "fair" price to be that which reflects insurers' expected costs. We formulate a cost-based gradient to summarize how these costs increase 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 the 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, households must purchase insurance to qualify for a mortgage. Thus, the purchase of a home places a household into an active insurance choice situation. Additional factors that could induce a homeowner to search for insurance actively include policy cancellation or a price shock. We assume that households making an active choice select a single contract to maximize indirect utility u_{ij}, where $u_{ij} = \delta_j - p_{ij}$. 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 switching costs for those households who already hold insurance.[23]

The value associated with choosing a firm other than j is given by $\bar{u}_{ij} = \max_{-j}(\delta_{-j} - p_{i,-j})$, where $-j$ indexes insurers other than insurer j. Demand for firm j is thus:

23. When two firms yield identical utility, we assume the household randomizes which to buy.

$$Q_j = \sum_i 1[\delta_j - p_{ij} \geq \bar{u}_{ij}]. \tag{1}$$

Insurer j's book of business, Ω_j, is comprised of the group of customers who are choosing, actively or passively, to purchase insurance from insurer j.

When considering 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_j.[24]

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:

$$c_j = \sum_i (l_i + a_i) 1[\delta_j - p_{ij} \geq \bar{u}_{ij}] + \phi(\Omega_j) + F_j, \tag{2}$$

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 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 ($l_i > 0; a_i = a$). The slope of this relationship is:

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

The β_{ij} parameter measures the increase in the insurance costs associated with a unit increase in expected disaster 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

24. 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.

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 with risk segmetnation

Due to modeling limitations and feasibility constraints, many 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 $s(l_i) \in \{s_0, s_1, ..., s_K\}$. 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 s_k. The expected cost associated with parcel i in segment k is now given by:

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

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.

Analogously to Equation 4, for a segment with positive risk ($\bar{L}_{k(i)} > 0$) compared to a segment with zero risk ($\bar{L}_0 = 0$), the cost-based price gradient β_{kj} can be formulated as:

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

The β_{kj} parameter measures the increase in the segment-average insurance costs associated with a unit increase in the segment-average expected loss. In general, $\beta_{kj} \neq \beta_{ij}$.

4.3 Marginal surplus calculations

To calibrate Equation 4, we need an estimate of insurers' 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:

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

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_j, the standard deviation of losses from the combined book of business S'_{ij} with the addition of parcel i, the standard deviation of annual losses associated with parcel i, σ_i, and the correlation of losses between the new parcel and the existing book of business, C_{ij} (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.

Appendix Table 3 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. For a representative 30 percent market share in high-hazard zip codes, we estimate that taking on an additional dollar of California wildfire risk exposure increases surplus requirements by about \$0.18.[25] The largest HO insurer in California claims less than a 20 percent share in higher-hazard zip codes (see Table 1). If we conservatively assume a market share of 30 percent, this implies that an additional dollar of wildfire risk exposure should increase insurance costs by no more than \$1.18. Additional insights are provided in Appendix C.

4.4 An illustrative example

In the following section, we will use these estimates of marginal surplus costs, together with parcel-level AAL metrics and categorical risk scores, to estimate relationships between wildfire risk and cost-based insurance pricing. Because different insurers use different risk segmentation strategies, we will calibrate Equation 6 differently for the various insurers in our data. First, we provide an example of the consequences of segment pricing for the measurement of this gradient.

Figure 3 illustrates an example of a hypothetical insurer that segments the market using CoreLogic's categorical risk scores. In other words, risk premiums vary across but not within risk score categories. 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 Core Logic risk segment. Average losses increase with the risk score values, making these categorical scores a valuable proxy for expected losses. The box plots also 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.

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

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 cost-based 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 solid 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 $\beta_{kj} = 1.18$.

The dashed line in Figure 3 shows a locally-weighted regression of these risk segment-based prices on *parcel*-level AAL values. This relationship between segment-based pricing and *parcel*-level risk exposure deviates significantly from the full-information, cost-based price gradient. 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 "errors" result from using segment-average AAL to proxy for parcel-level risk exposure. More granular risk pricing would lower (increase) prices on average for low-risk (high-risk) customers. Thus, pricing wildfire risk on the basis of more granular information would change the distribution of insurance costs across households.

Figure 3 illustrates a cost-based risk pricing gradient benchmark for one particular risk pricing strategy. In what follows, we will construct benchmarks for each of the insurers in the data according to their risk segmentation strategy. Absent selection concerns, segment-level average costs provide a reasonable proxy for an insurer's expected costs. We later extend the analysis to consider the potential cost implications of risk information asymmetries.

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. First, we establish the risk segmentation strategy used by each insurer whose prices we can reconstruct. Then we estimate empirical risk price gradients for each insurer and compare these against corresponding, cost-based benchmarks.

5.1 Market segmentation strategies

The six insurers we analyze can be grouped into three risk pricing strategy types:

- **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 use CoreLogic wildfire risk scores to segment the market, price insurance, and define eligibility criteria.
- **Type 3 firms** include USAA and State Farm. USAA uses wildfire-specific zip code factors that are calibrated using granular, probabilistic wildfire catastrophe model predictions. State Farm assesses wildfire risk at a 1 square km resolution using wildfire CAT model predictions.

To illustrate these different risk segmentation strategies, we use a regression-based variance decomposition exercise. 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:

$$p_{ijk} = g_j(R_i) + X_i\psi_j + \sum_k \varsigma_{jk} D_k + f(L_i;\varphi_j) + \varepsilon_{ijk}. \tag{8}$$

We parameterize a flexible function of parcel-specific CoreLogic AAL values $f(L_i)$ using a step-wise function of L_i with bin widths of \$25. 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. The variable φ_j is an insurer-specific vector of coefficients that summarize the relationship between residual variation in assessed AAL and insurance premia.

We estimate Equation 8 using increasingly granular sets of risk segmenting variables D_k. 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 red lines in these panels summarize the average relationship between insurance premiums and AAL, controlling only for reconstruction cost. 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. The purple lines summarize the φ_j coefficients when including indicators for CoreLogic wildfire risk scores, in addition to protection class and reconstruction costs, but without zip code fixed effects.

For Type 2 firms, Allstate and Nationwide, adding the CoreLogic wildfire risk score indicators absorbs all of the variation in p_{ijk} because these controls capture all of the risk information that these firms use to price wildfire risk. For Type 1 firms, Liberty Mutual and AAA Southern California, all residual price variation is absorbed by zip code fixed effects.

Results differ for the two firms with the most sophisticated risk pricing strategies: USAA and State Farm. USAA uses CAT modeling results 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, inclusion of zip code dummies and fire protection class fully absorbs the relationship between L_i and USAA 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 risk 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, which we investigate in more detail in Section 6.

5.2 Econometric specifications and identification

Having identified the risk segmentation strategies used by each insurer, we can now estimate the empirical analog of Equation 6. We use different empirical approaches for insurers based on their risk segmentation strategy.

5.2.1 Econometric specification for Type 2 insurers

For Type 2 insurers, Allstate and Nationwide, we have many parcel observations within each risk segment. This allows us to estimate segment-level average AAL values with precision. Let D^*_{jk} be indicator variables for the k segments that firm j uses to price wildfire risk. For each insurer, we estimate the following two equations:

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

$$p_{ijk} = \mu_j + \sum_{k=1}^{K_j} \gamma_{jk} D^*_{jk} + X_i \theta_{2j} + g_j(R_i) + \xi_{ijk}, \tag{10}$$

where L_{ik} denotes the parcel-level AAL and p_{ijk} denotes the insurance premium charged by insurer j for parcel i. The variables $g_j(R_i)$ and $h_j(R_i)$ 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 parameters ψ_j and μ_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_{kj} parameters defined by Equation 6. These β_{kj} parameters can be estimated by simple bivariate regression of the estimated γ_{jk} on the estimated λ_{jk}. We weight this bivariate regression according to the number of homes in each risk segment and calculate standard errors for β_{kj} by bootstrapping all steps of the estimation procedure using a zip code-level block bootstrap.

These regressions will consistently estimate β_{kj} 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, which focus on variation across segments, we also estimate a specification that models insurer profits within a risk segment. The dependent variable is the parcel-level insurance premium net of assessed parcel-level AAL:

$$(p_{ijk} - L_{ik}) = \iota_j + \sum_k \omega_{jk} D^*_{jk} + X_i\theta_{3j} + m_j(R_i) + \sum_b \kappa_{jb} B_{ib} + \nu_{ijk}. \tag{11}$$

The ω_{jk} parameters recover the average difference between insurance prices and parcel-level measures of AAL within a risk segment. We assign parcels to AAL bins b, with $B_{ib} = 1$ when parcel i is in bin b. The κ_{jb} coefficients estimate the average residual difference in net revenues relative to the omitted lowest wildfire risk category. Within a market segment, parcels associated with wildfire risk will yield lower net revenues.

5.2.2 Econometric specification for Type 1 and Type 3 insurers

The econometric approach for the Type 1 and Type 3 firms that use a larger number of risk segments (i.e. zip codes or location rating factors) is similar, but involves an additional step to address attenuation bias in the estimated risk-price gradient. When firms use many risk segments, we observe a small number of parcels in each risk segment. As a result, there is greater sampling error in the estimated λ_{jk} coefficients from Equation 9. This sampling error introduces measurement error into the bivariate OLS regression of γ_{jk} on λ_{jk} that yields the risk price gradient β_{kj}, leading to attenuated estimates of β_{kj}. To mitigate this problem, we estimate the bivariate regression of γ_{jk} on λ_{jk} by two-stage least squares (2SLS), using the CDI measure of wildfire risk introduced in Section 3.1 as an instrument for γ_{jk}. This approach of instrumenting for one noisy measure of risk with another noisy measure of risk reduces attenuation bias[26]. Appendix D discusses this IV

26. See for example Wooldridge (2010), Section 5.3

strategy in detail.

5.3 Empirically-estimated risk price gradients

The empirical exercises described above generate a large number of risk segment-specific 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 empirical risk price gradients, i.e. the β_{kj} parameters.

5.3.1 Empirical risk price gradients for Type 2 insurers

Figure 5 summarizes the γ_{jk} and λ_{jk} coefficient estimates for the Type 2 firms, Allstate and Nationwide. The vertical axis plots the λ_{jk} coefficient estimates with confidence intervals from Equation 10. The horizontal axis plots the γ_{jk} estimates with confidence intervals from Equation 9. Each marker corresponds to a different market segment. In the top panel of Figure 5, all regressions include indicators for Allstate's market segments. The bottom panel summarizes a similar exercise that includes indicators for Nationwide's market segments, which are defined more coarsely.

Panels (a) and (d) report results from the specifications that omit zip code fixed effects. In these specifications, 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 (a) 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 span the upper and lower bounds of the cost-based gradients given the market segmentation strategy used by Allstate and Nationwide, respectively.

The empirical β_{kj} gradient implied by the λ_{jk} and γ_{jk} estimates is reported in each panel, along with bootstrap standard errors. For both Allstate and Nationwide, the estimated slope parameters are significantly steeper than the 1.18 benchmark.

Panels (b) and (e) in Figure 5 report 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.

For comparison, panels (c) and (f) report results from estimating the regression equations reported in panels (b) and (e) using State Farm's prices as the dependent variable in Equation 10. The linear approximation to State Farm's gradient parameters is noticeably less steep. This estimated gradient is not statistically different from the cost-based benchmark if we omit the highest wildfire risk score bins. See Appendix Table 2.

We fit a linear approximation to the segment-level risk price gradient to facilitate comparisons with the benchmark β_{kj} parameter. However, the empirical relationships we observe between segment-level average prices and segment-level average AAL show some degree of concavity in the highest risk segments. This shape could be due to regulations that constrain insurer pricing, a topic which we return to in Section 6.5.

5.3.2 Empirical risk price gradients for Type 1 and Type 3 insurers

Table 3 reports the results of the 2SLS estimation described in Section 5.2.2 for all six firms in the data. In the top panel, we regress an insurer's segment-level average prices on the corresponding segment-level average AAL predicted values. The 2SLS β_{kj} estimates for the Type 2 firms, Allstate and Nationwide, are very similar to those reported in Figure 5. This result suggests minimal attenuation bias given the large number of parcels we observe in the risk segments used by these firms. The risk price gradient estimates for USAA and Liberty Mutual are 2.17 and 2.46, respectively. Both are significantly steeper than the corresponding cost-based benchmarks. AAA Southern California uses the least granular risk pricing strategy of all the insurers we study. We estimate a very noisy relationship between zip code average AAL measures and risk pricing for this firm because this insurer does not risk price discriminate within coarsely defined market segments. The State Farm price gradient estimate is very close to the cost-based gradient benchmark; we fail to reject a slope of 1.18.

For comparison purposes, the bottom panel estimates the average State Farm premium for each risk segment used by the other insurers by regressing the segment-level average prices on the corresponding instrumented mean AAL values. This exercise illustrates the stark difference in pricing strategies across more- versus less-informed firms.

5.3.3 Empirical net revenue gradients

Table 4 reports the results from estimating Equation 11, in which the dependent variable is the difference between an insurer's price and the corresponding CoreLogic AAL. In each regression specification, we control for the segmentation strategy used by an insurer.[27] The omitted AAL category contains parcels associated with assessed AAL values in the range of 0-50. As noted above, the AAL bin indicators are identified using residual, within-risk segment variation.

In columns (1) and (2), given the significant variation in AAL within risk segments used by Allstate and Nationwide, increases in risk exposure within a segment are associated with commensurate decreases in revenue net of expected losses. We see a different pattern when we estimate this regression using State Farm premiums to construct the net revenue variable, but conditioning on Allstate market segments. 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

27. For example, in column (1) of the table, Equation 11 conditions on reconstruction costs, the age of the home, protection class, roof type, and an indicator for each wildfire risk segment used by Allstate to price wildfire risk.

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 Mechanisms

We have documented significant differences in the risk pricing strategies used by major property insurers in the California market. The pricing gradient associated with the most sophisticated firm, State Farm, tracks the cost-based benchmark quite closely. In contrast, among firms using relatively less granular pricing strategies, risk pricing gradients are significantly steeper. In what follows, we consider possible explanations for these findings.

6.1 Adverse selection

The cost-based gradients we have used to define the risk pricing benchmark are based on segment-level average measures of wildfire risk exposure. These average cost measures could significantly underestimate the costs a firm will face if it is at an information disadvantage vis-à-vis its competitors.

When there are asymmetries in the risk information held by competing firms, the probability that a relatively uninformed firm will win a customer will be correlated with expected disaster claims L_i. 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. Insurers at an information disadvantage should increase premiums in high risk segments to account for this curse.

6.1.1 Contextualizing the risk price gradient

With these incentives in mind, we compare the risk prices we observe insurers charging across different risk segments with the corresponding conditional quantiles of the distribution of assessed wildfire AAL values. More precisely, we compare the empirically estimated risk price gradients against quantile regression estimates that summarize the distribution of expected wildfire insurance costs in each risk segment bin, holding constant the controls in the main regressions. Results are summarized in Figure 6. The colored markers denote the average wildfire prices charged by

Allstate, Nationwide, and State Farm within each WRS category. The solid black line shows the mean wildfire AAL (multiplied by 1.18 to reflect assumed risk load). The dashed lines show the 90th and 95th conditional quantiles of 1.18 × wildfire AAL in each segment.

For wildfire score segments below 50 (the level CoreLogic considers "low"), all three firms charge prices that are very close to wildfire risk segment mean AAL plus risk load. For higher risk scores, State Farm continues to price close to segment mean cost, whereas Allstate and Nationwide charge much higher prices. Allstate's prices approximately follow the 90th percentile of customer AAL, while Nationwide's are between the 90th and 95th. Thus, the risk pricing gradients we observe for Nationwide and Allstate could possibly be rationalized by high levels of adverse selection in this market.[28]

6.1.2 Modeling adverse selection

Assessing the degree of adverse selection that actually manifests in this market would require detailed information about which firms are insuring each home. We do not have access to these proprietary details. But we can quantify selection under a set of assumptions about market structure and consumer preferences. We consider a stylized, static duopoly model that features State Farm competing with a less-informed firm. We begin with a homogeneous product duopoly setting in which the δ_j parameters in Equation 1 are assumed to be zero. The insurer offering the lowest price p_{ij} "wins" parcel i. For each of the less-informed firms in the data, we define 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. We estimate the following equation:

$$\log(L_i) = \sum_{k=1}^{K_j} \tilde{\gamma}_{jk} D^*_{jk} + X_{ij}\theta_{4j} + \vartheta_j 1[Win]_{ij} + e_{ij}, \tag{13}$$

where L_i is the AAL of parcel i, D^*_{jk} are indicators for firm j's risk segments, and X_{ij} includes all other variables used by the less-informed firm. The coefficient ϑ_j estimates the log difference in wildfire AAL for properties won by firm j, relative to those won by its more informed rival.

Table 5 shows how the prices we observe would generate adverse selection in this static duopoly setting. The households to 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 all economically and statistically significant.[29]

The results in Table 5 will overstate the extent of adverse selection if choice frictions limit switching behavior. Recall that rates of consumer switching in this insurance market are low. Prior work

28. We cannot extend this analysis to the firms that price at the zip code level because zip code fixed effects absorb all the insurance price variation.

29. The bottom panel reports the fraction won by the relatively uninformed firms in these Bertrand duopoly games. The market is roughly evenly split between the two firms, with State Farm winning lower-risk homes on average.

has documented substantial search and switching costs in insurance markets with high rates of customer retention. In automobile insurance markets, for example, Honka (2014) estimates search costs in the range of \$35 to \$170 and average switching costs of \$40. In a health insurance context, Heiss et al. (2021) estimate switching costs in the range of \$300 to \$600.

We extend the Bertrand duopoly model to assess how the degree of adverse selection varies with choice frictions. In a first stage, we assume that both firms use the same coarse information to price wildfire risk. Under this assumption, households are randomly assigned to one of the two duopolists. In a second stage, State Farm invests in risk information that supports a more granular risk pricing strategy. The challenger firm alters its pricing in response. The cost of switching insurers, as perceived by a household making an active choice, is given by δ.[30] Table 6 shows how adverse selection varies with these switching costs. Intiutively, the degree of adverse selection is declining with switching costs (or brand preferences). With δ values of \$500, which would fall in the range of the health insurance switching costs in Heiss et al. (2021), households won by less-informed firms have AAL values that are 5 to 10 percent higher, on average, than the properties lost by State Farm.

6.2 Alternative risk models

The CoreLogic CAT modeling estimates are one of several available sources of wildfire risk exposure information. Alternative sources include proprietary CAT models, such as those generated by Verisk or the First Street Foundation, and publicly provided estimates from sources like the US Forest Service. Differences in CAT model projections could potentially explain some disparities in risk pricing that we observe across firms.

Notably, State Farm uses both the CoreLogic and Verisk AIR models of wildfire risk;[31] The correspondence we document between segment-average CoreLogic AAL estimates and risk pricing in Section 5.2 suggests that the Verisk AIR model generates similar relative differences in AAL across market segments. Still, the possibility remains that disparities in risk pricing could be due to CAT model differences.

We cannot access proprietary AAL metrics generated by other leading providers. We can, however, use some publicly available metrics to assess the robustness of our findings to alternative measures of wildfire risk exposure. The US Forest Service (USFS) has developed the Risk to Potential Structures (RPS), a gridded data product which estimates the annual probability of parcel destruction from wildfire, for a representative house, at any point in the United States (Scott et al. 2024). When multiplied by the replacement cost of a structure, this measure can roughly be interpreted as an AAL. Use of the USFS product carries some caveats. First, it is primarily a measure of hazard and the does not consider the responsiveness of parcel characteristics, such as roof or construction

30. We assume the prices we observe prevail over a period during which all households are induced to evaluate their insurance choice actively at some point.

31. See, for example, State Farm rate filing 21-1404 to CDI, April 2021.

material, to wildfire. Second, it does not model suppression or fire department resources in a locally explicit way. Third, the underlying simulations do not model urban areas as burnable, so burn probability for urban areas is estimated ex-post using a smoothing procedure. Nevertheless, the USFS product provides a simulation-based risk measure.

Appendix E replicates the variance decomposition of Figure 4, the risk price gradient of Figure 5, and the winner's curse estimates of Table 5 using the USFS data as a measure of wildfire risk. We observe similar qualitative patterns as with the CoreLogic AAL. State Farm displays an information advantage, as its prices explain more residual variation in AAL after controlling for various risk segmenting strategies. In addition, the Type 2 risk score pricers, Allstate and Nationwide, show a steeper risk price gradient than State Farm. However, State Farm's segment-mean prices lie below USFS-based wildfire AALs. Lastly, the USFS-based AALs produce an even larger winner's curse in favor of State Farm, owing to larger average AALs using this measure. See Appendix E for further discussion.

6.3 Ambiguity loading

Premium markups in high-risk market segments could additionally represent a response to uncertain loss probabilities. A series of studies has shown that insurers demand premiums in excess of expected costs when loss probabilities are ambiguous (Dietz and Niehörster 2021; Kunreuther et al. 2009; Kunreuther et al. 1995). More recent work has estimated ambiguity loads -– i.e. the extra insurance premium due to ambiguity — and shown how these can vary with the insurer's degree of ambiguity aversion (see, for example, Dietz and Niehörster 2021).

Climate change increases the ambiguity in climate risk projections (Moore 2024). If insurers are adjusting their premiums to account for this ambiguity, this could help explain the steep wildfire risk pricing gradients we estimate. We cannot fully rule out this explanation. However, to fully rationalize the significant differences in risk pricing gradients we observe across firms, we would need to assume that firms using more granular risk information are significantly less ambiguity-averse. We also note that ambiguity loading and the winner's curse are not necessarily distinct mechanisms. Mumpower (1991) and Kunreuther et al. (1995) discuss how ambiguity loading may be a response to the winner's curse, as firms anticipate that uncertain loss probabilities will increase the dispersion of predicted losses and thus offered prices.

6.4 Risk load differences

Insurers must purchase reinsurance or hold large capital reserves to be ready to pay out significant claims when a natural disaster strikes. Firms with higher costs of capital, more limited access to reinsurance, or a less diversified catastrophe risk portfolio will face higher capital reserve costs. For example, Appendix Table 3 shows how risk loads vary with levels of hurricane exposure. Thus, one possible explanation for the differences in the risk gradients we observe could be underlying differences in risk load costs.

In 2022, State Farm, Allstate, Liberty Mutual, Nationwide, and USAA were all among the top ten writers of property insurance in the United States.[32] These insurers look quite similar along dimensions we can readily observe. Consider, for example, a comparison between the two largest writers of homeowners multi-peril insurance: State Farm and Allstate. These two firms account for approximately 9 percent and 5 percent of the U.S. property and casualty insurance market, respectively. In 2022, they had similar loss ratios (60 percent for State Farm and 63 percent for Allstate). They also look similar in terms of the share of premiums written in states with high hurricane risk. For example, in 2022, the high-risk state of Florida was home to 4 percent of State Farm's written premiums and 3.9 percent of Allstate's. Although these comparisons are far from comprehensive, similarities along the dimensions we can observe do not provide evidence that differences in rate schedules are explained by differences in risk load costs.

6.5 Regulation

Section 6 has considered explanations for the steeper slope of the risk price gradient for firms with less granular segmentation strategies. However, as noted in Section 5, the price gradients we observe also display a concave shape. This could be due to binding regulation. Our risk price gradients and other results provide some indirect evidence on this topic.

Public discussion of California's wildfire insurance situation has emphasized the potential for rate suppression, where prior approval regulations limit firms' ability to charge prices that fully reflect risk. The observed bunching in Figure 2 clearly establishes that regulatory constraints on overall price increases are salient to insurers. At the same time, the estimated risk price gradients show that prices keep pace with or exceed the average wildfire insurance costs for homes in most risk segments. This would not be the expected result if regulatory constraints on wildfire-specific pricing were the only factor contributing to limited insurance availability.

Still, the empirical relationships we observe between segment-level average prices and segment-level average AAL suggest some degree of concavity in the highest risk segments. For example, in Figures 5 and 6, the State Farm price gradients track our cost-based benchmark very well with the exception of the highest risk segments. The Nationwide and Allstate gradients are also concave. While it is not completely dispositive, one interpretation is that risk price gradients are compressed by regulation in the highest-risk market segments.

This compression could also have implications for insurance availability, particularly among firms using coarse risk pricing strategies. We have shown how a rational firm should adjust prices upwards to account for adverse selection when competing with a rival that prices risk using superior information. If price regulations limit firms' ability to shade up premiums in high hazard areas, relatively uninformed firms may elect to stop writing new policies in high-risk market segments. Empirically, this is what we observe among the subset of insurers in the data for whom we can reconstruct eligibility rules. Figure 7 plots the fraction of homes in the dataset by wildfire risk

32. Source: NAIC data, sourced from S&P Global Market Intelligence, Insurance Information Institute.

score that would have been eligible for a new insurance policy in 2021. Allstate and Nationwide generally were not offering new policies to parcels with risk scores above 30, whereas State Farm has historically maintained much higher acceptance rates in higher risk categories. We posit that this is because State Farm uses more granular information to distinguish between above- and below-average risk parcels in these market segments. Taken together, these results reinforce the importance of the interaction between rate regulation and imperfect information about wildfire risk.

Finally, we note that the risk price gradients we estimate are most informative about wildfire risk-related rate *compression*. Insurers assert that California's insurance rate regulations are, more broadly, limiting their ability to cover rising insurance costs including inflation in construction materials and personal liability claims. These broader rate *suppression* concerns have prompted insurers to pause new policies throughout the state.

We have documented evidence that points to important interactions between regulation and asymmetric information on wildfire risk. Section 7 explores this topic in greater detail.

7 An Equilibrium Model of Asymmetric Information and Binding Regulation

Motivated by the empirical evidence on asymmetric information and binding price regulation, we develop an equilibrium model of an insurance market to explore the implications of our findings. We analyze a single risk segment, such as a geographic area (e.g. a zip code) or a set of properties assigned to a particular risk score. We 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 (or 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 expected 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 regulatory constraints and consider the affordability and availability implications of policy reform.

7.1 Setup

Firms offer insurance to a group of property owners within a wildfire 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 the 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 modeled risk.[33]

Consumers buy one unit of insurance to maximize utility $u = I(0, \delta) - p$. The total number of consumers within the risk segment is normalized to 1. Once a consumer purchases insurance coverage from 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. Specifically, after an initial period in which consumers are matched with an insurer, they need to be offered a price more than δ below another firm's price to induce them to switch.

Similar to the Bertrand model introduced at the close of Section 6.1, we specify a two-stage model. In an initial stage, all firms have the same information about how risk is distributed within a market segment, but firms do not know 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. We ignore the uncertainty and ambiguity that can complicate the interpretation of wildfire risk modeling and metrics, focusing exclusively on modeling interactions between information asymmetries and binding price regulation.[34] 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 the initial period, firms and consumers enter the market. Firms compete in prices knowing only the risk distribution $U(0, l^*)$. In equilibrium, firms make zero expected profits, which occurs at the price $p_0 = \bar{l}$. Between time 0 and t, once a consumer has selected an insurer, it has no incentive to switch insurers because there is a single price for insurance.

To approximate the market structure we observe, we assume that one firm captures a relatively large share α of the market and the remaining "fringe" of competing insurers share the rest of the market.[35] We assume that the losses of dominant firm's customers are distributed according to $\alpha U(0, l^*)$, implying that the losses of the fringe's customers are distributed according to $(1 - \alpha)U(0, l^*)$.

7.3 The value of information

In time t, firms decide whether to adopt a more sophisticated information technology, accounting for the cost of adoption and expected equilibrium profits. In this section, we assume there are no regulatory constraints on pricing.

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 homeowners policy.

34. 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.

35. 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.

7.3.1 Pricing by the dominant firm at the initial equilibrium

If only the dominant firm adopts the technology, it can segment 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.[36] It will be convenient below to define $\tau = \frac{\bar{l}}{\delta}$; thus, the assumption is restated as $\tau > \frac{1+\alpha}{1-\alpha}$. 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 panel (a) of Figure 8, 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.

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 $\tau > \frac{1+\alpha}{1-\alpha}$, 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

36. 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.

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 $p^D(l) > p^F + \delta$.[37] 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) $\tau = \frac{\bar{l}}{\delta} > \frac{1+\alpha}{1-\alpha}$, 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 F.

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.[38] 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 panel (b) of Figure 8. 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[39] and declining coverage to high-risk customers. It earns positive profits given by:

$$\pi^D = \frac{1}{2}\left\{\tilde{l}(2p^F - 2\delta - \tilde{l}) + \alpha(p^F + \delta - \tilde{l})^2\right\} > 0. \tag{16}$$

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:

$$\pi^F = \frac{1}{2}\left\{(1-\alpha)(p^F - \tilde{l})^2 - (l^* - p^F)^2 + \alpha\delta^2\right\} = 0. \tag{17}$$

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 Equation 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

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

38. 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.

39. 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.

if:

$$\tau < \frac{1}{2} + \left(\frac{1+3\alpha}{1-\alpha}\right)^{0.5}, \tag{18}$$

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

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

The variable τ measures the relative magnitude of switching costs, specifically the size of δ compared to the average AAL ($\bar{l}$) in the segment. For $\alpha < 1$, the right-hand side of Equation 18 is increasing in α and has an asymptote at infinity as α goes to one. Thus, for a given value of τ, there is always a market share α at which VOI is increasing in the market share.

The adoption of the information technology by the dominant firm affects equilibrium insurance prices. The average price of insurance following adoption is given by:

$$\bar{p} = (p^F - \delta)\frac{\tilde{l}}{l^*} + \alpha(p^F + \delta)\frac{l_1 - \tilde{l}}{l^*} + (1-\alpha)p^F\frac{l_1 - \tilde{l}}{l^*} + p^F\frac{l^* - l_1}{l^*} \tag{19}$$

We show in the following proposition that $\bar{p}$ is greater than the average price under the initial equilibrium in Section 7.2:

Proposition III: The average price of insurance, $\bar{p}$*, under the market equilibrium with technology adoption (Proposition I) is greater than the average price under the original market equilibrium* ($p_0 = \bar{l}$)*.*

Proof: See Appendix F.

The model generates the following predictions that are consistent with empirical findings and analysis presented throughout the paper: (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) Low-information firms set higher prices to avoid selling money-losing policies to high-risk consumers; (4) For some parameter values, the value of adopting the information technology is increasing in market share; (5) Asymmetric information among firms leads to higher average prices for insurance.

7.4 Equilibrium with price regulation

In California, the extent to which an insurer can raise its average price – evaluated across a book of business – is constrained by its historical loss experience. In this section, we approximate this price regulation by imposing upper bounds on the average prices charged by the dominant firm and the competitive fringe, respectively. 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. As shown above, once the dominant firm adopts and uses superior risk information, the fringe firms must raise their prices to remain profitable. If they cannot raise prices sufficiently, their profits will be negative and they will exit 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:

$$\bar{p}^D = \eta(p^F - \delta) + (1 - \eta)(p^F + \delta), \tag{20}$$

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:

$$\max_{\tilde{l}} \pi^D \quad s.t. \quad \bar{p}^D \leq \bar{p}^R, \tag{21}$$

where π^D and $\bar{p}^D$ are given in Equations 16 and 20, 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 Equation 20 to derive the chosen value of $\tilde{l}$ as:

$$\tilde{l} = \frac{\bar{p}^R \alpha(p^F + \delta) - \alpha(p^F + \delta)^2}{p^F(1 - \alpha) - \delta(1 + \alpha) - \bar{p}^R(1 - \alpha)}. \tag{22}$$

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[40]:

$$p^F = \frac{l^* - \tilde{l}(1 - \alpha)}{\alpha} - \frac{1}{\alpha}\sqrt{(1 - \alpha)(l^* - \tilde{l})^2 + \alpha^2\delta^2}. \tag{23}$$

For a given value of $\bar{p}^R$, the constrained market equilibrium is given by the values $\{p^{F*}, \tilde{l}^*\}$ that satisfy Equations 22 and 23. The equilibrium can be illustrated with isoclines in $\{p^F, \tilde{l}\}$ space corresponding to the zero profit and average price conditions (Appendix Figure 5). We show in Appendix F that at the unconstrained equilibrium[41] 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 τ, requiring large values of δ relative to $\bar{l}$, the zero profit isocline has a steeper slope than the average price isocline, as shown in Appendix Figure 5. We adopt this as the empirically relevant case, although we also consider the alternative.

An admitted market insurer in California who experiences a cost increase can file a regulatory request to raise its prices. The model represents this as an increase in $\bar{p}^R$, which shifts up the $\bar{p}^D$

40. In Equation 23, 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^*.

41. The unconstrained equilibrium is the values $\{p^{F*}, \tilde{l}^*\}$ such that $\tilde{l}^*$ is freely chosen in Equation 21. Associated with this value of $\tilde{l}^*$ is an average price $\bar{p}^D$ according to Equation 20.

isocline (see Appendix F). As shown in Appendix Figure 5, 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 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 $\bar{p}_1^R$.

The government could take steps to help insurers access and use superior risk information in their pricing and underwriting decisions. We consider how the market equilibrium changes when fringe firms gain access to more granular risk information. In panels (c) and (d) of Figure 8, we allow 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 $U(0, l^*)$. If $\tilde{l} > \bar{l}$ under the original equilibrium, the overall average price unambiguously declines. Prices do not change on the interval $[\bar{l}, l^*]$ and are lower on the interval $[0, \bar{l})$.[42] In this scenario, a policy intervention that improves access to better information can improve affordability and availability insofar as average premiums fall and the fringe firms can remain in segments of the market that would otherwise be associated with negative profits. Under the alternative scenario wherein $\tilde{l} < \bar{l}$, the effect on the overall average price is unclear. However, Appendix F provides numerical results showing that average price falls for a large range of parameter values.

Although the cost of information provision would need to be considered, our results suggest that this may be a more effective way to address affordability and availability objectives than price caps.

8 Conclusion

In the face of escalating climate risk, well-functioning property insurance markets can provide households and businesses with crucial protection from economic losses as well as incentives to reduce risk exposure. However, there are signs that property insurance markets are not adapting well to climate change pressures. This study investigates some of the reasons that private insurance markets are struggling to manage climate change risk, with a focus on wildfire risk and homeowners insurance in California.

Our analysis combines proprietary parcel-level wildfire risk analytics with information in insurers' public rate filings to analyze how insurers are pricing wildfire risk in California. We document significant variation in the information insurers use to price wildfire risk. A critical policy question

42. On the interval $[0, \bar{l})$, 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 $[0, \bar{l})$, implying a lower overall average price.

for future research is to understand why there is such wide dispersion of wildfire risk model quality across insurers. We also find economically significant differences between the price schedules we observe and cost-based benchmarks that account for expected losses, operating costs, and a loading factor that reflects the costs of ensuring insurer solvency. We show that the empirical evidence is consistent with an adverse selection story in which less-informed firms face a winner's curse in high-wildfire risk market segments.

Motivated by the empirical evidence on asymmetric information and economic regulation, we develop an equilibrium model of the property insurance market that incorporates both information asymmetries and binding economic regulation. In the model, insurers can access detailed risk information through the costly adoption of sophisticated modeling tools. We show that if the costs of adopting and using more sophisticated risk information is sufficiently high, there are conditions under which only the firms with the largest market shares will adopt the information. This is consistent with what we observe in the California market. The model also predicts that the high-information firm will use its superior information to win the lower-risk customers within a risk segment, and that low-information firms will set high prices to mitigate effects of adverse selection. The overall effect is an increase in the average price of insurance, indicating that the uneven adoption of risk information may be part of the explanation for observed increases in insurance premiums in California. If regulation prevents upward price adjustments, insurers wary of the winner's curse may exit high-risk market segments to limit their exposure. Thus, in markets characterized by asymmetric information, regulations limiting premium increases can have unintended consequences. Policies that improve market-wide understanding of wildfire risk could improve affordability without sacrificing availability.

Our findings are relevant to current policy discussions about property insurance market reform in California and elsewhere. As of 2024, several leading insurers (including State Farm and Allstate) have begun to limit the writing of new policies and tighten underwriting standards for existing customers. Major insurers have been requesting rate increases in excess of 20 to 30 percent. Wildfire risk exposure is just one of many factors driving these developments. Other factors include increases in non-catastrophe liability claims and construction cost inflation. Our results highlight the underappreciated importance of wildfire risk information, and more specifically, the winner's curse as a barrier to participation in insurance markets for large, hard-to-model risks. Further investigation of the potential for adverse selection, the implications for insurance pricing and underwriting, and the policy changes that could be warranted will be critical to informing insurance market policies in an era of changing climate.

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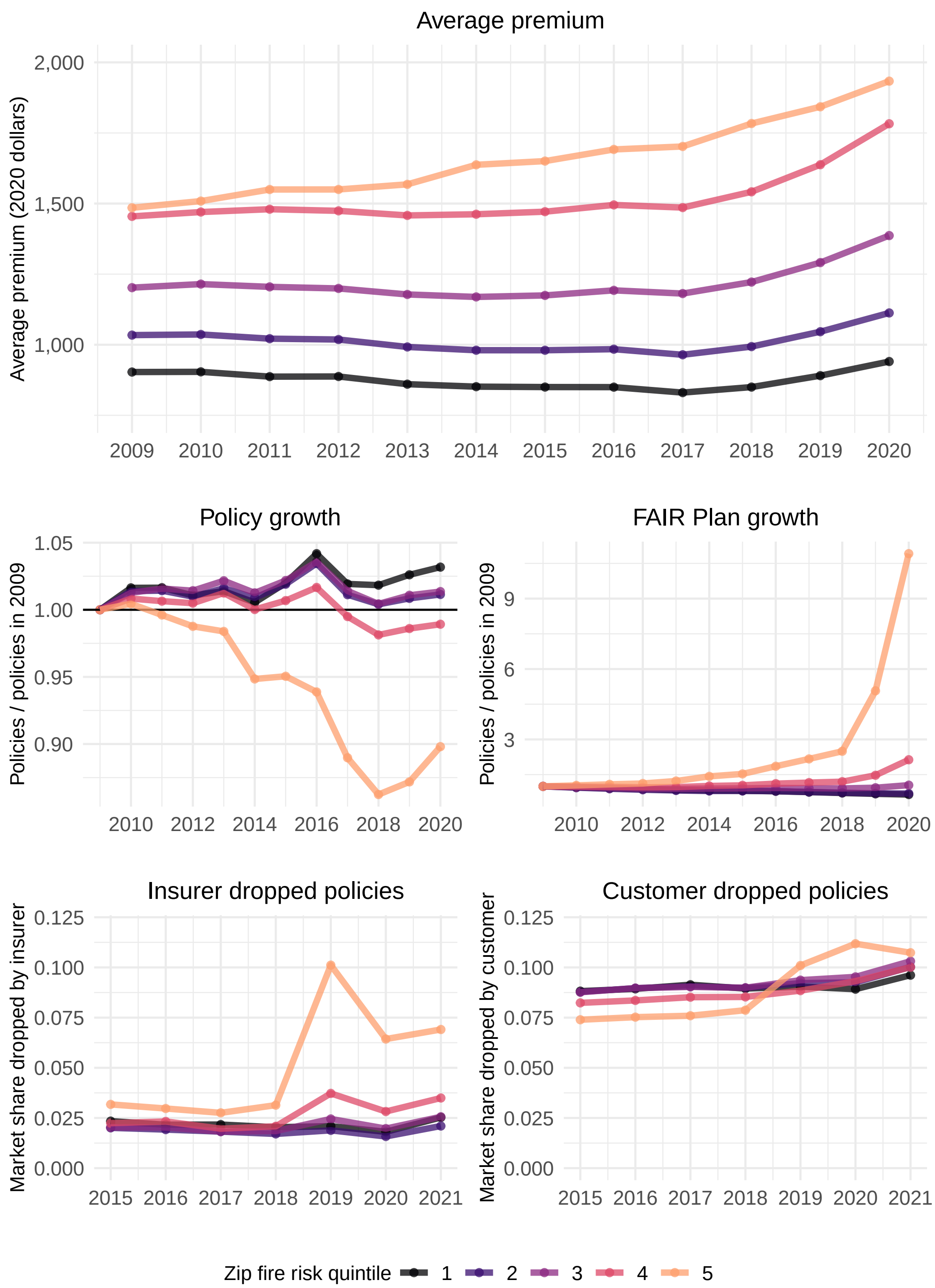
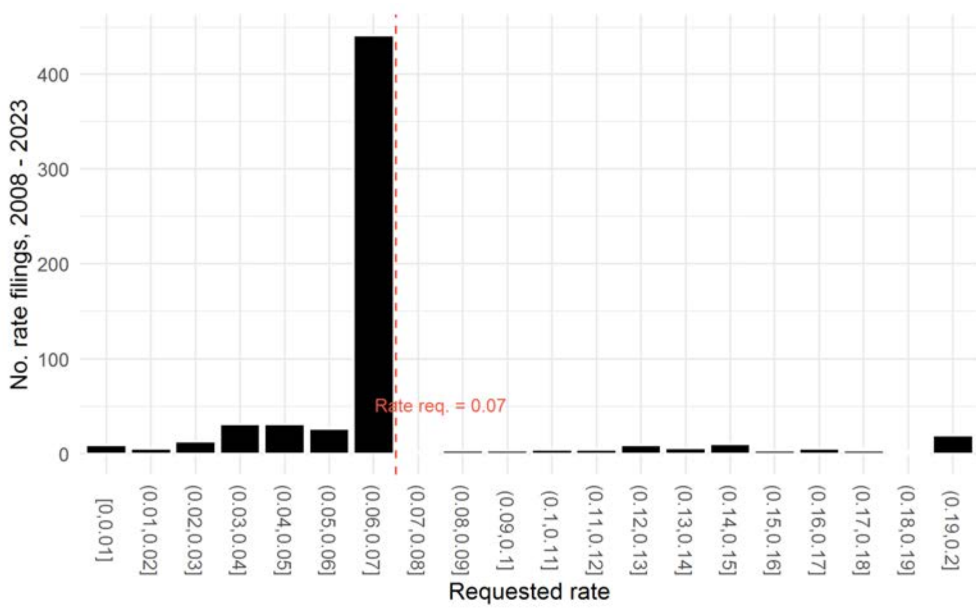
Figure 1: California homeowners insurance by year



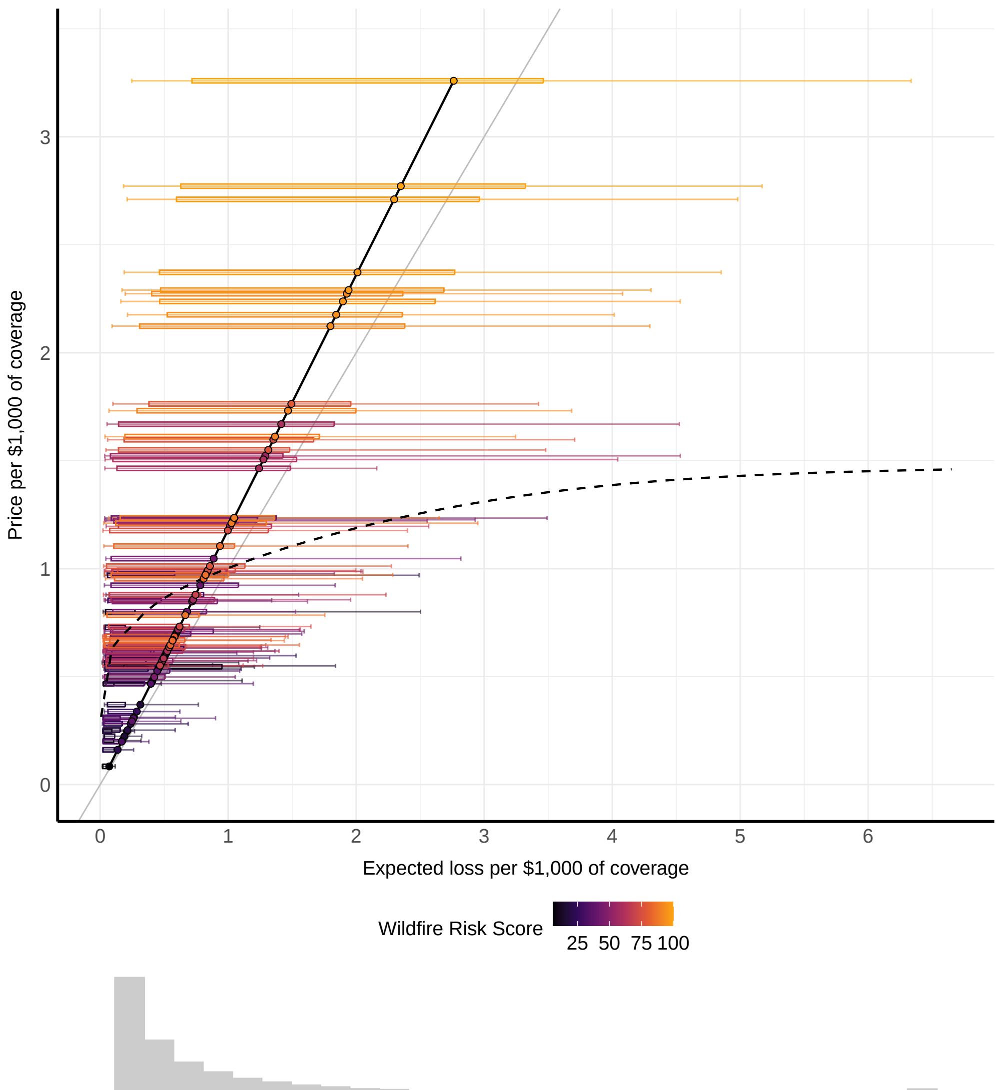
Notes: Figure summarizes zip code-level outcomes over time. Zip codes are classified into wildfire risk quintiles on the basis of zip code average risk. Risk scores are derived from California Department of Insurance Wildfire Risk Information Reporting, which lists proportions of insurance policies in 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. Premium is in 2020 dollars.

Figure 2: Rate filing behavior



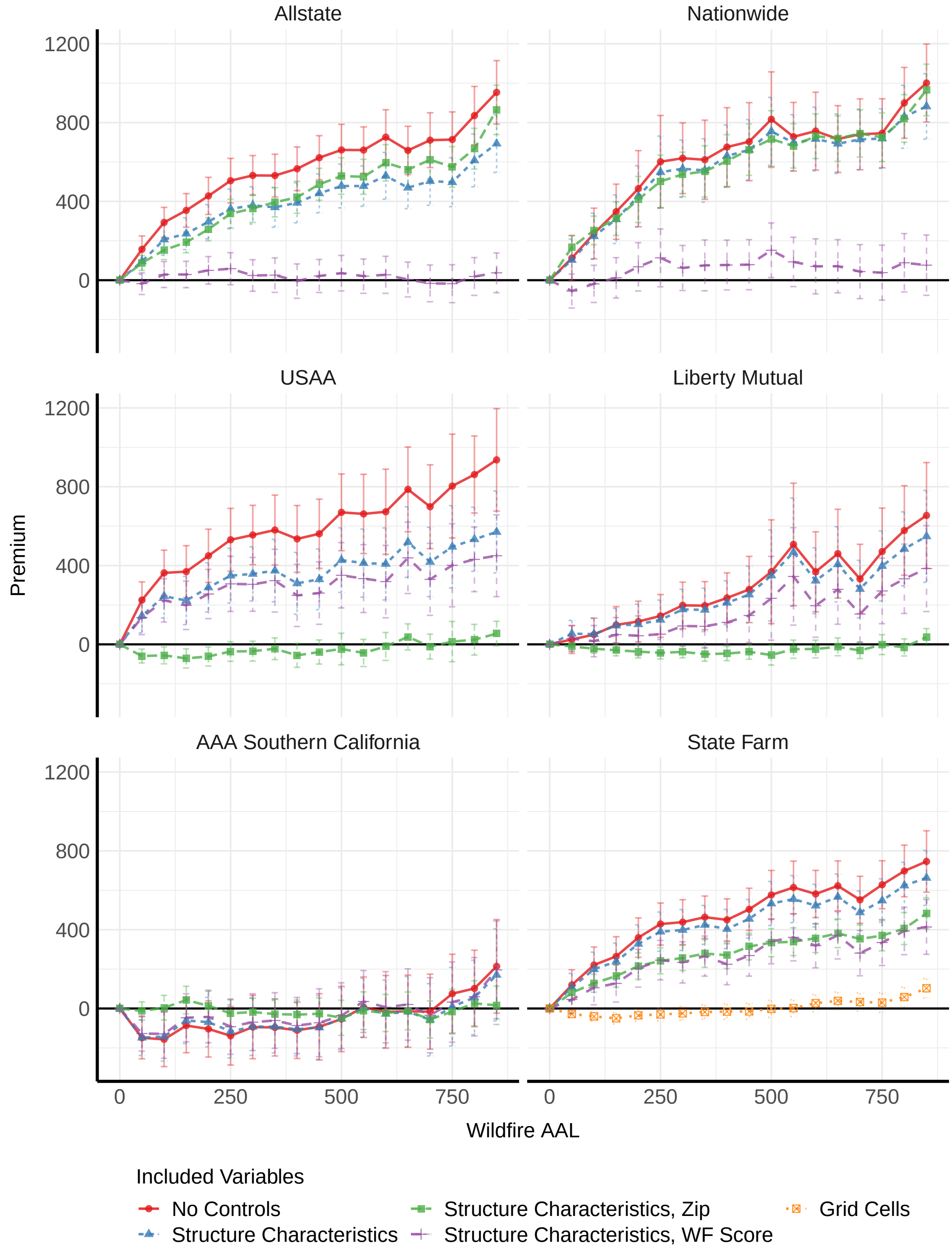
Notes: Figure displays the distribution of all 636 requested rate increases to CDI from 2008 to 2023 for owner-occupied homeowners' insurance (HO-3) policies for all insurers in California. Firms tend to request rate increases just below 7 percent, a threshold above which they face costly public rate hearings.

Figure 3: Comparison of a cost-based, segment-level pricing schedule and assessed AAL metrics



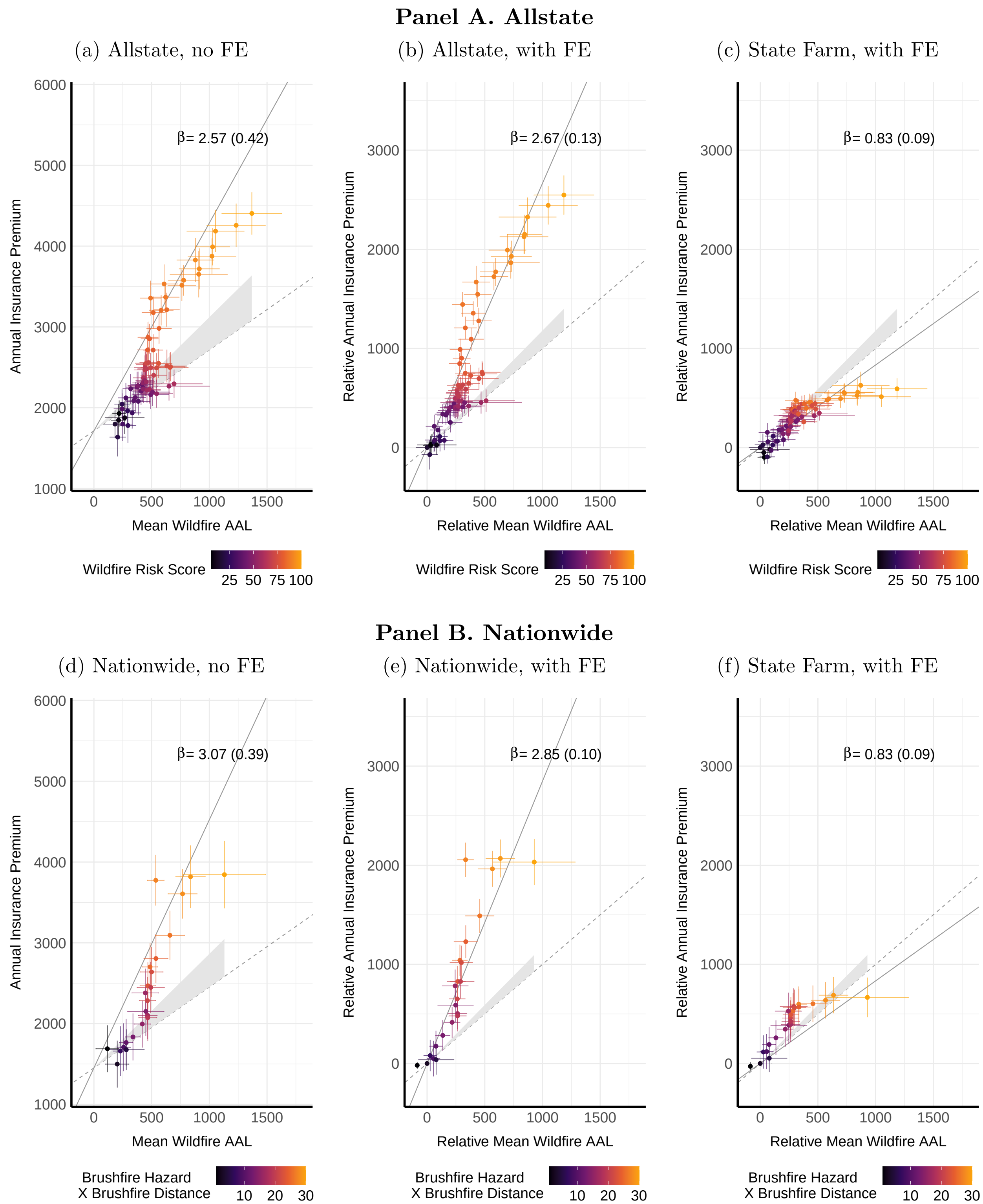
Notes: Horizontal box plots show the distribution of individual expected losses within each wildfire risk score. Whiskers show the 10th and 90th percentiles; notches show the interquartile range; circular markers are means. The vertical axis shows prices for a hypothetical firm that pools customers by 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.

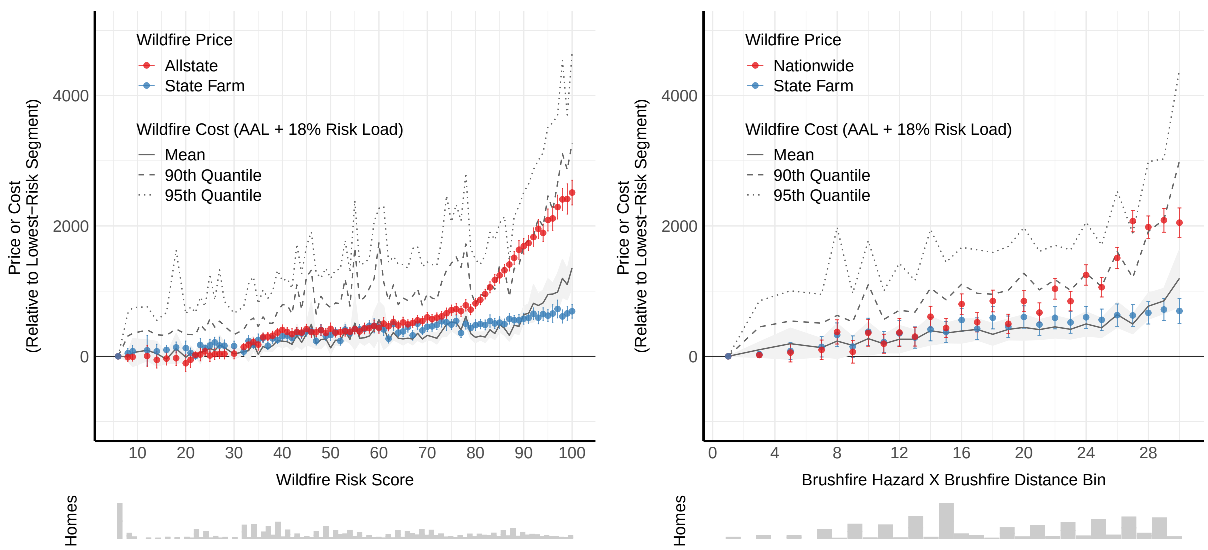
Figure 5: Wildfire price gradients for Allstate and Nationwide



Notes: Each panel shows a separate regression of annual premium on wildfire score dummies, with additional controls for fire protection class and reconstruction cost. The regressions used to create the figures in the second and third columns also include zip code fixed effects. 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.

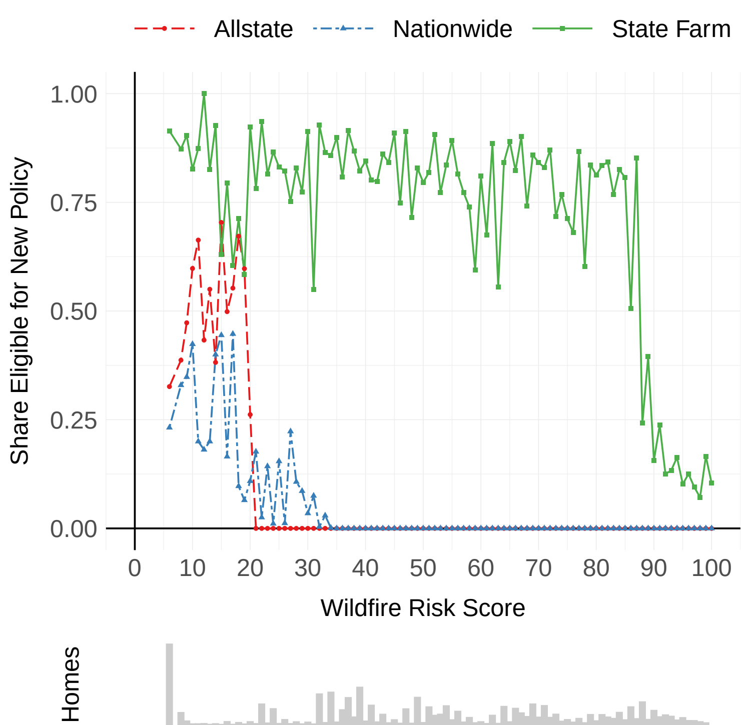
Figure 6: Price and Cost by Risk Segment

(a) Allstate-State Farm Price Comparison (b) Nationwide-State Farm Price Comparison



Notes: Figures compare price and cost across risk segment bins, holding constant the controls in the main regressions of the paper. The colored markers denote the average wildfire prices charged by Allstate, Nationwide, and State Farm within each WRS category. The solid black line shows the mean wildfire AAL, multiplied by 1.18 to reflect assumed risk load. The dashed lines show the 90th and 95th conditional quantiles of 1.18 $\times$ wildfire AAL in each segment. The gray histograms show the share of homes in each risk segment.

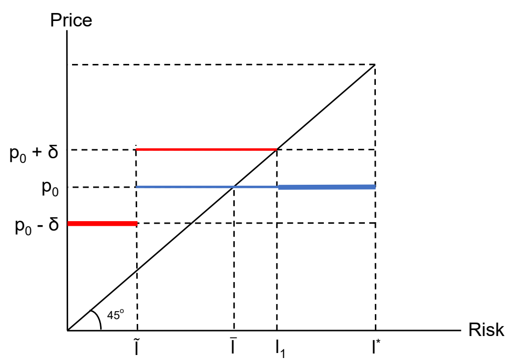
Figure 7: New policy eligibility versus parcel wildfire scores

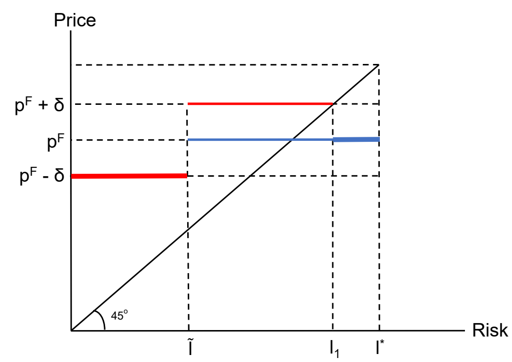


Notes: Figure reports the fraction of homes in each risk score bin that would have been eligible for a new homeowners policy in 2021 from each firm.

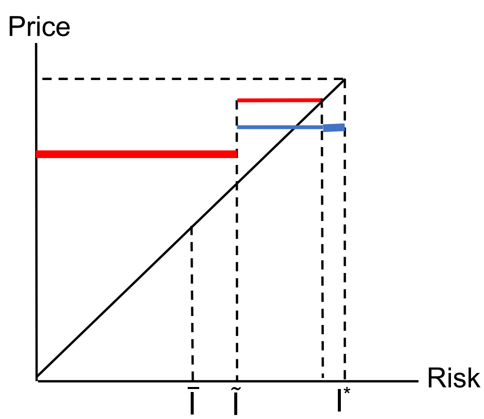
Figure 8: Equilibrium pricing by dominant firm and competitive fringe

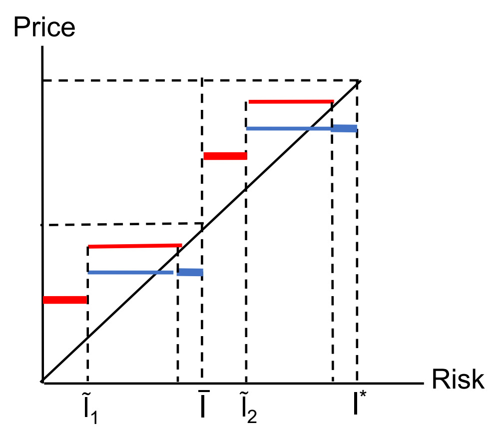
(a) Dominant firm best response at initial p_0 (b) Equilibrium when fringe profit is zero





(c) Baseline, limited information for fringe (d) Information provision





Notes: Panel (a) 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. Panel (b) shows the market equilibrium prices at which the profits of the competitive fringe are zero. Panels (c) and (d) show how equilibrium prices change when new information is provided to the competitive fringe firms. Panel (c) is the baseline case in which fringe firms know only that properties are distributed according to $U(0, l^*)$ and for the case $\tilde{l} > \bar{l}$. In Panel (d), the firms can distinguish whether properties are distributed according to $U(0, \bar{l})$ or $U(\bar{l}, l^*)$.

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: Summarizing Structure Characteristics, Wildfire Risk, and Insurance Prices

	Mean	SD	p5	p95	N
Structure Characteristics					
Reconstruction Cost	594,671	290,183	270,724	1,191,194	95,352
Year Built	1976	21	1937	2006	95,352
Square Feet	2,135	954	953	3,965	88,503
Wildfire Risk Score	52	27	6	92	95,352
Wildfire Average Annual Loss	303	596	9	1,298	95,352
Insurance Price Schedules					
Allstate	2,362	1,443	924	5,181	95,352
Nationwide	2,466	1,735	866	5,661	95,351
Liberty Mutual	2,389	1,229	1,176	4,763	94,290
State Farm	2,309	1,201	1,007	4,735	95,351
USAA	2,470	1,704	998	5,724	95,297
AAA Southern CA	2,756	1,914	964	8,290	55,641
Within-Home Dispersion of Offered Prices					
Average of Offered Prices	2,419	1,337	1,070	5,219	95,352
Lowest Offered Price	1,805	927	808	3,675	95,352
Std. Dev. of Offered Prices	578	546	148	1,716	95,352
Range of Offered Prices	1,488	1,447	384	4,470	95,352

Notes: Units for reconstruction cost, average annual loss, and insurance price are dollars. Within-home dispersion of offered prices describes the variation in insurance prices for each individual home across the six insurers in the data.

Table 3: IV estimates of price gradients by firm

	(1)	(2)	(3)	(4)	(5)	(6)
			Segment Definition			
	Allstate Scores	Nationwide Scores	USAA Territories	Liberty Mutual Territories	AAA SoCal Territories	State Farm Grid Cells
Own Price						
Segment-Mean AAL	2.87***	3.42***	2.17***	2.46***	-1.44	1.10
SE	(0.26)	(0.43)	(0.40)	(0.41)	(1.78)	(0.14)
State Farm Price						
Segment-Mean AAL	0.95***	0.95***	1.01	0.91***	1.99	
SE	(0.10)	(0.13)	(0.19)	(0.15)	(8.98)	
First Stage F-Statistic	255.6	61.1	62.1	88.8	9.1	1694.2
Zip Code FE	Yes	Yes	No	No	No	No
Number of Segments	94	30	323	393	19	11946

Notes: Table reports estimates of β_{kj} from a two-step estimation procedure that first calculates regression-adjusted mean prices and wildfire AAL by segment following Equations 9 and 10, and then regresses these segment-level prices against segment-level mean wildfire risk. The first-step estimation of segment means includes zip code fixed effects for Allstate and Nationwide, where there is cross-cutting variation in zip codes and wildfire segments. The second-step regression of mean price on mean wildfire AAL is estimated by two-stage least squares to remove measurement error in segment-mean wildfire AAL due to sampling variation. See text for details. Standard errors are calculated by bootstrapping the full estimation procedure 500 times. Stars indicate statistical significance against a null of 1.18, the benchmark cost gradient.

Table 4: 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 5: The winner's curse in stylized Bertrand duopoly

	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

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 log of wildfire AAL. Structure characteristics include reconstruction cost, age of home, class A roof indicator, and public protection class. Standard errors are clustered by zip code.

Table 6: Winner's curse in Bertrand duopoly, alternative switching costs

	Allstate vs. State Farm	Nationwide vs. State Farm	USAA vs. State Farm	Liberty Mutual vs. State Farm	AAA SoCal vs. State Farm
δ=0					
1[Win]	0.52	0.33	0.44	0.39	0.56
SE	(0.08)	(0.08)	(0.03)	(0.04)	(0.09)
δ=50					
1[Win]	0.48	0.34	0.37	0.36	0.56
SE	(0.08)	(0.07)	(0.03)	(0.03)	(0.08)
δ=100					
1[Win]	0.24	0.22	0.15	0.12	0.27
SE	(0.04)	(0.04)	(0.02)	(0.01)	(0.04)
δ=500					
1[Win]	0.10	0.08	0.05	0.05	0.10
SE	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
$\delta = \infty$					
1[Win]	0.01	0.00	0.00	0.00	-0.01
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mean AAL	$302	$302	$302	$299	$236
Observations	95295	95295	95295	94241	55606

Notes: Table summarizes estimates from twenty-five OLS regressions following the specification in Table 5. In each regression, each home is randomly assigned to one of the duopolists, so that the home's perceived price for the other firm is incremented by the indicated switching cost. Customers then choose the firm with the lower perceived cost.

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

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.[43] 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 Appendix 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.[44] 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 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-

43. 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.

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

renewed policies, and the number of cancelled policies. These data are used to show the cancellation panels of Figure 1.

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 1.

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.[45]

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.

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).

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.[46] 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.

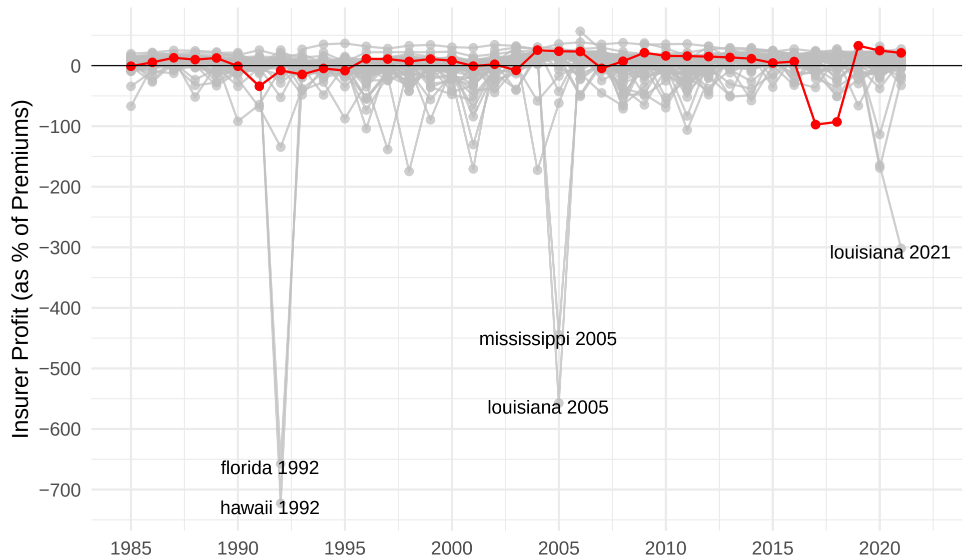
45. California Department of Insurance (CDI). (2024). Web Access to Rate and Form Filings (WARFF). http://www.insurance.ca.gov/0250-insurers/0800-rate-filings/0050-viewing-room.

46. 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.

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: 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.

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 a bootstrap by zip code.

C Risk Load

This section describes how we approximate the risk load associated with covering the high wildfire hazard homes in the 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.[47] 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 w_i. Define the probability of destruction, conditional on exposure, as d_i, so home i's annual probability of destruction is $w_i d_i$. Let $Cor(W_i, W_j)$ be the correlation in annual wildfire experience between homes i and j. Assume d is independent across homes. One can show that the correlation in annual losses across homes i and j is

$$Cor(W_i D_i, W_j D_j) = \frac{d_i d_j \sqrt{w_i(1-w_i)}\sqrt{w_j(1-w_j)}}{v_i v_j},$$

where

$$v_i = \sqrt{w_i d_i(1-d_i) + d_i^2 w_i(1-w_i) + w_i(1-w_i)(d_i)(1-d_i)}.$$

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

47. 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.

annual exposure probabilities of 1 percent for all homes.[48] 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 $Cor(W_iD_i, W_jD_j)$, 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

$$\rho_i(\Omega_j) = l_i + a_i + \phi'_{ij}(\Omega_j),$$

where l_i is the average annual loss of the contracts being added, $\phi'_{ij}(\Omega_j)$ is the change in risk load from the contracts being added, and a_i is a constant that captures administrative costs. Let S_j be the standard deviation of losses from the existing book of business, S'_{ij} the standard deviation of losses from the combined book of business, C_{ij} the correlation of losses on the new contracts with the existing 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 (1990) shows that:

$$\phi'_{ij}(\Omega_j) = \underbrace{\frac{y}{1+y}}_{\text{capital cost}} \times \underbrace{z}_{\text{“distribution statistic”}} \times \underbrace{\frac{(2S_jC_{ij} + \sigma_i)\sigma_i}{S_j + S'_{ij}}}_{\text{change in s.d. of firm's losses}} .$$

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 $Var(X+Y) = Var(X) + Var(Y) + 2Cov(X, Y)$.

$$\begin{aligned}
(S'_{ij})^2 &= S_j^2 + \sigma_i^2 + 2C_{ij}S_j\sigma_i \\
(S'_{ij})^2 - S_j^2 &= \sigma_i(\sigma_i + 2C_{ij}S_j) \\
(S'_{ij} + S_j)(S'_{ij} - S_j) &= \sigma_i(\sigma_i + 2C_{ij}S_j) \\
(S'_{ij} - S_j) &= \frac{\sigma_i(\sigma_i + 2C_{ij}S_j)}{(S'_{ij} + S_j)}.
\end{aligned}$$

Given an assumed correlation structure across homes, the data allow us to calculate σ_i 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_j 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).[49] We assume that this insurer faces another catastrophe peril (e.g., hurricane, fire following earthquake) with expected

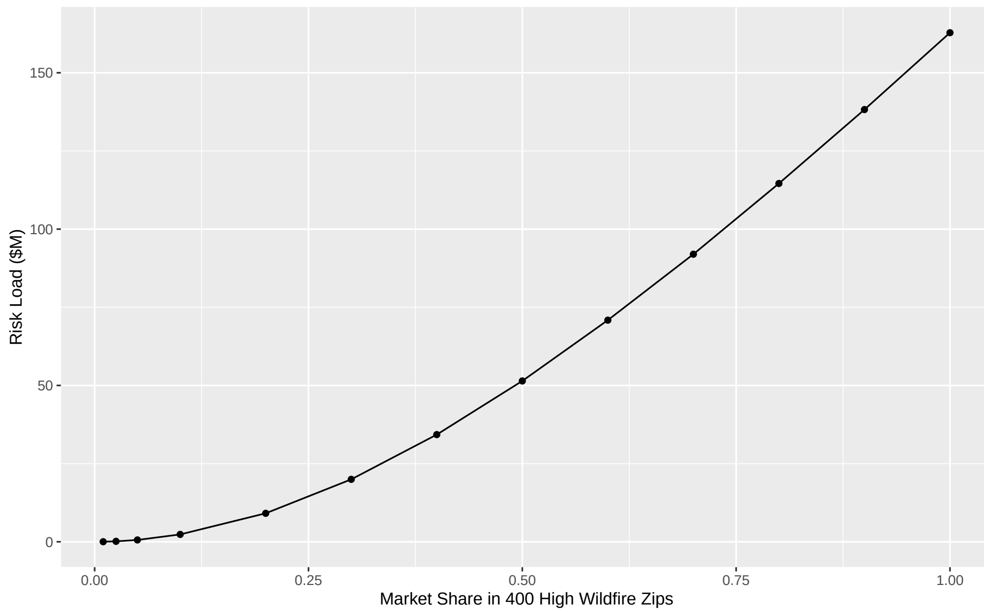
48. Based on data in Buechi et al. (2021), we estimate that the average annual share of acres in California that experience a wildfire was 0.3 percent to 0.7 percent in each decade between 1979 and 2018.

49. This 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.

annual losses of $200 million and coefficient of variation of 2.5.[50] 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 2 shows the relationship between risk load $\phi(\Omega_j)$ and market share. There is a clear convex relationship, reflecting the shrinking diversification benefit as the portfolio becomes relatively more concentrated in wildfire risk.

Appendix Figure 2: 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.

Appendix Table 3 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_i) would be $15.7 million. The standard deviation of losses on the rest of the portfolio (S_j) 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'_{ij}). 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

50. 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."

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.

A key insight is that 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.

Relatedly, the marginal surplus also depends on exposure to other catastrophe perils, as illustrated by panel B of Appendix Table 3. This exercise illustrates how diversification in insurers' overall risk profile can generate meaningful variation in marginal surplus costs. To generate these results, we focus on hurricanes and assume a high-hazard market share of 10 percent. As with the baseline scenario of panel A, we assume a coefficient of variation of hurricane losses of 2.5, but vary the insurer's expected hurricane losses. 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 illustrate how variation in insurers' overall risk profile can generate meaningful variation in marginal surplus costs.

C.3 Derivation of correlation in losses

Let W_i and W_j be Bernoulli random variables with success probabilities w_i and w_j and correlation $Cor(W_i, W_j)$. Let D_i and D_j be independent Bernoulli random variables with success probabilities d_i and d_j. The correlation of realized losses W_iD_i and W_jD_j is, by definition,

$$Cor(W_iD_i, W_jD_j) = \frac{Cov(W_iD_i, W_jD_j)}{\sqrt{Var(W_iD_i)}\sqrt{Var(W_jD_j)}}.$$

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

$$\begin{aligned} Cov^*(W_iD_i, W_jD_j) = E[W_i]E[W_j]Cov(D_i, D_j) + E[W_i]E[D_j]Cov(W_j, D_i) \\ +E[W_i]E[D_j]Cov(W_j, D_i) + E[D_i]E[D_j]Cov(W_i, W_j). \end{aligned}$$

The Ds are independent, so this simplifies to:

$$\begin{aligned} &= E[D_i]E[D_j]Cov(W_i, W_j) \\ &= d_id_jCor(W_i, W_j)sd(W_i)sd(W_j) \\ &= d_id_jCor(W_i, W_j)\sqrt{w_i(1-w_i)}\sqrt{w_j(1-w_j)}. \end{aligned}$$

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

$$Var(W_iD_i) = E[W_i]^2Var(D_i) + E[D_i]^2Var(W_i) + Var(W_i)Var(D_i)$$
$$= w_i^2 d_i(1-d_i) + d_i^2 w_i(1-w_i) + w_i(1-w_i)d_i(1-d_i).$$

Combining yields

$$Cor(W_iD_i, W_jD_j) = \frac{d_i d_j \sqrt{w_i(1-w_i)}\sqrt{w_j(1-w_j)}}{\upsilon_i \upsilon_j},$$

where

$$\upsilon_i = \sqrt{w_i d_i(1-d_i) + d_i^2 w_i(1-w_i) + w_i(1-w_i)(d_i)(1-d_i)}.$$

Appendix Table 3: Approximate risk load from marginal surplus

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

Market Share (%)	Policies	Wildfire AAL ($M)	σ_i ($M)	S_j ($M)	S'_{ij} ($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_i ($M)	S_j ($M)	S'_{ij} ($M)	Risk Load ($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. See Section 4.3 and Appendix C for details and assumptions.

D Instrumenting to remove measurement error in segment-mean wildfire risk

This section elaborates on the two-stage least squares specification for β_{kj}. We first show that sampling variation in structure-level wildfire risk generates biased β_{kj} estimates when we observe few homes per territory. We then show that instrumenting for territory mean risk with an auxiliary risk measure alleviates this issue.

D.1 Measurement error

To estimate β_{kj} for a given firm, we calculate average wildfire risk and insurance premium in each of the firm's wildfire pricing segments. These estimates are potentially susceptible to bias from measurement error in the reconstruction of segment-mean wildfire risk. Measurement error in segment-mean price is less of an issue both because a firm's prices do not vary within its pricing segments (see Figure 4) and because the classical errors-in-variables model implies measurement error in the dependent variable is less important. The mean wildfire risk for a territory k in the sample can be represented as $\tilde{l}_k = l_k + \nu_k$, where ν_k is a mean-zero sampling error whose variance is inversely proportional to sample size. An OLS regression of p_{jk} on $\tilde{l}_k$ will yield a biased estimate of β_{kj}, with the size of the bias depending on ν_k and thus the number of segments that the firm uses for pricing. For example, Liberty Mutual uses 393 wildfire segments, meaning that we observe 100,000/393 = 254 homes per segment on average; while Nationwide uses 30 wildfire segments, meaning that we observe 3,333 homes per segment on average. Appendix Table 4 shows that OLS estimates of β_{kj} for firms using more than about one hundred pricing segments are notably smaller than the other estimates, with values substantially below one. This suggests measurement error in segment-mean risk due to sampling variation is causing attenuation in the OLS estimates for firms with many segments.

D.2 Instrumenting for measurement error

A common approach to address measurement error is to instrument for the mis-measured regressor with auxiliary data on the mis-measured quantity. In this setting, we observe a zip code level measure from the California Department of Insurance that summarizes the distribution of wildfire risk for all homes in the zip code.[51] Appendix Table 5 reports first-stage regressions of segment-mean wildfire risk on this auxiliary measure. The dependent variable in these regressions is the regression-adjusted segment mean wildfire AAL that comes from Equation 9. The independent variable is the weighted mean of CDI zip code risk for the zip codes containing the homes that we observe in the segment. CDI zip-code risk summaries strongly predict the mean risk in the data, with first stage F statistics exceeding 60 for all but the insurer with the least-sophisticated wildfire risk pricing.

Appendix Table 4 shows OLS and 2SLS estimates of β_{kj} for each firm. The OLS and 2SLS estimates are similar for firms with few territories (Allstate, Nationwide) and different for firms with many territories (USAA, Liberty Mutual, State Farm). This is true for the relationship between the firm's own prices and territory risk (panel A) and State Farm's prices and each firm's territory-level mean risk (panel B). The exception is AAA Southern California. For this firm, the IV and OLS specifications differ meaningfully even though the firm only has 19 territories. Both slope estimates

51. These reports aggregate survey information from all major insurers, were required by SB 824. See Appendix A for discussion.

Appendix Table 4: OLS versus IV price gradients

Firm Segmentation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Allstate		Nationwide		USAA		Liberty Mutual		AAA SoCal		State Farm	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Own Price												
Segment-Mean AAL	2.67***	2.87***	3.57***	3.42***	0.67***	2.17***	0.65***	2.46***	-0.32***	-1.44	0.36***	1.10
SE	(0.22)	(0.26)	(0.37)	(0.43)	(0.14)	(0.42)	(0.16)	(0.40)	(0.36)	(1.82)	(0.05)	(0.14)
State Farm Price												
Segment-Mean AAL	0.83***	0.95**	0.96**	0.95**	0.48***	1.01	0.45***	0.91**	1.09	1.99		
SE	(0.09)	(0.10)	(0.11)	(0.13)	(0.08)	(0.20)	(0.08)	(0.15)	(0.31)	(4.33)		
First Stage F-Statistic		255.6		61.1		62.1		88.8		9.1		1694.2
Zip Code FE	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No
Number of Segments	94	94	30	30	323	323	393	393	19	19	11946	11946

Notes: Table reports estimates of β_{kj} from ordinary least squares and a two-step estimation procedure that first calculates regression-adjusted mean prices and wildfire AAL by segment following Equations 9 and 10, and then regresses these segment-level prices against segment-level mean wildfire AAL. The first-step estimation of segment means includes zip code fixed effects for Allstate and Nationwide, where there is cross-cutting variation in zip codes and wildfire segments. The second-step regression of mean price on mean wildfire AAL is estimated by two-stage least squares when there are many territories to remove measurement error in segment-mean wildfire AAL due to sampling variation. Standard errors are calculated by bootstrapping the full estimation procedure 500 times.

Appendix Table 5: IV First Stage Results

Segmentation Definition	(1) Allstate Scores	(2) Nationwide Scores	(3) USAA Territories	(4) Liberty Mutual Territories	(5) AAA SoCal Territories	(6) State Farm Grid Cells
Segment-Mean Risk Coefficient	599.68***	434.95***	276.05***	293.22***	221.55***	327.99***
SE	(37.51)	(55.63)	(35.02)	(31.11)	(73.51)	(7.97)
Zip Code FE	Yes	Yes	No	No	No	No
Number of Segments	94	30	323	393	19	11946

Notes: This table reports estimates of a regression of regression-adjusted segment-level prices against segment-level mean wildfire risk. This is the first stage of the two-stage least squares approach explained in the text. Standard errors are calculated by bootstrapping the estimation procedure 500 times. "Zip Code FE" indicates whether zip code fixed effects are included in the initial estimation of regression-adjusted segment-level prices. This is only possible for firms that segment on wildfire risk scores, since there is cross-cutting variation in wildfire risk score and zip code.

for AAA Southern California also have a negative sign. We note that the first stage relationship for AAA is weak, with a first-stage F statistic of about 9. The AAA Southern California results may also be related to the general difference in observed wildfire pricing behavior for AAA Southern California throughout the paper.

E Alternative Models of Wildfire Risk

Section 6.2 discusses how alternative risk models could explain the differences in risk pricing strategies. In this section, we reproduce the pricing and adverse selection results of the main text using an alternative, publicly-available measure of parcel-level wildfire risk from the United States Forest Service (USFS). The USFS has produced a "Risk to Potential Structures" (RPS) model that reports annual, location-specific probabilities of structure loss at a 30-meter resolution (Scott et al. 2024). For each home in the dataset, we calculate a rough USFS-based AAL by multiplying the USFS loss probability by the structure reconstruction cost from CoreLogic.[52]

These USFS-based AALs require a number of caveats. Unlike the CoreLogic wildfire catastrophe model, the USFS RPS model is not designed for insurance use or for single-location analysis. The model assumes constant vulnerability to wildfire, regardless of structure characteristics (roof, year built, etc.). Furthermore, the underlying wildfire model is not capable of representing fire spread in developed urban areas, which includes many of the neighborhoods in our study. Scott et al. (2024) assign burn probabilities in these areas through post-processing and interpolation ("oozing"). Finally, the USFS RPS model includes a limited treatment of fire suppression (firefighting). For all of these reasons, we view the USFS-based AALs as a possible illustration of the range of variability that might exist in other models of wildfire risk, as opposed to a measure that should be taken literally as a competing prediction of annual wildfire loss.

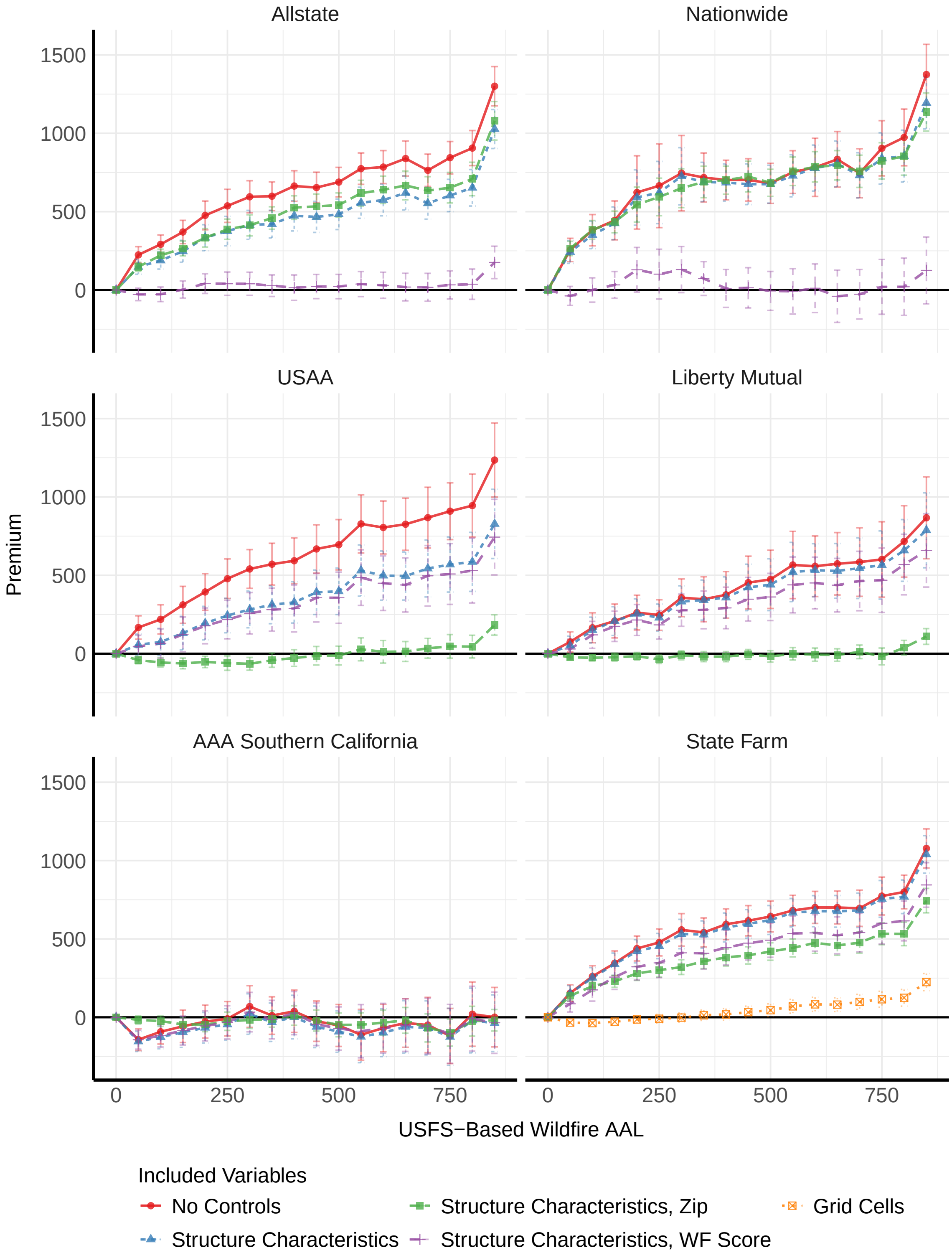
Appendix Figure 3 reproduces the variance decomposition of Figure 4 using the USFS-based AAL. As in the main text, State Farm's prices display a clear information advantage. There is a strong residual relationship between State Farm prices and USFS-based AAL even after controlling for zip code or wildfire risk score segment dummies.

Appendix Figure 4 reproduces the risk price gradient of Figure 5 using the USFS-based AAL. The estimated segment-mean AALs are somewhat larger with the USFS-based AAL than with CoreLogic. Nevertheless, the qualitative pricing patterns are similar for the two fringe firms. Both Allstate and Nationwide charge prices above the calibrated 1.18 benchmark in most high-risk segments. The highest-risk segments for one of the firms (Allstate) fall below this benchmark, perhaps consistent with rate compression due to binding rate regulation. For State Farm, segment-mean prices are substantially below the segment-mean USFS-based wildfire AALs.

Appendix Table 6 compares the the winner's curse in Bertrand duopoly when using the USFS-based (panel A) vs. CoreLogic (panel B) wildfire AALs. We estimate the regression with AAL in levels, instead of logs as in the main text, because there are some zero values for the USFS-based AAL. Compared to the CoreLogic AALs, the magnitude of the winner's curse is substantially larger using the USFS-based AALs. One reason for this difference is that the wildfire risk is higher on average for all homes using the USFS-based AAL, as evidenced by the dependent variable mean of \$509 in panel A vs. \$302 in panel B. Moreover, the degree of adverse selection is also higher in panel A. Using the example of Allstate, the USFS-based AALs imply that customers won by Allstate are $329/509 = 65\%$ costlier than those won by State Farm. Using the CoreLogic AALs implies a difference of $116/302 = 38\%$.

52. The RPS loss probabilities include a handful of extremely high values up to more than 6 percent per year. To reduce influence of these outliers, we winsorize (i.e., top-code) loss probabilities at the 99.75th percentile, which is 1.72 percent per year.

Appendix Figure 3: Validating firms' reported pricing variables, using USFS AAL

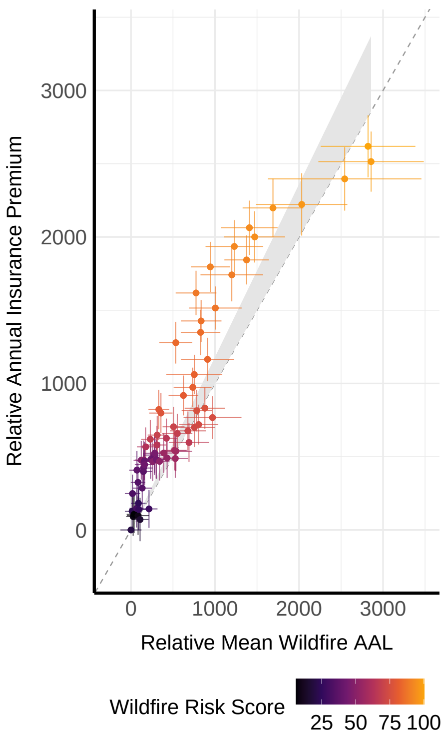


Notes: Constructed similarly to Figure 4, using USFS-based wildfire AAL instead of CoreLogic wildfire AAL.

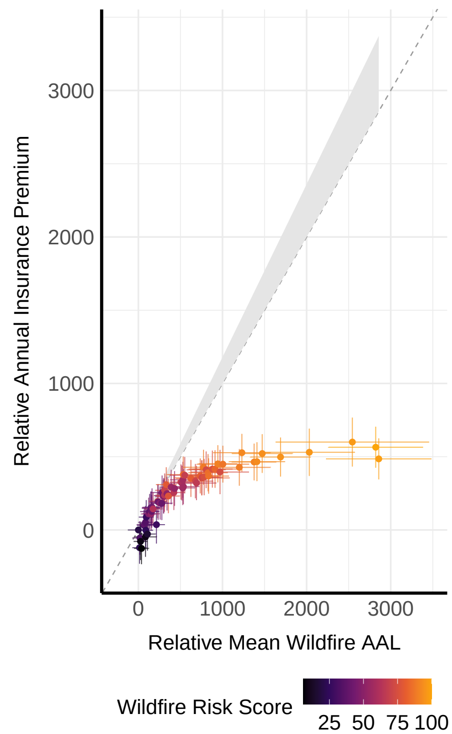
Appendix Figure 4: Wildfire price gradients for Allstate and Nationwide using USFS-based AALs

Panel A. Allstate

(a) Allstate, with FE

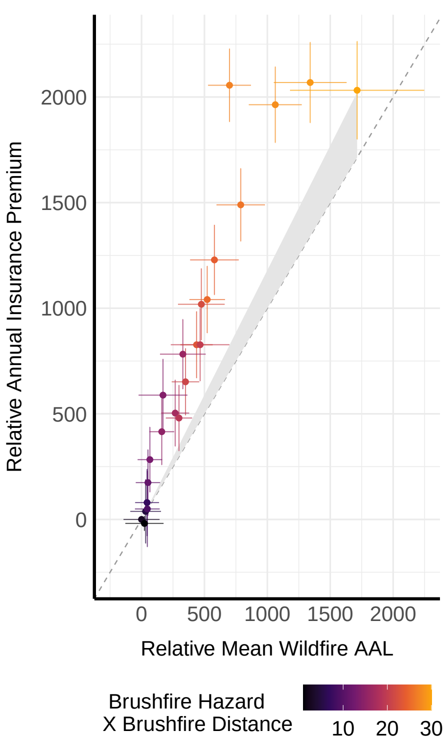


(b) State Farm, with FE

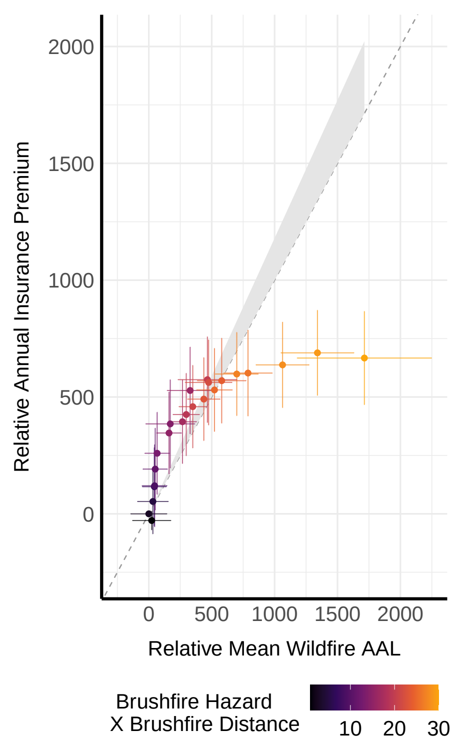


Panel B. Nationwide

(c) Nationwide, with FE



(d) State Farm, with FE



Notes: Constructed similarly to Figure 5, using USFS-based wildfire AAL instead of CoreLogic wildfire AAL.

Appendix Table 6: The winner's curse in stylized Bertrand duopoly, alternative wildfire risk models

Panel A: USFS-based wildfire AAL

	USFS-based Wildfire AAL				
	Allstate	Nationwide	USAA	Liberty Mutual	AAA SoCal
	(1)	(2)	(3)	(4)	(5)
1[Win]	328.65***	326.23***	358.09***	369.79***	356.38***
	(42.68)	(45.63)	(43.49)	(53.99)	(52.87)
Structure Characteristics	✓	✓	✓	✓	✓
seg FE	✓	✓	✓	✓	✓
Observations	95,295	95,295	95,295	93,976	55,606
R^2	0.25	0.20	0.37	0.40	0.15
Dependent variable mean	508.77	508.77	508.77	512.61	494.24
Fraction Won	0.53	0.55	0.50	0.44	0.50

Panel B: CoreLogic wildfire AAL

	CoreLogic Wildfire AAL				
	Allstate	Nationwide	USAA	Liberty Mutual	AAA SoCal
	(1)	(2)	(3)	(4)	(5)
1[Win]	115.71***	75.51***	138.75***	82.37***	96.73***
	(25.51)	(27.43)	(17.12)	(14.42)	(19.73)
Structure Characteristics	✓	✓	✓	✓	✓
seg FE	✓	✓	✓	✓	✓
Observations	95,295	95,295	95,295	93,976	55,606
R^2	0.19	0.16	0.44	0.48	0.20
Dependent variable mean	302.21	302.21	302.21	299.09	235.61
Fraction Won	0.53	0.55	0.50	0.44	0.50

Notes: Follows Table 5, using alternative models for the dependent variable. Regressions are estimated with the AAL in levels, rather than logs as in the main text, because there are some zero values for the USFS-based AAL.

F 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:

$$\pi^D = p^F - \delta - \tilde{l} = \alpha(p^F + \delta - \tilde{l}) \tag{24}$$

Equation 24 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 $\tilde{l} > 0$. The price p^F satisfies:

$$\pi^F = \frac{1-\alpha}{2}(p^F - \tilde{l})^2 - \frac{1}{2}(l^* - p^F)^2 + \frac{\alpha}{2}\delta^2 = 0. \tag{25}$$

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

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

$$\bar{l} > \delta\sqrt{\frac{1+3\alpha}{1-\alpha}}, \tag{27}$$

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 $\tilde{l}$:

$$p^F = \tilde{l} + \delta\frac{1+\alpha}{1-\alpha} > \bar{l}; \tag{28}$$

$$\tilde{l} > \bar{l} - \delta\frac{1+\alpha}{1-\alpha} > 0, \tag{29}$$

where the last inequality uses $\bar{l} > \delta\frac{1+\alpha}{1-\alpha}$. We have shown the first part of result (2) of the proposition: The price $p^D = p^F - \delta$ is the dominant firm's best response for $l \in [0, \tilde{l})$. The second part of result (2) is established from Equation 24, where it was shown that $p^D = p^F + \delta$ yields the highest profits for $l > \tilde{l}$. The price $p^D = p^F + \delta$ 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 to 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. Proof of Proposition III

Under the market equilibrium in Proposition I, the dominant firms earns positive profits (Equation 16) and the fringe earns zero profits (Equation 17). Total profits for the dominant and fringe firms with technology adoption (T) can be written:

$$\begin{aligned}\pi^T = \int_0^{\tilde{l}} (p^F - \delta - l)\frac{1}{l^*}dl + \alpha \int_{\tilde{l}}^{l_1} (p^F + \delta - l)\frac{1}{l^*}dl \\ + (1-\alpha)\int_{\tilde{l}}^{l_1} (p^F - l)\frac{1}{l^*}dl + \int_{l_1}^{l^*} (p^F - l)\frac{1}{l^*}dl.\end{aligned} \tag{30}$$

Similarly, profits under the initial conditions (0) can be written:

$$\begin{aligned}\pi^0 = \int_0^{\tilde{l}} (p_0 - l)\frac{1}{l^*}dl + \alpha \int_{\tilde{l}}^{l_1} (p_0 - l)\frac{1}{l^*}dl \\ + (1-\alpha)\int_{\tilde{l}}^{l_1} (p_0 - l)\frac{1}{l^*}dl + \int_{l_1}^{l^*} (p_0 - l)\frac{1}{l^*}dl.\end{aligned} \tag{31}$$

Solve the integrals in Equations 30 and 31 and evaluate the inequality $\pi^T > \pi^0$. After cancelling common terms, obtain:

$$\bar{p} = (p^F - \delta)\frac{\tilde{l}}{l^*} + \alpha(p^F + \delta)\frac{l_1 - \tilde{l}}{l^*} + (1-\alpha)p^F\frac{l_1 - \tilde{l}}{l^*} + p^F\frac{l^* - l_1}{l^*} > p_0. \tag{32}$$

3. Results for the Equilibrium Model with Regulation

We show that the zero profit and average price isoclines in Equations 22 and 23, respectively, are upward sloping at the unconstrained equilibrium, as shown in panel (a) of Appendix Figure 5. From Equation 17, equilibrium profits for the fringe firms are given by:

$$\pi^F = \frac{1}{2}\left\{(1-\alpha)(p^F - \tilde{l})^2 - (l^* - p^F)^2 + \alpha\delta^2\right\} = 0. \tag{33}$$

Applying the Implicit Function Theorem, we obtain:

$$\frac{dp^F}{d\tilde{l}} = -\frac{\pi^F_{\tilde{l}}}{\pi^F_{p^F}} = \frac{(1-\alpha)(p^F - \tilde{l})}{(1-\alpha)(p^F - \tilde{l}) + l^* - p^F} > 0, \tag{34}$$

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 Equation 20, we have:

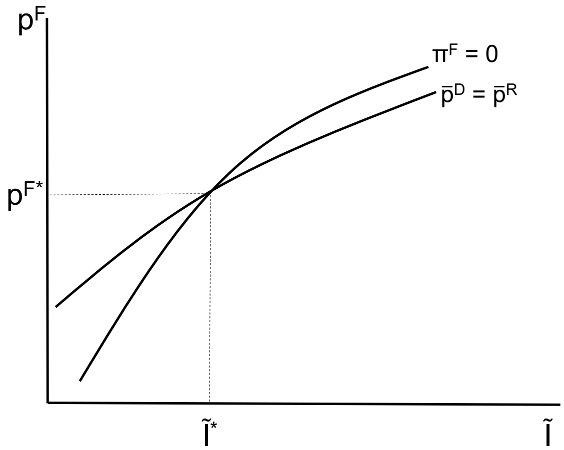
$$M = \bar{p} - \eta(p^F - \delta) - (1-\eta)(p^F + \delta) = 0, \tag{35}$$

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

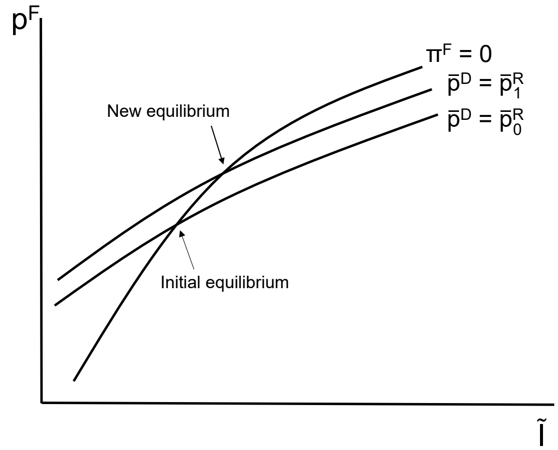
$$\frac{dp^F}{d\tilde{l}} = -\frac{M_{\tilde{l}}}{M_{p^F}} = \frac{2\delta(p^F - \delta)}{2\delta\tilde{l} + (p^F - \delta)^2} > 0. \tag{36}$$

Appendix Figure 5: Market equilibrium with regulatory price constraints

(a) Isoclines for profit and price conditions



(b) Equilibrium with relaxed constraint



Notes: Panel (a) shows the isoclines corresponding to the zero profit and average price conditions in Equations 22 and 23. The intersection of the isoclines defines the equilibrium for $\bar{p}^D = \bar{p}^R$. Panel (b) shows how the equilibrium changes when the average price constraint on the dominant firm is relaxed ($\bar{p}_1^R > \bar{p}_0^R$).

Numerical analysis is used to show that at the unconstrained equilibrium the relative magnitudes of the isocline slopes in Equations 34 and 37 are indeterminate. It can be shown that scaling δ and l^* by a constant factor leaves the slopes in Equations 34 and 37 unchanged. Therefore, we need only consider how the slopes vary with $\tau = \frac{\tilde{l}}{\delta}$. Appendix Figure 6 shows that for $\alpha = 0.2$, the difference in slopes can be positive or negative. Except for small values of τ, 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 Equation 20, as shown in panel b) of Appendix Figure 5. Fixing p^F and applying the Implicit Function Theorem to Equation 35, we obtain:

$$\frac{d\tilde{l}}{d\bar{p}} = -\frac{M_{\bar{p}}}{M_{\tilde{l}}} = -\frac{[\tilde{l} + \alpha(p^F + \delta - \tilde{l})]^2}{2\delta\alpha(p^F + \delta)} < 0. \tag{37}$$

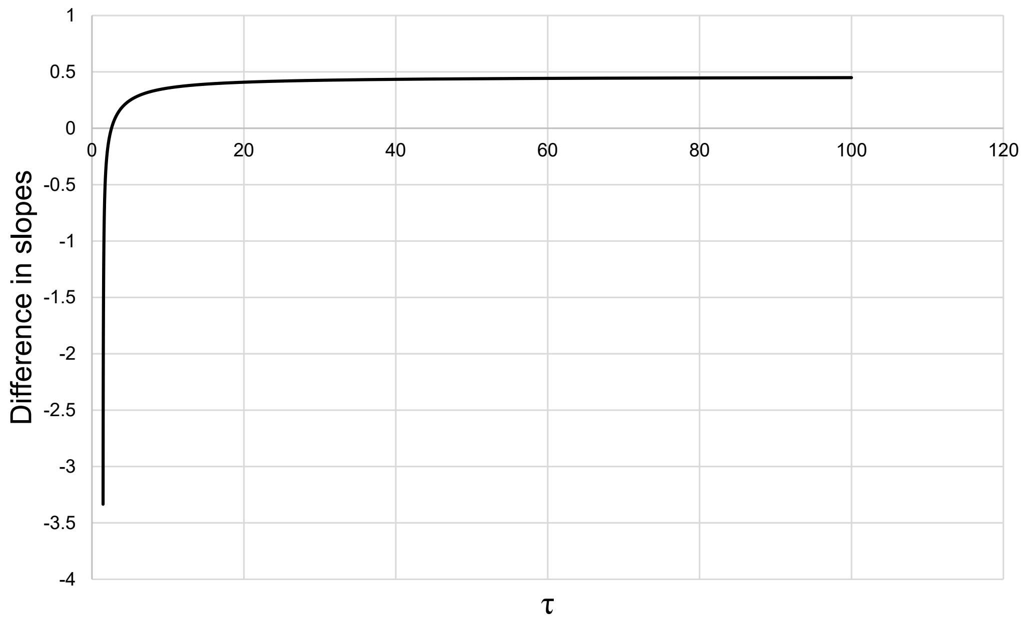
The decline in $\tilde{l}$ for fixed p^F gives the upward shift in the average price isocline depicted in Figure 5.

4. <u>Results for the Equilibrium Model with Information Provision</u>

Panels (c) and (d) of Figure 8 depict the case in which $\tilde{l} > \bar{l}$ under the original equilibrium. However, if $\tilde{l} < \bar{l}$ initially, then with information provision there will not exist values of $\tilde{l}$ below which the dominant firm wants to use the low price strategy. To see this, consider that under the original equilibrium, $\tilde{l} = l^{max} - \delta\sqrt{\frac{1+3\alpha}{1-\alpha}} - \delta\frac{1+\alpha}{1-\alpha}$. This value is unaffected by the division of the risk segment, implying that it will fall outside of the interval $[\bar{l}, l^*]$ defining the new, higher-risk segment. Since the new, lower-risk segment is symmetric, $\tilde{l}$ will also fall outside of $[0, \bar{l})$. Rather than a two-part pricing strategy, 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 (see Appendix Figure 7).

We use numerical analysis to explore how the overall average price changes in this case. We set

Appendix Figure 6: Difference in isocline slopes for different values of τ

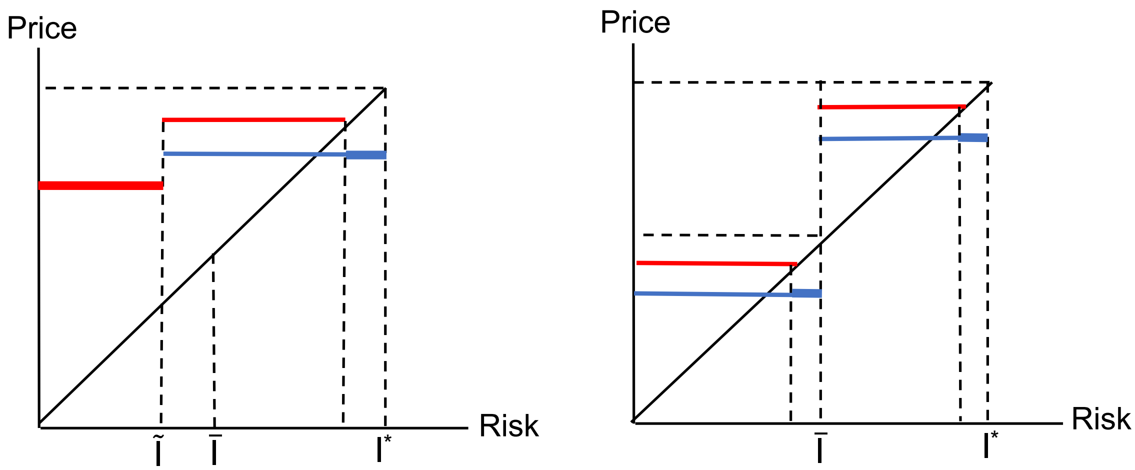


Notes: Figure shows the slope of the zero profit isocline in Equation 34 minus the slope of the average price isocline in Equation 37 for $\alpha = 0.2$ and different values of $\tau = \frac{\bar{l}}{\delta}$. Results show that the zero profit isocline is steeper than the average price isocline at the unconstrained equilibrium for values $\tau \geq 2.6$.

$\alpha = 0.2$ 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 $\tilde{l}$ under the original equilibrium just below $\bar{l}$ and the upper value yields an $\tilde{l}$ just above zero. Appendix Figure 8 shows that information provision reduces average prices for all values of δ.

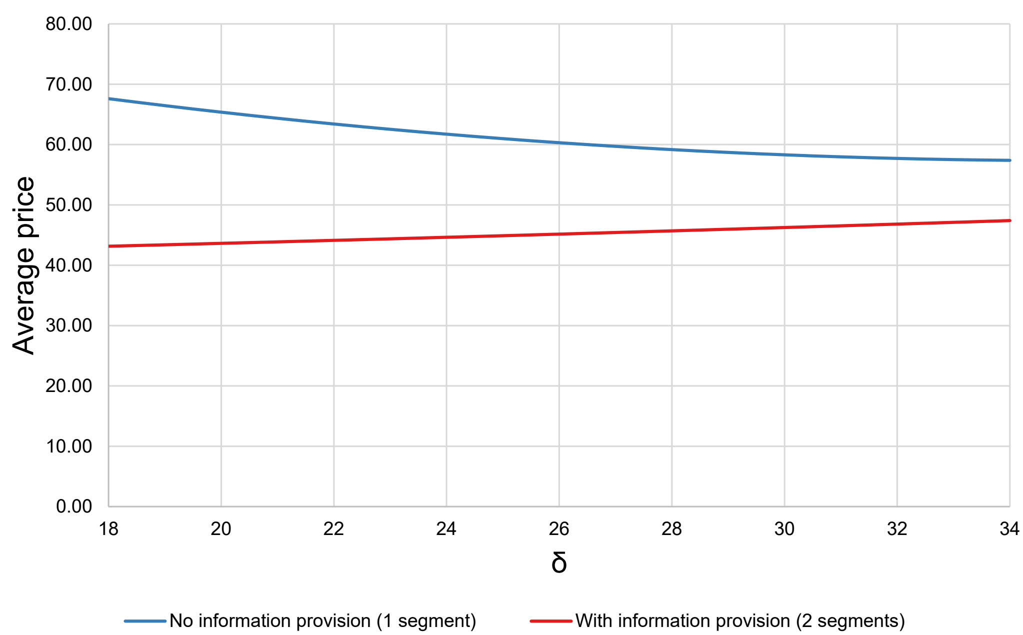
Appendix Figure 7: Effects of information provision on market equilibrium: $\tilde{l} < \bar{l}$ under the original equilibrium

(a) Baseline case (b) Effect of information provision



Notes: The two panels show how equilibrium prices change when new information is provided to the competitive fringe firms. Panel (a) is the original case in which fringe firms know only that properties are distributed according to $U(0, l^*)$. In panel (b), the firms can distinguish whether properties are distributed according to $U(0, \bar{l})$ or $U(\bar{l}, l^*)$.

Appendix Figure 8: Difference in overall average prices with information provision



Notes: Figure shows differences in overall average prices with information provision (see Appendix Figure 7). 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 $\bar{l}$ under the original equilibrium, 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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