# Coverage Neglect in Homeowners Insurance*

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**Abstract**

Most homeowners do not have enough insurance coverage to rebuild their house after a total loss. Using contract-level data from 24 homeowners insurance companies in Colorado, we show that widespread underinsurance is largely driven by differences in average coverage limits across insurers, as opposed to policyholder characteristics, and is enabled by homeowner inattention to coverage limits (*coverage neglect*). Underinsurance matters for disaster recovery. Across households that lost homes to a major wildfire, 10 p.p. higher underinsurance is associated with a 5 p.p. decline in the likelihood of filing a rebuilding permit within a year of the loss. We build a discrete choice insurance demand model to understand why consumers select underinsured policies. Our model shows that consumers value lower premiums while neglecting coverage limits. Under a counterfactual without coverage neglect, annual average consumer surplus increases by $300.

**Keywords:** Disaster Insurance; Disaster Recovery; Inattention; Information Frictions and Limited Attention; Insurance Demand
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# 1 INTRODUCTION

Three-quarters of American homeowners report being confident that their property insurance is sufficient to fully replace their house in the event of a disaster (Swartz and Howard, 2020; Metlife, 2010). However, for decades, survivors of total loss events have routinely reported that they lack the coverage needed to rebuild their homes and expressed confusion about how their policy limits were originally set (Klein, 2018; United Policyholders, 2020; Hassani, 2013). As climate change intensifies, so too does the importance of understanding the factors contributing to the longstanding problem of underinsurance. Nonetheless, the economics literature is mostly silent on the topic. This paper aims to fill this gap, asking why homeowners are underinsured against total losses and what characteristics of households and insurers lead to underinsurance.

The ideal data set for this exercise would contain granular information on the menu of insurance contract characteristics (e.g., premiums, coverage limits, provisions for extended coverage), matched with policyholder characteristics (e.g., income, home value, credit score) and the insurance companies they select. Moreover, an analysis of *under*insurance also depends on an accurate estimate of rebuilding costs. Finally, to gauge the economic significance of underinsurance, it is important to know if disaster-stricken households with larger gaps in insurance coverage experience worse recovery outcomes. Existing insurance data sources fall short of this ideal, typically reporting only premiums at an aggregate level and lacking policy-level detail.

In this paper, we examine new data that closely approximate this ideal. From the Colorado Division of Insurance (DOI), we have homeowners insurance contract details for 4,859 policyholders affected by the Marshall Fire, a major, unexpected wildfire that burned through a suburban area between Denver and Boulder, Colorado on December 30, 2021. These data cover 24 different insurance companies operating in the same market. For each insurance contract in our estimation sample, we see the property address as well as the insurer's name, standardized premiums calculated from regulatory rate filings, the date the policy was first written, the last renewal date before December 30, 2021, and detailed characteristics of the insurance contract, including coverage limits and any provisions for extended or full replacement cost coverage.[1] Critical for tracking underinsurance over time, we see changes in coverage amounts between the original policy incep-

[1] Our analysis does not disclose details that can be traced back to any particular insurer or homeowner.

tion date and the date of the fire.

We merge these detailed insurance contracts with anonymized data on the property and household characteristics of policyholders. In particular, we estimate the replacement cost of the insured structure using detailed physical characteristics and a construction cost estimator. We recalibrate these cost estimates according to the real-world construction quotes from a subsample of disaster survivors. Next, we merge each policyholder to Experian credit data, which include information on credit score, estimated household income, and mortgage and credit card balances. For households that experienced a total loss, we obtain deeds and permitting records, allowing us to track their recoveries and understand the real consequences of underinsurance. All told, these data provide an unprecedented level of detail to study the drivers of underinsurance.

Our data confirm the widespread and severe underinsurance reported after the Marshall Fire. We estimate that 74% of policyholders were underinsured after the fire, and 36% were *severely* underinsured with dwelling coverage limits equal to less than three-quarters of their home's replacement cost. The sharp increase in rebuild costs after the fire does not fully explain the extent of underinsurance. Moreover, older policies are no more underinsured than newer ones, suggesting that underinsurance is not driven by policyholders failing to update their coverage limits over time. Policyholders with high mortgage balances are also no more or less underinsured than those without mortgages, suggesting that leveraged homeowners do not strategically underinsure and mortgage lenders do not prevent underinsurance by monitoring coverage amounts. Although higher-income households were less likely to be underinsured than lower-income homeowners, a majority of both groups had insufficient coverage to rebuild.

Instead, the most important predictor of a policyholder's underinsurance is their chosen insurance company. Not only is there substantial variation in underinsurance across insurers, but the potency of insurer choice in predicting underinsurance is robust to accounting for policyholder characteristics. We do not find meaningful selection by policyholder income, credit score, or home values across insurers with different average coverage ratios. Interestingly, we find insurers with more "local knowledge," as proxied by the number and age of their policies, are less likely to underinsure. These patterns suggest a supply-side effect in which insurers employ heterogeneous models to estimate replacement costs and are more likely to underestimate replacement costs when they have less expertise. Overall, these findings suggest that insurers themselves play

a crucial role in anchoring consumers' choices of coverage limits relative to replacement costs.[2]

Turning to the consequences, it is not *ex ante* obvious that household welfare is lower because of underinsurance. Underinsurance can arise rationally if, for example, homeowners face liquidity constraints or anticipate post-disaster aid (Ericson and Sydnor, 2018; Billings, Gallagher, and Ricketts, 2022). Similarly, canonical insurance models predict that some households, particularly wealthy ones, may optimally self-insure (Mossin, 1968; Lewis, 1989; Koijen, Van Nieuwerburgh, and Yogo, 2016), though recent work shows that high-income households buy more insurance (Gropper and Kuhnen, 2023). If underinsured households self-insure or access other funding sources (e.g., Federal disaster loans), underinsurance might not predict recovery outcomes. In contrast to this rational, full information view, boundedly rational homeowners may inadvertently underinsure due to not knowing their home's replacement cost or understanding the precise details of their insurance contract. To the extent that underinsurance is unintentional, it may lead to worse recovery outcomes.

Consistent with the latter hypothesis, we find that more underinsured policyholders fare significantly worse after the fire. Exploiting variation in the tendency to underinsure across insurance companies, we find that underinsured wildfire survivors with destroyed homes are less likely to file rebuilding permits and more likely to sell their property. Our estimates signal that underinsurance reduced the number of rebuilding permits filed within one year of the fire by 25% and contributed to over half of the destroyed property sales in the 18 months after the fire. This is an important result, not only because it suggests that some homeowners underinsure inadvertently, but also because decisions to rebuild generate large positive externalities on disaster-affected communities (Fu and Gregory, 2019).

To shed light on why homeowners choose insurance policies that leave them underinsured, we estimate a discrete choice model of insurance demand that contrasts two hypotheses regarding homeowner demand. The first "full information" hypothesis is that homeowners shop for insurance rationally, comparing policies based on premiums per dollar of coverage. The second "coverage neglect" hypothesis proposes that prospective policyholders are inattentive to differences in coverage. Rather, buyers shop solely on the headline premium, mistaking less coverage

[2]Related to this idea, policyholder advocates argue that the software insurers employ underestimates home replacement costs, thus allowing insurers to cater to premium-sensitive buyers who are inattentive to true replacement costs (United Policyholders, 2024; Phillips, 2022).

for a lower cost. Under this scenario, insurers can offer contracts with less coverage to reduce premiums, and thus, entice premium-sensitive buyers.

To evaluate these two hypotheses, we model the predicted coverage offered to each homeowner by each insurer according to the homeowner's financial and property characteristics. To calculate the quoted premiums across insurers, we use premium schedules gathered from rate filing data. Homeowners select from contracts offered by each insurer. In line with the demand estimation literature, the choice model includes insurer fixed effects, which capture unobserved differences in average insurer (brand) quality that are allowed to vary by flexible functions of homeowner and property characteristics. This model contrasts the full information and coverage neglect hypotheses by allowing latent utility to depend on both the *total premium* offered by each insurer and the *premium per dollar of coverage*.

We estimate a significant loading on total premium, but not on premium per dollar of coverage. These findings are consistent with coverage neglect and inconsistent with the full information hypothesis. There is little heterogeneity in our estimates across incomes or mortgage status, which indicates that coverage limits are not salient to a wide range of consumers, and may not be disciplined by mortgage lenders. We interpret these findings as evidence that homeowners neglect differences in coverage limits as they shop across insurers. Even though coverage limits are prominently displayed on homeowners insurance contracts and adjustable by the policyholder, homeowners do not fully internalize how proposed limits vary across insurers while comparing quotes. As in other finance contexts, consumers may struggle to compare prices across contracts that vary along multiple dimensions (Campbell, 2016). In addition, the salience of dwelling coverage limits may be reduced by the difficult of estimating a home's true replacement cost. There are no free, independent estimators available to homeowners seeking to validate the level of coverage necessary to rebuild their homes Fuqua (2024).

To quantify the cost of coverage neglect, we estimate how consumer welfare would change if they chose their insurer based on coverage-adjusted rather than absolute premiums. We estimate that the average homeowner would benefit by nearly $300 per year under a "full information" counterfactual. Although it is difficult to forecast the impact of any specific market intervention, we conclude that alleviating information frictions that prevent policyholders from comparing quotes on a coverage-adjusted basis would drive buyers towards higher-quality insurers that are

less likely to underinsure.

Most directly, this paper contributes to literature on the impact of climate risk on real estate markets. A growing literature examines whether future climate risks are capitalized into real estate prices (Bernstein, Gustafson, and Lewis, 2019; Keys and Mulder, 2020; Bakkensen and Barrage, 2022; Baldauf, Garlappi, and Yannelis, 2020; Giglio, Maggiori, Rao, Stroebel, and Weber, 2021; Murfin and Spiegel, 2020). More recent papers evaluate the impact of disaster risk and state insurance regulations on the homeowners insurance market (Issler, Stanton, Vergara-Alert, and Wallace, 2020; Sastry, Sen, and Tenekedjieva, 2023; Eastman, Kim, and Zhou, 2024; Keys and Mulder, 2024; Boomhower, Fowlie, Gellman, and Plantinga, 2024). These papers find sharp increases in premiums rates in disaster-prone regions and attempts by well-capitalized insurers to either pull out of these markets or spread the risk (and rate increases) to less risky areas. Our paper complements this emerging research by studying, at a micro-level, the determinants of the quantity of coverage provided.

As such, our paper also relates to studies of the *ex ante* decisions that households and firms face when managing climate risk – including work on expectations, shifting beliefs, and mitigation efforts (Painter, 2020; Bernstein, Billings, Gustafson, and Lewis, 2022; Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2023) – and studies of inequalities in the resources available to households to recover from natural disasters (Billings et al., 2022; Begley, Gurun, Purnanandam, and Weagley, 2024). In the context of flood insurance through the National Flood Insurance Program, Sastry (2022) finds that lenders respond to coverage limits, while Collier and Ragin (2020) find that insurance agents influence coverage limit choices. Particularly related to our work is Cookson, Gallagher, and Mulder (2023), which examines post-disaster crowdfunding also in the context of the Marshall Fire. That paper focuses on the use of GoFundMe as a form of informal social network insurance that can be tapped after disasters but disproportionately benefits high-income households. Both papers find that underinsurance, be it formal or informal, hinders recovery, thereby highlighting how lower-income households systematically lack the resources for post-disaster recovery.

Given our focus on the drivers of underinsurance in homeowners contracts, our paper is closely related to the contemporaneous work of Sastry, Scharlemann, Sen, and Tenekedjieva (2024). Their paper provides a complementary national picture of underinsurance. The authors estimate

underinsurance by inferring premiums from mortgage escrow payments (net of taxes) and comparing inferred premiums to the cost of full coverage based on the average premiums in insurer rate filings. Relative to this approach, our data provide a more direct and granular picture of each homeowner's insurance contract features, premium paid, and coverages purchased. Importantly, we uniquely observe the insurance provider chosen by the household. As a result, we can precisely estimate the role of insurer heterogeneity in driving underinsurance and construct a discrete choice model to test whether consumer demand-side frictions contribute to underinsurance. Because we study insurance contracts in force as of a major wildfire, we can also link coverage to disaster recovery outcomes, pointing to real effects. In sum, our contribution is to provide a detailed study of the market forces that generate underinsurance and to document the real consequences in the specific context of a major disaster.

Our findings also relate to the literature on limited attention and neglected attributes in consumer choice. Consumers have been shown to be inattentive to key product attributes across a variety of domains, including mortgage, auto, and online retail markets (Agarwal, Song, and Yao, 2022; Lacetera, Pope, and Sydnor, 2012; Brown, Hossain, and Morgan, 2010; Ellison and Ellison, 2009). When consumers are faced with complicated financial products, inattention and shrouded attributes can lead to pricing and quality responses by suppliers (Hortaçsu and Syverson, 2004; Roussanov, Ruan, and Wei, 2021; Célérier and Vallée, 2017; Guiso, Pozzi, Tsoy, Gambacorta, and Mistrulli, 2022). Like aspects of these markets, we present empirical evidence suggesting that homeowners neglect the total loss coverage amount, which might lead consumers to accept the coverage suggestions of insurance agents without knowing the methodology or doing an independent assessment, as described in the qualitative interviews in Hassani (2013). More generally, our findings relate to recent attempts to understand consumer inattention to first order financial product attributes (Kulkarni, Truffa, and Iberti, 2021; Berwart, Higgins, Kulkarni, and Truffa, 2024) and to the literature on search frictions (McDevitt, 2014; Hastings, Hortaçsu, and Syverson, 2017; Hortaçsu, Madanizadeh, and Puller, 2017). Our results suggest that coverage neglect by homeowners can cause underinsurance to persist in competitive markets.

Finally, this paper advances research on behavioral biases and information frictions in insurance markets (Sydnor, 2010; Handel and Kolstad, 2015; Abito and Salant, 2019; Boyer, De Donder, Fluet, Leroux, and Michaud, 2020; Collier, Schwartz, Kunreuther, and Michel-Kerjan, 2022). Most

similar to our paper, Abaluck and Gruber (2011) identifies demand patterns that are inconsistent with rational, full-information decision making from a model of Medicare plan choice. In the context of disaster insurance, the literature focuses on applying these models to the take-up of public flood insurance (Mulder, 2021; Wagner, 2022; Weill, 2023). In this paper, we provide evidence that suggests substantial choice frictions affecting private homeowners insurance coverage decisions. Unlike in the public flood insurance setting, where the National Flood Insurance Program is the dominant provider, suboptimal coverage choices stem from the interaction between consumer inattention and heterogeneity in coverage offerings across insurers. Thus, even in competitive disaster insurance markets where a large majority of homeowners buy coverage, choice frictions can still lead to suboptimal coverage decisions with potentially large welfare consequences.

# 2 Data, Sample, and Measurement

## 2.1 Data

We investigate the determinants of underinsurance with a novel combination of data on insurance contracts, premiums, property characteristics, and household financial attributes. These data are detailed below.

### Colorado Department of Insurance Policy Data

The Colorado Department of Insurance (DOI) collected data on individual homeowner's insurance contracts in the wake of the Marshall Fire. The data contain 4,859 policies from 24 insurers of homeowners who filed claims linked to the Marshall Fire. These insurers collectively insure a large majority of the Colorado market. The data include 989 policies linked to homes that were completely destroyed. The remainder of policies are linked to claims for smaller damages.

The DOI required all insurers to report the contract information for all policies in which the homeowner submitted a claim for losses from the Marshall Fire. For each insurance contract, we observe the total coverage for the main dwelling ("coverage A"), including any guaranteed or extended replacement coverage, other structures ("coverage B"), and contents ("coverage C") at the time of the loss and at policy inception. For each policy, the insurer name is listed, as is the policyholder's property address, which we use to merge with the other datasets described below.

Once the datasets are merged, the insurer and homeowner names/addresses are deleted and the merged, anonymized data are moved to a separate secured server.

The insurance data have limitations. First, insurers do not report deductible amounts, additional endorsements (e.g. for furs and jewelry), or insurers' estimates of the replacement costs of insured dwellings. The DOI requested that insurers report the premium charged on each policy for coverage A. However, only 9 out of the 24 insurers, representing about three-quarters of policies, populated this field. Others reported limitations in their ability to separate out the coverage A premium from the total premium charged. To overcome this limitation, we augment the DOI's insurance policy data with the other datasets described below.

### Boulder County Housing Data

The Boulder County assessor's office provides property-level information on tax assessment values, property characteristics (e.g., square footage, bedrooms, finished basement), construction permitting, and property sales. We use these property attributes to estimate replacement costs and to model insurer coverage limits and premiums. In addition, we use post-fire rebuilding permits and home sales as outcome variables in some analyses. We supplement the housing data with market valuation estimates (Zestimates) manually gathered for each home from Zillow.com at the time of the fire.

### Quadrant Insurance Company Rate Filing Data

Homeowners insurance pricing is heavily regulated by states. A company's quoted premiums must be calculated from rate manuals previously approved by each states' department of insurance. Quadrant Information Services ("Quadrant") is an insurance services company that reconstructs insurers' pricing formulas from those rate filings.[3] Using the 2021 Colorado rate filings, we obtain standardized premiums for each of the properties in our data at multiple levels of coverage A for each insurance company in the Colorado DOI data and available in Quadrant. Other coverages are held fixed (e.g. liability limits) or allowed to vary with coverage A according to company standards (e.g. contents coverage C is often 10% of coverage A).

Premiums are rated according to the following characteristics: zip code, credit score (as

[3] Quadrant data are representative of publicly sourced data and should not be interpreted as bindable quotes.

sourced from the Experian data described below), year built, basement type, building frame and walls, roof type, garage type, number of stories, and construction materials. Quadrant has available rates for 10 out of the 14 insurance companies in our estimation data, representing two-thirds of policies. The other four insurers in the estimation sample reported their premiums to the Colorado DOI. For these four insurers, we use their reported premiums in the Colorado DOI fildings to infer their rate manuals following a procedure described in Appendix Section B. Validating this method, we observe a strong correlation between the premiums implied from Quadrant pricing formulas and the premiums reported by the same insurance companies to the Colorado DOI.

#### Experian Credit Data

We also obtain Experian data for adults in each policy-holding household present in the DOI data. Experian data includes approximately 2,000 credit attributes, including mortgage balances and credit scores.[4] More details on the match process for this sample are described in Cookson et al. (2023). To measure household income, we use Experian's Income Insights data. Experian estimates individual incomes from a proprietary predictive model trained on the credit data matched to Form 1040 income tax data (see Cookson, Gilje, and Heimer 2022 for an example of research using these data). We use data from December 31, 2021, the day after the fire. We sum or average credit attributes, as appropriate, across adults in the household.

### 2.2 Estimation Sample

We restrict the data in the following ways to obtain a consistent and fully populated estimation sample. First, we subset the 4,859 policies in the Colorado DOI data to include only policies on single-family, owner-occupied, detached homes, thus, dropping 1,207 policies. This restriction ensures that the policies in our sample cover the same basic features. By contrast, insurance on attached homes, for example, often excludes the home's exterior, which is separately insured by homeowners associations. Next, we exclude 35 policyholders who either contracted with boutique insurers that tend to only insurer very high value or risk prone structures, or insurers that wrote

[4] Copyright 2023 Experian. All rights reserved. Experian and the Experian marks used herein are trademarks or registered trademarks of Experian Information Solutions, Inc. Other product and company names mentioned herein are the property of their respective owners. Per the academic use of Experian data, we present only aggregate statistics of credit data (e.g., summary statistics and regression coefficients) that do not identify the individuals in our sample.

no new policies in the five years before the Marshall Fire indicating that they are likely no longer writing new business in the area. We also drop 111 policyholders who could not be linked to Experian credit data and 91 policies missing important housing attributes from Boulder County or Zillow. Finally, we exclude four insurers with 74 policyholders that neither report premiums to the DOI nor have available Quadrant rate filings. Our final estimation sample contains 14 out of the 28 insurers who responded to the DOI data call and 3,089 policies, representing over 90% of the single-family policies in the original DOI data.

### 2.3 Measuring Underinsurance

We classify a home as underinsured according to its "coverage ratio." Specifically, a home's "coverage ratio" is its coverage A divided by the cost to rebuild the home, such that ratios below 1 indicate underinsurance and those above 1 overinsurance. Building costs increased dramatically in Boulder County, first with post-pandemic inflation period and again following correlated losses associated with the wildfire. To separate temporary trends from the structural causes of underinsurance, we calculate separate "pre-fire" and "post-fire" coverage ratios.

To calculate these two coverage ratios, we must first estimate pre- and post-fire replacement costs for each property. The base of our replacement cost estimates comes from RSMeans, a replacement cost estimation model commonly used in the construction industry (RSMeans, 2024). RSMeans estimates the cost of building a home as a function of its quality, square footage, other characteristics, its market, and time period. Following best practices for Boulder County, we estimate replacement costs for "luxury" quality construction in Boulder County in the first quarter of 2023 using square footage and other housing characteristics in the county assessor data. Although the first quarter of 2023 is over a year after the Marshall Fire, very few of the survivors with total losses had rebuilt their home by then – only approximately 30% had filed rebuilding permits, which is one of the first steps in the reconstruction process. Thus, 2023 construction costs are what most survivors would need to pay to rebuild.

To estimate the cost of replacing a home, insurance companies frequently rely on third-party software (e.g., RSMeans, CoreLogic Marshall & Swift, 360Value, among others). Consumer advocates in multiple states have raised concerns that the overly simplistic use of these software products may lead insurance agents to understate replacement costs (Hassani, 2013; Phillips, 2022).

Therefore, when measuring underinsurance, we are careful to account for potential underestimation in construction cost software. We do this by, first, gathering rebuilding cost quotes from the Colorado DOI, Marshall Fire survivors, and the Homebuilders Association of Metro Denver. Altogether, these sources suggest that average rebuilding costs after the Marshall Fire were around $350 per square foot. Then, we use RSMeans to generate cross-sectional heterogeneity in build costs after the Marshall Fire according to variation in home characteristics. Finally, we inflate the RSMeans construction cost estimate for each home such that the average across our estimation sample equals $350 per square foot.[5]

The post-fire replacement costs generated by this estimation method reflect both the surge in demand for labor and materials after the fire and the coincident supply chain issues brought by the COVID-19 Pandemic. These inflationary factors increased rebuilding costs substantially between 2021, when the policies in our sample were last renewed, and 2023, when most Marshall Fire survivors began rebuilding. To measure underinsurance at the time policies were being renewed, we generate a separate pre-fire replacement cost estimate for each policy by deflating the post-fire replacement cost estimates by the time-series change in the RSMeans historic cost index for residential homes in the Denver-region between Q1 2021 and Q1 2023 (22%). This method relies on the assumption that RSMeans accurately describes the change in construction costs even if, in any given year, the average level may be off. By indexing pre-fire replacement costs to the earliest possible date when policies in force at the time of the fire were last renewed, we generate the smallest replacement cost, which gives the most conservative estimate of pre-fire underinsurance.

Next, we calculate each policy's pre- and post-fire insurance coverage, i.e. the numerators of our coverage ratios. First, it is helpful to understand dwelling coverage A in the context of homeowner's insurance policies. The software used by insurers to help policyholders set their coverage A limits is supposed to reflect the cost of rebuilding a home at current construction costs. Thus, the pre-fire coverage ratio is the coverage A limit divided by the pre-fire replacement cost:

$$R_i^{Pre} = \frac{\text{Coverage A}_i}{Replacement_i^{Pre}}.$$

$R_i^{Pre}$ measures policyholder $i$'s coverage A relative to the cost of replacing their home at the time

[5]While this adjustment affects our estimate of the fraction of underinsured policyholders, it does not affect our estimation results since our results rely on cross-sectional variation in coverage ratios across companies or homeowners.

they last renewed their policy before the fire.

A standard line item in an insurance contract is extended replacement cost coverage, which augments a policyholder's coverage A when inflation would otherwise cause the policyholder to be underinsured. Extended replacement cost coverage is typically sold as a percentage of a policyholder's coverage A (e.g. 25%). Unlike coverage A, which pays out immediately after a verified total loss, homeowners must prove that rebuilding costs truly exceed coverage A limits to access their extended coverage (i.e., hire an architect and contractor to design and price the destroyed home). Our measure of the post-fire coverage ratio adds extended replacement cost provisions to policyholders' coverage A limits because these provisions are designed for precisely the kind of cost inflation that came after the Marshall Fire. Approximately 87% of the policyholders in our estimation sample have extended replacement cost coverage, and the average percentage is 28% of coverage A.[6]

We calculate the post-fire coverage ratio as the extended dwelling A coverage divided by the post-fire replacement cost estimates:

$$R_i^{Post} = \frac{(1 + ext_rate_i) \times \text{Coverage A}_i}{Replacement_i^{Post}}$$

where $ext_rate_i$ is the extended replacement cost coverage rate for policyholder $i$.

## 2.4 Summary Statistics

Table 1 describes the mean, standard deviation, 25th percentile, and 75th percentile statistics of key variables in our estimation sample. Our full dataset combines information on insurance policy contract characteristics, the identity of the insurer, policyholder and structure characteristics, and information on disaster losses and recovery.

We note several significant characteristics of the data. First, the policyholders in the estimation sample have generally high average household incomes ($197,000), credit scores (798), and home values ($977,500). Despite this fact, the typical policyholder is underinsured against a total loss before and after the fire, a fact that we document in detail in the following section.

[6] An additional 6.9% of policyholders have guaranteed replacement cost coverage which guarantees full coverage of replacement costs. We set the post-fire coverage ratio of guaranteed replacement cost holders to the maximum of their coverage A divided by post-fire replacement costs and 1.

Around these averages, there is substantial heterogeneity across policyholders. Policyholders at the 75th percentiles are fully insured (according to both pre-fire and post-fire coverage ratios). There is also significant variation in homeowners insurance premiums per dollar of coverage. To fully insure against a total loss, policyholders at the 75th percentile would pay 75% more per $100 of coverage than those at the 25th percentile.

# 3 Results

This section describes the extent of underinsurance before detailing the policyholder and insurer factors that predict more or less underinsurance. This section also documents the consequences of underinsurance, in terms of rebuilding outcomes. The next section investigates the mechanism using a discrete choice model of policyholder demand for insurance.

## 3.1 The Prevalence of Underinsurance

Using pre-fire coverage ratios, we estimate that 74% of the homeowners in our sample were underinsured after the Marshall Fire. For 36% of homeowners, we estimate their dwelling coverage was less than three-quarters of their home's replacement cost. These findings suggest that underinsurance is widespread and severe.

Figure 1 plots the histograms of pre-fire (top) and post-fire (bottom) coverage ratios, where a coverage ratio less than 1 indicates underinsurance. Although the distributions of pre-fire and post-fire underinsurance differ, it is striking to note that the average coverage ratios are similar across both measures at 87.1% pre-fire and 86.7% post-fire. A frequently cited cause of underinsurance is sudden increases in construction costs. In our data, this rise was largely offset by extended replacement cost provisions. Thus, the high prevalence of pre-fire underinsurance, signals that policyholders were underinsured, not because of cost inflation, but because they bought too little coverage.

Next, we explore some of the policyholder characteristics that might explain the wide distribution of coverage ratios. Figure 2 plots the average pre-fire coverage ratio by bins of household income (top), pre-fire home value (middle), and credit score (bottom). Consistent with recent research showing that richer households tend to buy more insurance (Armantier, Foncel, and Tre-

ich, 2023; Gropper and Kuhnen, 2023), we see that coverage ratios are positively associated with both incomes and home values. However, there is a flat relationship between credit scores and underinsurance.

Despite the positive relationship between income and home values and coverage, it is striking to note that, even among households with incomes above the sample median of $180,000, 72% of policyholders were underinsured before the Marshall Fire. The prevalence of underinsurance across the wealth distribution suggests that additional factors besides ability-to-pay drive underinsurance. We test potential drivers of underinsurance in more detail below.

### 3.2 Do Policyholders Fail to Update their Coverage?

One commonly proposed cause of underinsurance is that homeowners fail to update their coverage A over time to account for inflation or improvements to their homes (Biswas, Biswas, and Zink, 2023; Sastry et al., 2024). Under a "failure to update" mechanism, policies may have accurate coverage limits when they are first written, but become increasingly underinsured over time as policyholders fail to update their coverage. If this hypothesis were true, we would expect the older policies in the data to be more underinsured.

As a visual test of this idea, Figure 3 plots the share of policyholders underinsured according to their pre-fire coverage ratio versus the year when their policy was first written. In contrast to failing to update coverages, the figure shows that the oldest policies originally written before 2000 are *less* likely to be underinsured than newer policies. From 2000 through 2021, the relationship between underinsurance and policy age is relatively flat.

Table 2 further tests the failure to update mechanism via several linear regressions with the pre-fire coverage ratio as the dependent variable and the age of the policy as the primary explanatory variable. In column (1) where we test the bivariate relationship between policy age and underinsurance, we see a weak and positive relationship between the age of a policy and its coverage ratio – the opposite relationship we would expect if policyholders failed to update. This relationship persists in column (2) as we add policyholder and structure characteristics, and in column (3) when we introduce company fixed effects. In contrast to the failure to update mechanism, we find no evidence that policies become more undeirnsured over time.

### 3.3 Does Underinsurance Vary with Mortgage Debt?

Mortgage contracts may interact with underinsurance through several avenues. Given that the insured property is collateral for mortgage loans, lenders typically require it to be adequately insured. Per Fannie Mae's property insurance requirements for mortgages it purchases, structure coverage must equal 100% of the property's estimated replacement cost as of the policy effective date or the maximum of the unpaid loan balance and 80% of the estimated replacement cost (Mae, 2024). Thus, if lenders are accurately monitoring these coverage requirements, policyholders with mortgages should be less underinsured than those without.

Alternatively, if monitoring is weak, then homeowners with highly leveraged mortgages may have less incentive to fully insure their home. If a borrower defaults after a total loss, their loss is limited by their home equity plus any economic costs of mortgage default. Studies have found that high leverage reduces flood insurance take-up, reduces labor market participation, and investment in home renovations (Liao and Mulder, 2021; Melzer, 2017; Bernstein, 2021).

We test whether monitoring or risk shifting incentives drive underinsurance in our data by comparing the pre-fire coverage ratios of policyholders with varying degrees of leverage. Our results are shown across several linear regressions in Table 3. In a simple regression in column (1), we see that policyholders with a mortgage have an average of 2.5 percentage point lower coverage ratio than those without. This relationship weakens as we introduce policyholder and structure characteristics (column 2) and becomes statistically insignificant with insurer fixed effects (column 3). Thus, rather than a positive relationship between mortgage status and coverage as predicted by the monitoring hypothesis, we instead observe a weak negative relationship.

In column (4), we test whether homeowners with high LTVs are more likely to underinsure per a risk-shifting channel. Instead of a binary indicator for mortgage debt, we deploy a series of indicators for policyholders' loan-to-value ratios in ten percentage point bins. Contrary to the risk shifting hypothesis, we observe no clear relationship between LTV and coverage.

Contrasting with both the monitoring and risk shifting mechanisms, our results suggest that heterogeneity in mortgage balances explains little of the variation in underinsurance. Notably, Fannie Mae's servicing guidelines state that the replacement cost estimates can come directly from the insurance company themselves. Thus, these leveraged policyholders must meet the minimum

coverage requirements according to their insurer's estimate of their home's replacement cost, despite being on average underinsured.

### 3.4 The Role of Insurance Companies

While policyholder characteristics explain some of the variation in coverage, a large amount of underinsurance persists even after accounting for demand-side factors. As a first indication of the importance of supply-side factors, Figure 4 plots the distribution of average policyholder coverage ratios across the insurers in our estimation sample. There is significant variation in coverage by insurer, with the highest average coverage ratios showing full insurance and the lowest underinsurance of more than 25% of policyholders' pre-fire replacement costs.

Next, we test whether the heterogeneity in average insurer coverage ratios in Table **??** persists conditional on policyholder and structure characteristics. To do so, we estimate Equation 1 which models the coverage ratio of policyholder $i$ as a function of policyholder characteristics $X_i$ and insurance company fixed effects $\lambda_j$:

$$R_{ij}^{Pre} = \alpha + \lambda X_i + \lambda_j + \epsilon_{ij}, \tag{1}$$

where $R_{ij}^{Pre}$ is the pre-fire coverage ratio, the vector $X_i$ captures policyholder income, credit score, mortgage status, housing value, estimated replacement cost, whether the policyholder purchased extended coverage, the premium rate per $100, and quadratics of years since the home was purchased, the age of the home, and the home's square footage. Standard errors are clustered by insurer. In this specification, if observable policyholder characteristics drive variation in underinsurance across insurers, we would expect the coefficients on the insurer fixed effects, $\lambda_j$, to be insignificantly different from each other.

Figure 6 plots the fitted insurer fixed effects $\widehat{\lambda_j}$ from estimating Equation 1 first without policyholder and property covariates, $X_i$, (red) and then including these covariates (blue).[7] Adding our rich set of policyholder characteristics does little to change the ordering or magnitude of coverage heterogeneity across insurers. Without covariates, moving a policyholder from the insurer with the second-highest average coverage ratio to the one with the second lowest coverage ratio

[7] Appendix Table A1 shows the non-fixed effects coefficients from estimating model 1 with controls.

predicts a decrease in coverage of 27.4% of their estimated replacement cost. Adding policyholder and structure characteristics, the same counterfactual predicts a decrease of 25.7%.

A potential explanation for the heterogeneity in Figure 4 is that policyholders sort across insurers in a way that correlates with policyholders' propensities to underinsure. Figure 5 plots average policyholder income (top), home values (middle), and credit score (bottom) on the y-axis with average pre-fire coverage ratio on the x-axis by insurer. Although incomes and home values are both positively associated with coverage ratios across policyholders (Figure 2), we see no clear relationship between these policyholder characteristics and average coverage ratios across insurers, and a similarly weak relationship with average credit scores.

We more systematically test the ability of differences in policyholder characteristics across insurers to explain average underinsurance by estimating the following equation:

$$\overline{R(-i)}_{ij}^{Pre} = \beta_0 + \beta_1 X_i + \epsilon_{ij}. \tag{2}$$

In equation 2, $\overline{R(-i)}_{ij}^{Pre}$ is the average pre-fire coverage ratio of policyholders with insurer $j$ excluding policyholder $i$, i.e the leave-one-out (LOO) average coverage ratio. If heterogeneity across insurers can be explained by the differential sorting of policyholders, then we would expect policyholder characteristics to explain a large share of the variation in Equation 2.

We show the results of estimating Equation 2 as we include progressively more policyholder and structure characteristics in Table 4. Even with the full set of covariates in column (3), the $R^2$ shows that we can only explain approximately 3% of the variation in average underinsurance with our rich set of policyholder and structure characteristics. These findings suggest that differences in observable policyholder characteristics do not explain the heterogeneity in average underinsurance across insurers.

One explanation for the importance of insurance company in predicting the degree of underinsurance across policyholders is that policyholders receive coverage recommendations from insurance agents when shopping for insurance. Agents use software-based costs models to estimate rebuilding costs at the time of insurance quote and companies vary, not just in the type of software used, but in the housing inputs deemed relevant to include in the cost model. Insurance agent recommendations may serve as important anchors for homeowners determining their cov-

erage limits. In fact, insurance company recommendations may be the sole source of rebuild cost information used by homeowners since the main alternative source – hiring an appraiser – is a significant expense. It is, therefore, likely that homeowners anchor their replacement cost coverage to the recommendations provided by insurance companies such that variation in rebuilding cost estimates across companies translates into variation in underinsurance across policyholders.

As a suggestive test of systematic differences in the modeling approaches of different insurers, we evaluate whether average underinsurance varies by insurer tenure in the local market. Similar to the literature in mortgage lending that has documented the importance of soft information in accurate loan underwriting (see e.g. Agarwal and Hauswald (2010) or Berger, Miller, Petersen, Rajan, and Stein (2005)), we suspect that insurers with better local information may select more relevant inputs when estimating rebuilding costs. We proxy for insurer soft information with (1) the number of policies in the estimation data and (2) the number of years since we first observe the insurer writing contracts in the estimation sample.

We show how well these local knowledge proxies predict insurer average coverage ratios in Table 5. The results in column (1) show that 100 additional policyholders in the estimation sample is associated with a 3.6 percentage point increase in the insurer average coverage ratio, while column (2) indicates that an additional decade since their oldest policy was written is correlated with a 5.8 percentage point higher ratio. These relationships are little changed by adding our full suite of policyholder characteristics as additional covariates in columns (3) and (4).

It is also striking to compare the local knowledge proxies against policyholder characteristics in explaining the variation in average coverage ratios across insurers. As shown by $R^2$ statistics in columns (1) and (2), the number of policyholders and age of the oldest policy explain 39.2% and 31.3% of the variation in insurer average coverage ratios, respectively, and jointly explain nearly half the variation as shown in column (5). By comparison, the full suite of policyholder characteristics explain 3.1% of the variation in insurer average coverage ratios (Table 4). Thus, the characteristics of the insurers themselves rather than their policyholders best explain the underinsurance heterogeneity across insurers.

### 3.5 The Consequences of Underinsurance

Our results so far show that variation in underinsurance is driven largely by insurance companies and less so by policyholder attributes. In this section, we use cross-insurer variation in underinsurance to isolate variation in coverage that is plausibly unrelated to policyholder characteristics – since such characteristics could be endogenous to both underinsurance and disaster recovery outcomes.

Our identification assumption is that recovery outcomes are uncorrelated with the choice of insurer except through differences in coverage. Supporting this assumption, our previous analysis shows little systematic difference in policyholder characteristics across insurers. However, we cannot separate the influence of the propensity to underinsure from other unobserved insurer characteristics that may influence recovery (e.g., quality of customer service or speed of paying out claims). Still, our estimates provide a plausible baseline for the impact of underinsurance on recovery outcomes for two reasons. First, while insurers may vary along unobserved dimensions, differences in coverage are likely to play a first-order role in rebuilding. Second, estimating the bundled "insurer effect" (including unobserved quality factors as well as coverage) still offers a valuable insight into how insurer choice affects disaster recovery.

The first stage of our estimating equation is:

$$R_{ij}^{Post} = \lambda_0 + \lambda_1 X_i + \lambda_2 \overline{R}_{j,-i}^{Post} + \mu_{ij}, \tag{3}$$

where $R_i^{Post}$ is the post-fire coverage ratio, and $X_i$ are policyholder and associated housing characteristics. We use $\overline{R}_{j,-i}^{Post}$, the mean post-fire coverage ratio for insurer $j$ excluding policyholder $i$, as our excluded instrument.

The second stage is:

$$Y_{ij} = \beta_0 + \beta_1 X_i + \beta_2 \widehat{R_{ij}^{Post}} + \epsilon_{ij}, \tag{4}$$

where $Y_i$ is a measure of disaster recovery and $\widehat{R_{ij}^{Post}}$ is the fitted value from 3. Standard errors are clustered by insurer. Our sample includes the 736 policyholders in our estimation sample who suffered total losses, although $\overline{R}_{j,-i}^{Post}$ is calculated from the full estimation sample.

We estimate a strong first stage, shown in Appendix Table A2, with an F-stat of 175.19. Conditional on our controls, a 10 percentage point increase in the average post-fire coverage ratio of other policyholders with the same insurer predicts an 8.2 percentage point higher post-fire coverage ratio in the first-stage.

Given widespread reports that underinsurance can cause liquidity issues that delay reconstruction, the first outcome we consider is the speed of rebuilding. In columns (1)-(4) of Table 6, we define $Y_i$ as an indicator variable that equals 1 if household $i$ has filed for a rebuilding permit by December 2022 (one year after the fire), February 2023, July 2023, and October 2023, respectively. We see positive and statistically significant effects of insurance coverage on rebuilding permits in December 2022 and February 2023. For example, a policyholder with a 10% higher coverage ratio is approximately 4.9 percentage points (25% of the dependent variable mean) more likely to have filed a rebuilding permit by December 2022 At the two later snapshots, the estimates are positive but statistically insignificant.

Next, we consider whether the owner of a destroyed home sold their property. This could indicate that the homeowner could not afford to rebuild and left the community. In column (5) of Table 6, we find that higher insurance coverage is associated with a statistically significant reduction in the probability of sale.

Finally, one may be concerned that the choice of insurer is correlated with unobservable policyholder characteristics. As a falsification test, we regress sale on coverage ratios for homes that were not destroyed and find null results in column (6).

Our estimates show that underinsurance is an economically meaningful impediment to disaster recovery. Extrapolating from our reduced-form results, if all homeowners in our sample had been fully insured (i.e., with a post-fire coverage ratio of 1 instead of the average of 0.87), then 25.1% of homeowners would have filed for a rebuilding permit by December 2022 instead of 18.7% and 5% of homeowners would have sold their homes as of July 2023 instead of 9.5%.

## 4 Mechanism: The Role of Consumer Demand

Our results so far show meaningful heterogeneity in average underinsurance across insurers that is largely uncorrelated with and robust to controlling for policyholder characteristics. Further-

more, we find that the policyholders of insurers with lower coverage ratios are slower to rebuild and more likely to sell their homes after wildfire losses. Why then would a policyholder select an underinsured policy?

One hypothesis is a "coverage neglect" mechanism where insurance buyers rely on the replacement cost estimates provided by insurance companies to set their dwelling coverage limits only to learn after a total loss that this limit was insufficient to rebuild. Furthermore, buyers may not realize how widely these suggested limits vary across insurers on initial quotes. A "coverage neglect" mechanism is consistent with qualitative interviews after wildfires during which survivors commonly report assuming that insurance companies all offer the same complete coverage at varying premiums (Hassani, 2013; United Policyholders, 2020; Phillips, 2022; Fuqua, 2024). Alternatively, underinsurance may reflect a revealed preference on the part of fully informed policyholders. This section tests the "coverage neglect" hypothesis, where policyholders are inattentive to differences in coverage limit suggestions across insurers, against the "full information" hypothesis where policyholders consciously choose to underinsure. To do so, we estimate a discrete choice insurance demand model that nests the coverage neglect hypothesis and the full information hypothesis.

We begin by describing buyer insurance choices in the full information case. Buyers $i$ have some desired coverage ratio $R_i^*$. We do not need to specify exactly how $R_i^*$ is set, simply noting it as $i$'s revealed coverage preference. Buyer $i$ chooses among insurers $j = 1, ..., J$ from whom to buy $R_i^*$, noting that each insurer offers a buyer specific premium per dollar of coverage $p_{ij}$. The buyer's utility from their insurance decision with full information, $U^F$, is given by:

$$U_{ij}^F = \sigma_j X_i + \zeta_j - \alpha^F p_{ij} + \epsilon_{ij}. \tag{5}$$

Buyers receive utility depending on an insurer-specific constant $\zeta_j$, their characteristics $X_i$, and an idiosyncratic taste term $\epsilon_{ij}$, but receive disutility from premiums.[8]

Next, we contrast the full information utility function with the coverage neglect utility function. In the coverage neglect case, insurers set coverage ratios $R_{ij}$ for each buyer $i$. As with $R_i^*$, we can be flexible about how exactly $R_{ij}$ is set. What distinguishes $R_{ij}$ chosen under coverage neglect

[8]The buyer's utility from $R_i^*$ does not vary across insurer and so is absorbed in utility normalization.

from $R_i^*$ chosen by the buyer with full information are two factors:

1. $R_{ij}$ varies across insurers for the same buyer
2. Differences in $R_{ij}$ across insurers do not enter the buyer's utility function

Thus, the coverage neglect utility function $U^N$ is a slight alteration of $U^F$,

$$U_{ij}^N = \sigma_j X_i + \zeta_j - \alpha^N p_{ij} * R_{ij} + \epsilon_{ij}. \tag{6}$$

Under coverage neglect, the price term reflects that premiums vary across insurers by both the rate per unit of coverage, $p_{ij}$, and the amount of coverage quoted, $R_{ij}$. While buyers account for the differences in premiums in $U^N$, they do not account for differences in coverage, evaluating their choices as if each insurer were offering the same coverage.

### Discrete Choice Model

To test whether buyers choose to insure based on $U^F$ or $U^S$, we estimate a discrete choice demand model that nests both utility functions:

$$argmax_j \; \sigma_j X_i + \zeta_j - \alpha^F p_{ij} - \alpha^N p_{ij} * R_{ij} + \epsilon_{ij}. \tag{7}$$

Equation (7) includes two "price" terms: the premium rate per dollar of coverage $p_{ij}$ at the buyer's full information coverage $R_i^*$ and the total premium, $p_{ij} * R_{ij}$, if she instead chooses the insurer-specific coverage $R_{ij}$ under coverage neglect. The full information hypothesis makes a sharp prediction that $\alpha^N = 0$. If the buyer has made her own decision about the coverage she wants to buy, then the cost of the insurer's recommended coverage would have no impact on her utility conditional on the insurer's rate. In contrast, under the coverage neglect hypothesis, $\alpha^F = 0$, because buyers focus only on premiums and not on the cost relative to the amount of coverage. We estimate a discrete choice model that includes both price terms, which essentially performs a horse race between these alternative prices via consumers' revealed preferences.

Turning to the empirical approach, for each policyholder, we observe $R_i^*$, which is the observed pre-fire coverage ratio. Based on quoted and reported premium schedules for each insurer,

we calculate the premium per $10,000 of coverage using this insurance amount.[9] We denote this as $p_{ij}(R_i^*)$.

For consumers who neglect coverage, and thus, choose insurers based on total premium $p_{ij}(R_{ij}) \times R_{ij}$, we need to approximate the coverage limits set by each insurer $j$ for policyholder $i$, $R_{ij}$. To do this, we calculate $\widehat{R_{ij}}$ as the fitted values from regressing $R_{ij}$ on policyholder characteristics and insurer fixed effects as in Equation eq:insurer$_underinsurance.Atthispredictedlevelofcoverage, wecalculat$ $\times \widehat{R_{ij}}$ again using the quoted and estimated premium schedules.

Our specification employs both prices in a standard multinomial discrete choice model with latent utility $V_{ij}$:

$$V_{ij} = \sigma_j X_i + \zeta_j - \alpha^F p_{ij}(R_i^*) - \alpha^N p_{ij}(\widehat{R_{ij}}) * \widehat{R_{ij}} + \epsilon_{ij}. \tag{8}$$

where $\epsilon_{ij}$ follows a Type I extreme-value distribution. With this structure and the optimization problem above, the discrete choice model can be estimated using a multinomial logit model (McFadden, 1972). In addition to insurer fixed effects $\zeta_j$, our specification allows for insurer brand values to vary across consumers according to individual characteristics (specifically, income, credit score, estimated replacement cost, home value, mortgage status, home age, and years since home purchase), captured in the $\sigma_j X_i$ terms.

The inclusion of insurer fixed effects $\zeta_j$ ensures that the $\alpha^F$ and $\alpha^N$ terms are not driven by correlation between prices and unobserved insurer quality. Instead, we identify the price parameters from variation in relative premiums within insurers across different buyers. Because we observe or estimate the full rate schedules for each potential insurer-by-policyholder pair in our data, we observe substantial difference in the cost per unit of coverage driven by idiosyncracies in insurers' pricing schedules. Premiums can vary widely across insurers, even for the same coverage on the same home. Consistent with this idea, we observe wide variation in relative premium rates depending on a policyholder's rating characteristics.

To understand the source of variation in the coverage neglect premium $p(\widehat{R_{ij}}) * \widehat{R_{ij}}$, note that $\widehat{R_{ij}}$ varies within buyers across insurers. We can see this variation in coverage in the wide variation in estimated insurer fixed effects $\widehat{\lambda_j}$ from Equation 1. However, the price differences in

[9] See Appendix Section B for more details.

our specification are necessarily within-insurer—i.e., the differences in $\widehat{R_{ij}}$ are absorbed by the insurer fixed effects in Equation 8. Thus, variation in the coverage neglect premium is driven by heterogeneity in the "steepness" of premium rates with respect to coverage. For example, a given insurer $j'$ may on average write 20% less coverage than insurer $j''$. Because of differences in $p(\widehat{R_{ij'}})$ relative to $p(\widehat{R_{ij''}})$ across different buyers, this will result in differences in the relative coverage neglect premium between $j'$ and $j''$.

A remaining identification concern is that within insurer variation in rates could be correlated with the idiosyncratic preference term $\epsilon_{ij}$. Supporting our identification strategy, property insurance premiums are highly regulated and approved at the state level. While insurers can set specific premiums across the state based on characteristics such as a home's age or zipcode, they cannot target premiums to specific buyers through targeted discounts or bargaining. This makes it unlikely that premium variation is correlated with unobservable demand shocks conditional on our covariates $X_i$.

One may also be concerned that variation in observed premiums is driven by other coverage choices, such as deductible, or the availability of discounts from bundling home and auto coverage that might be correlated with unobserved insurer demand. This possible source of endogeneity motivates our decision to use Quadrant rate filings as our main measure of price. The Quadrant rates create standardized premiums that hold fixed other coverages, contract characteristics, and discounts across buyers. Since these prices do not contain bundling, the identifying variation in premiums is driven by the truly idiosyncratic differences in how insurers price certain property characteristics at different amounts of coverage.

### Discrete Choice Estimation Results

Table 7 shows the results of estimating Equation 8. In column (1), we estimate the model assuming that the full information hypothesis is true and restrict $\alpha^N = 0$. We observe a statistically significant coefficient on the coverage rate with the expected sign, indicating that buyers tend to prefer insurers who offer lower premium rates (per dollar of coverage). The coefficient results in an average price elasticity of 0.6, suggesting relatively price inelastic demand. In column (2), we assume the coverage neglect hypothesis and restrict $\alpha^F$ to be zero. We once again observe a statistically significant $\alpha$ parameter suggesting buyers prefer lower total premiums. Noting the

difference in units between the premium rates and premiums, the coefficient on $\alpha^S$ suggests a higher price elasticity of 1.3, more than double the price elasticity given by $\alpha^F$ in column (1).

Comparing the results between columns (1) and (2) of Table 7 already suggest that buyers are more sensitive to the predicted coverage neglect premium than the full information premium. In column (3), we run a horse race model between the full information and coverage neglect hypotheses and show the results of estimating an unrestricted Equation 8. The price sensitivity of buyers loads entirely on the total premium rather than the premium rate, rejecting the full information hypothesis that $\alpha^N = 0$. Any economically meaningful sensitivity to premium rates is outside the 95% confidence interval of the $\alpha^F$ estimate.

The results in column (3) demonstrate choice inconsistencies under the full information hypothesis. If the observed $R_i^*$ in the data represented each buyer's revealed preference coverage choice, then buyers should prefer the insurer that offers that level of coverage at the lowest premium rate, *ceteris paribus*. Instead, the estimates suggest that buyers are "leaving money on the table" by choosing insurers who appear to be offering a lower premium but are in reality just offering less coverage. In contrast, the fact that variation in the coverage neglect premium predicts price sensitivity suggests that, consistent with the coverage neglect hypothesis, the predicted coverage $\widehat{R_{ij}}$ determines the relative price that is salient to buyers.

We test for heterogeneity in the sensitivity to premiums in Table 8. In column (1), we allow the coefficients on the premium rate and the total premium to vary by whether the household is above the median income in the estimation sample. Higher income consumers may be more sophisticated and less price sensitive, and thus respond less to total premiums and more to premium rates (per dollar of coverage). In column (2), we consider heterogeneity between consumers with and without mortgages under the hypothesis that policyholders with mortgages may be more liquidity constrained and thus respond more to total premiums rather than to premium rates. Neither test reveals meaningful heterogeneity between the groups, suggesting that coverage neglect is widespread.

Many studies of insurance and other consumer financial products document substantial inertia effects, where policyholders face large costs of switching products after an initial decision (see e.g. Handel (2013) or Andersen, Campbell, Nielsen, and Ramadorai (2020)). Such inertia can attenuate discrete choice parameters if the relative product characteristics have changed since buy-

ers first chose their insurer. To test the sensitivity of our estimates to inertia, we re-estimate our discrete choice model in column (3) after subsetting to policyholders who purchased their coverage in the last five years. Consistent with inertia effects, more recent buyers are more sensitive to price, with an average price elasticity of 1.6. However, we continue to estimate a null coefficient on the premium rate and reject the full information hypothesis.

### The Cost of Coverage Neglect to Consumers

We use our multinomial choice model's estimates to infer a rational policyholder's willingness-to-pay to transparently view and compare rates across insurers. This counterfactual exercise allows us to place a dollar value on the cost of coverage neglect. Our evidence of coverage neglect suggests that consumers may mistake less coverage for lower prices. When evaluating potential reforms to combat underinsurance, such as publicly available replacement cost estimates or a platform for comparing insurance quotes with uniform coverage limits, it is important to understand the deadweight loss imposed by coverage neglect.

We posit that policyholders choose their insurer according to $U^N$ given by the coverage model in Equation 6, focusing on total premiums rather than premium rates (per unit coverage). However, policyholders' experienced utility is not equal to Equation 6, but instead:

$$U^*_{ij} = \sigma_j X_i + \zeta_j - \alpha^N p_{ij}(R_{ij}) * R_{ij} + f_{ij}(R_{ij} - R^*_i) + \epsilon_{ij}, \tag{9}$$

where variation in coverage across insurers does affect consumer welfare.

We consider a counterfactual that eliminates coverage neglect so that policyholders choose their insurer by maximizing $U^*$ rather than $U^N$. Our counterfactual ignores general equilibrium effects, holds insurer pricing fixed, and assumes that consumers act rationally (as in the full information scenario).

In principle, removing coverage neglect could improve consumer welfare via two channels. First, consumers no longer mistake less coverage for a lower price and shop for the best rates. Second, consumers no longer accidentally buy too little or too much coverage. Calculating these welfare effects requires taking a normative stance on how policyholders should value coverage. Because we cannot estimate the normative value of coverage in our setting, we make two assump-

tions about how coverage enters $U^*$:

$$U^*_{ij}(p_{ij}(R_{ij}), R_{ij}) = U^*(p_{ij}(R^*_i), R^*_i) \text{ if } R^*_i > R_{ij}$$

and

$$U^*_{ij}(p_{ij}(R_{ij}), R_{ij}) = U^*(p_{ij}(R_{ij}), R^*_i) \text{ if } R_{ij} \leq R^*_i$$

.

The first assumption implies that consumers are normatively indifferent between purchasing coverage $R_{ij}$ at rate $p_{ij}(R_{ij})$ and purchasing coverage $R^*_i$ at rate $p_{ij}(R^*_i)$ whenever $R_{ij} < R^*_i$. This condition conservatively assumes away any surplus policyholders might gain from buying more coverage. The second assumption says that consumers place no value on coverage above their revealed preference coverage choice $R^*_i$.

Following derivations in Leggett (2002) on the value of information in discrete choice models, policyholder $i$'s willingness-to-pay for removing coverage neglect can be expressed as:

$$WTP_i = \frac{1}{\alpha^N}(ln(\sum_j e^{U^*_{ij}}) - (ln(\sum_j e^{U^N_{ij}}) + \sum_j \pi^N_{ij}(U^*_{ij} - U^S_{ij}))), \tag{10}$$

where $\alpha^N$ is the estimated coverage neglect premium coefficient from column (2) of Table 7. The log summation terms are the usual expression for expected utility in multinomial discrete choice models. $\pi^N_{ij}$ is the probability that policyholder $i$ chooses insurer $j$ under the coverage neglect estimates.

The intuition of Equation 10 is to take the difference between expected utility under the information provision counterfactual ($U^*$) and the coverage neglect baseline ($U^N$). The adjustment term $\pi^N_{ij}(U^*_{ij} - U^N_{ij})$ corrects the expected coverage neglect welfare for the policyholder's misperception that utility is $U^N_{ij}$ when it is $U^*_{ij}$. To illustrate, consider the case where $R_{ij} < R^*_i$. Policyholder $i$ will perceive $j$'s premium as cheaper than it actually is, and thus will overestimate $U^N_{ij} > U^*_{ij}$. Then, the term $\pi^N_{ij}(U^*_{ij} - U^N_{ij}) < 0$ and correct the expected coverage neglect utility downward.

Figure 7 plots the distribution of $WTP_i$ from Equation 10. The average gains from removing

coverage neglect, indicated by the vertical line in the distribution, is approximately $300. This average is driven by a right tail of policyholders with very high gains, where coverage neglect substantially changes their predicted choice of insurer.

Figure 8 illustrates how the intervention could reshape the homeowners insurance market. The plot shows the average change in the probability of choosing a given insurer in the full information counterfactual versus the coverage neglect baseline as a function of the predicted coverage ratio (20 bins). Full information tilts consumers' choice toward insurers with low coverage ratios and more likely to choose insurers with higher coverage ratios.

Although removing coverage neglect would enable insurance buyers to compare prices more accurately, average premiums are only slightly lower under the full information counterfactual ($2,910 versus $2,870). Thus, most of the welfare gains from information come not from finding lower premiums but choosing higher-quality insurers that appeared expensive under coverage neglect.

We remain agnostic on whether removing coverage neglect might also improve welfare by changing coverage decisions. In the case of flood protection, underinsurance driven by information frictions has been shown to have large welfare consequences (Mulder, 2021; Wagner, 2022). Our findings on the consequences of underinsurance suggest that insurance coverage may induce rebuilding externalities that may create further potential welfare gains with higher coverage (Fu and Gregory, 2019; Issler et al., 2020).

## 5 Conclusion

This paper studies the causes and consequences of underinsurance utilizing detailed insurance contract data from homeowners affected by the Marshall wildfire in Colorado. We find that underinsurance was widespread both before and after the fire. Our analysis rejects hypotheses that underinsurance can be explained solely by lower income buyers, sudden increases in building costs, or a failure by policyholders to update their coverage over time.

Instead, we find large differences in average underinsurance across insurers. These differences cannot be explained by differential sorting of buyers and are robust to including a rich set of policyholder characteristics. Using these differences across insurers as an externally-determined

source of variation in coverage, we find that underinsurance significantly delays rebuilding and makes fire survivors more likely to sell their homes.

These findings are consistent with reports that consumers rely on insurers' models to set their coverage limits and have limited awareness of differences in coverage when comparing homeowners quotes. To test this coverage neglect model, we build a discrete choice model of homeowners insurance demand. Our estimates show that buyers are attentive to differences in premiums across insurers but not differences in coverage. We estimate that consumer welfare would improve by an average of $300 per year under a counterfactual that removes coverage neglect. Our results highlight the importance of information frictions facing homeowners as they navigate growing climate disaster risks.

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# 6 Tables

Table 1: Summary statistics of the estimation sample.

This table presents summary statistics of the main policyholder dataset. Variables are measured before the Marshall Fire except where otherwise specified. Insurance contract data come from the Colorado Division of Insurance (DOI). Housing characteristics come from the Boulder County Assessor's Office, corroborated with hand collection of Zestimates. Personal credit characteristics are from Experian.

| | mean | sd | p25 | p75 |
|---|---|---|---|---|
| **Insurance and Rebuild Characteristics** | | | | |
| Structure Coverage ($100s) | 5,253 | 2,481 | 3,680 | 6,194 |
| Extended Coverage (% of Structure Coverage) | 0.266 | 0.167 | 0.200 | 0.250 |
| Guaranteed Replacement Cost Coverage (0/1) | 0.0680 | 0.252 | 0 | 0 |
| Policy Age (Years) | 9 | 8.676 | 2 | 14 |
| Replacement Cost ($100s, Post-Fire) | 7,571 | 1,811 | 6,432 | 8,557 |
| Replacement Cost ($100s) | 5,911 | 1,414 | 5,022 | 6,680 |
| Coverage Ratio | 0.874 | 0.268 | 0.693 | 0.988 |
| Coverage Ratio (Post-Fire) | 0.873 | 0.272 | 0.688 | 1 |
| Premium per $100 at Full Coverage | 0.539 | 0.208 | 0.391 | 0.691 |
| **House and Personal Characteristics** | | | | |
| Square Footage | 2,305 | 888.9 | 1,698 | 2,802 |
| Home Value ($1,000s) | 978 | 355 | 758 | 1,083 |
| Mortgage Balance ($1,000s) | 437 | 375 | 222 | 536 |
| Household Income ($1,000s) | 197 | 101 | 120 | 263 |
| Credit Score | 798.3 | 40.76 | 785.5 | 824 |
| Has Mortgage (0/1) | 0.732 | 0.443 | 0 | 1 |
| Tenure in Home (Years) | 14.30 | 10.35 | 5 | 22 |
| Home Age (Years) | 31.59 | 12.32 | 26 | 34 |
| Policyholders: | 3089 | | | |
| Insurers: | 14 | | | |

Table 2: Underinsurance and Policy Age: Older policies are not more underinsured

This table presents OLS regression estimates from a regression of pre-fire coverage ratio (dependent variable) on policy age (i.e., years since policy inception) and other household and structure characteristics. Column (1) presents the simple relationship, whereas column (2) adds controls and column (3) additionally adds insurer fixed effects. Robust standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

| | Dep variable: Pre-Fire Coverage Ratio | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Policy Age (Years) | 0.007*** | 0.007*** | 0.003*** |
| | (0.001) | (0.001) | (0.001) |
| Log Income | | 0.049*** | 0.049*** |
| | | (0.010) | (0.009) |
| Credit Score (z) | | -0.010** | -0.007* |
| | | (0.004) | (0.004) |
| Log Home Value | | 0.541*** | 0.545*** |
| | | (0.040) | (0.041) |
| Has Mortgage = 1 | | -0.016 | -0.011 |
| | | (0.012) | (0.011) |
| Log Replacement Value | | -0.758*** | -0.756*** |
| | | (0.076) | (0.070) |
| Purchase Age (Years) | | -0.001 | 0.000 |
| | | (0.001) | (0.001) |
| Purchase Age$^2$ | | 0.000 | 0.000 |
| | | (0.000) | (0.000) |
| Home Age (Years) | | -0.009*** | -0.010*** |
| | | (0.001) | (0.001) |
| Home Age$^2$ | | 0.000*** | 0.000*** |
| | | (0.000) | (0.000) |
| Square Footage | | 0.000** | 0.000*** |
| | | (0.000) | (0.000) |
| Square Footage$^2$ | | 0.000 | -0.000 |
| | | (0.000) | (0.000) |
| Constant | 0.816*** | 3.161*** | 3.098*** |
| | (0.006) | (0.951) | (0.898) |
| Observations | 3,088 | 3,088 | 3,088 |
| R-squared | 0.047 | 0.375 | 0.478 |
| Insurer FE | N | N | Y |

Table 3: Underinsurance and Mortgages: Policyholders with mortgages and high leverage are not better insured

This table presents OLS regression estimates from a regression of pre-fire coverage ratio (dependent variable) on a mortgage indicator, controlling also for other household and structure characteristics. Columns 1-3 present the relationship between having a mortgage and pre-fire coverage ratio or mortgage loan-to-value ratio (column 4) and underinsurance. Columns (2) and (3) introduce as covariates log income, standardized credit score, log home value, log replacement value, and quadratics of time since home purchase, home age, and square footage. Column (4) adds insurer fixed effects. In column (4) the omitted category is policyholders without a mortgage. Robust standard errors in parentheses *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

| | Dep. variable: Pre-Fire Coverage Ratio | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Has Mortgage = 1 | -0.025** | -0.020* | -0.013 | |
| | (0.011) | (0.012) | (0.011) | |
| **Loan-to-Value Ratio (%)** | | | | |
| 0-10 | | | | 0.019 |
| | | | | (0.021) |
| 10-20 | | | | -0.009 |
| | | | | (0.016) |
| 20-30 | | | | -0.025* |
| | | | | (0.014) |
| 30-40 | | | | -0.038*** |
| | | | | (0.014) |
| 40-50 | | | | -0.006 |
| | | | | (0.015) |
| 50-60 | | | | -0.011 |
| | | | | (0.016) |
| 60-70 | | | | -0.000 |
| | | | | (0.019) |
| 70-80 | | | | 0.012 |
| | | | | (0.023) |
| 80-90 | | | | 0.019 |
| | | | | (0.035) |
| 90-100 | | | | 0.044* |
| | | | | (0.023) |
| Constant | 0.892*** | 2.987*** | 2.965*** | 2.879*** |
| | (0.010) | (0.980) | (0.906) | (0.906) |
| Observations | 3,089 | 3,089 | 3,089 | 3,089 |
| R-squared | 0.002 | 0.340 | 0.472 | 0.476 |
| Insurer FE | N | N | Y | Y |
| Policyholder Characteristics | N | Y | Y | Y |

Table 4: Selection Across Insurers? Policyholder characteristics do not explain typical underinsurance

This table presents regressions of the leave-one-out (LOO) average pre-fire coverage ratio, excluding the focal policy holder $i$, $R_{j(-i)}$ on policyholder $i$ characteristics and structure characteristics. Standard errors are clustered by insurer. *** p<0.01, ** p<0.05, * p<0.1

| | (1) | (2) | (3) |
|---|---|---|---|
| Dep. variable: Insurer LOO Average Pre-Fire Coverage Ratio | | | |
| Log Income | -0.002 | -0.004 | 0.005** |
| | (0.002) | (0.003) | (0.002) |
| Credit Score (z) | | -0.003 | -0.003 |
| | | (0.002) | (0.002) |
| Log Home Value | | 0.019 | 0.009 |
| | | (0.014) | (0.012) |
| Has Mortgage (0/1) = 1 | | | -0.009** |
| | | | (0.003) |
| Log Replacement Value | | | 0.002 |
| | | | (0.061) |
| Tenure in Home (Years) | | | 0.002* |
| | | | (0.001) |
| Tenure$^2$ | | | -0.000 |
| | | | (0.000) |
| Home Age (Years) | | | 0.000 |
| | | | (0.000) |
| Home Age$^2$ | | | 0.000 |
| | | | (0.000) |
| Square Footage | | | -0.000 |
| | | | (0.000) |
| Square Footage$^2$ | | | 0.000* |
| | | | (0.000) |
| Constant | 0.883*** | 0.640*** | 0.723 |
| | (0.047) | (0.192) | (0.887) |
| Observations | 3,089 | 3,089 | 3,089 |
| R-squared | 0.000 | 0.003 | 0.031 |

Table 5: Proxies for insurers' soft information explain differences in average coverage ratios

This table presents regressions of the leave-one-out (LOO) average pre-fire coverage ratio, excluding the focal policy holder $i$, $R_{j(-i)}$ on their insurer's number of policyholders (in 100s) and the age of the oldest policy (in decades) in the estimation sample. Columns (1) and (2) show the results of simple regressions with the number of policyholders and the age of the oldest policy, respectively. Columns (3)-(5) introduce the following policyholder characteristics as controls: log income, credit score, log home value, mortgage status, log replacement value, and quadratics of tenure in home, home age, and square footage. Standard errors are clustered by insurer. *** p<0.01, ** p<0.05, * p<0.1

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Dep. variable: Insurer LOO Average Pre-Fire Coverage Ratio | | | | |
| Insurer Policyholders (100s) | 0.036*** | | 0.035*** | | 0.026* |
| | (0.011) | | (0.011) | | (0.013) |
| Oldest Policy Age (Decades) | | 0.058** | | 0.057** | 0.029* |
| | | (0.022) | | (0.021) | (0.016) |
| Constant | 0.739*** | 0.676*** | 0.096 | 0.145 | -0.030 |
| | (0.040) | (0.059) | (0.703) | (0.692) | (0.695) |
| Observations | 3,089 | 3,089 | 3,089 | 3,089 | 3,089 |
| R-squared | 0.392 | 0.313 | 0.416 | 0.330 | 0.466 |
| Policyholder Characteristics | N | N | Y | Y | Y |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Underinsurance, Rebuilding and Home Sales

This table presents estimates from a series of linear probability models for whether the policyholder filed a rebuilding permit before December 2022 (col 1), February 2023 (col 2), July 2023 (col 3), October 2023 (col 4) and whether the property was sold before July 2023 (col 5). Column 6 presents a placebo test that regresses the sold outcome for properties that did not suffer total losses. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

| | Destroyed Homes: Recovery Outcome | | | | | Placebo |
|---|---|---|---|---|---|---|
| | Permit Dec22 | Permit Feb23 | Permit Jul23 | Permit Oct23 | Sold | Sold |
| Coverage Ratio | 0.488*** | 0.520*** | 0.376* | 0.616*** | -0.345*** | -0.025 |
| | (0.111) | (0.156) | (0.208) | (0.220) | (0.078) | (0.046) |
| Log Income | 0.063* | 0.105*** | 0.125*** | 0.053 | 0.000 | 0.006 |
| | (0.037) | (0.031) | (0.043) | (0.046) | (0.028) | (0.011) |
| Log Zestimate | -0.104 | -0.106 | -0.241*** | -0.343*** | 0.127*** | -0.000 |
| | (0.089) | (0.095) | (0.083) | (0.125) | (0.038) | (0.026) |
| Credit Score (z) | 0.016 | 0.016 | 0.015 | -0.004 | -0.004 | -0.007 |
| | (0.013) | (0.011) | (0.013) | (0.012) | (0.010) | (0.007) |
| Mortgage | -0.040 | -0.058* | -0.096** | -0.027 | -0.033 | 0.007 |
| | (0.040) | (0.030) | (0.039) | (0.037) | (0.027) | (0.011) |
| Purchase Age | -0.009*** | -0.013*** | -0.011* | -0.011** | 0.000 | 0.003 |
| | (0.003) | (0.004) | (0.005) | (0.005) | (0.002) | (0.002) |
| $PurchaseAge^2$ | 0.000*** | 0.000** | 0.000 | 0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Home Age | -0.003 | -0.002 | -0.008* | -0.003 | -0.002 | 0.002 |
| | (0.003) | (0.004) | (0.004) | (0.004) | (0.002) | (0.001) |
| $HomeAge^2$ | 0.000 | -0.000 | 0.000 | -0.000 | 0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| sqft | 0.000 | 0.000* | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $sqft^2$ | -0.000** | -0.000 | -0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Constant | 0.858 | 0.875 | 3.214*** | 4.906*** | -1.299*** | 0.013 |
| | (1.030) | (1.204) | (0.973) | (1.510) | (0.441) | (0.306) |
| Observations | 758 | 758 | 758 | 758 | 758 | 2,405 |
| Dep. Var. Mean | 0.187 | 0.305 | 0.449 | 0.637 | 0.095 | 0.059 |

Table 7: Discrete Choice over Insurers: Are Choices Sensitive to Per-Coverage Prices or Total Premium?

This table presents estimates of parameters from a multinomial choice model of the following latent utility function given in equation (8):

$$V_{ij} = \sigma_j X_i + \zeta_j - \alpha^F p_{ij}(R_i^*) - \alpha^N p_{ij}(\widehat{R_{ij}}) * \widehat{R_{ij}} + \epsilon_{ij}.$$

Premium per unit Coverage is defined as the cost per $10,000 of coverage at the observed coverage choice of the policyholder. Total Premium is defined as the premium in $100s at the predicted coverage offered by the insurer. All specifications include insurer fixed effects and policyholder characteristics (log income, credit score, mortgage status, log home value, log replacement cost, home age, and years since home purchase) interacted with insurer to flexibly account for different consumer preferences for specific insurers. Robust standard errors in parentheses. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

| | (1) | (2) | (3) |
|---|---|---|---|
| Premium per unit Coverage ($\alpha^F$) | 1.216*** | | -0.230 |
| | (0.326) | | (0.395) |
| Total Premium ($\alpha^N$) | | 0.0524*** | 0.0559*** |
| | | (0.00911) | (0.0119) |
| Insurer Fixed Effects | Y | Y | Y |
| Insurer × Policyholder Characteristics | Y | Y | Y |
| $N$ | 43246 | 43246 | 43246 |

Table 8: Discrete Choice over Insurers: Heterogeneity by Income and Mortgage Status

As in Table 7, this table presents estimates of parameters from a multinomial choice model of the following latent utility function given in equation (8), but in addition, we consider heterogeneity in price sensitivity by *High Income*, an indicator for above median income (results in column 1), and *Mortgage*, which indicates whether the household has a mortgage (results in column 2). Column 3 considers the subsample of households that purchased their policy in 2017 or later. Premium per unit Coverage is defined as the cost per $10,000 of coverage at the observed coverage choice of the policyholder. Total Premium is defined as the premium in $100s at the predicted coverage offered by the insurer. All specifications include insurer fixed effects and policyholder characteristics interacted with insurer to flexibly account for different consumer preferences for specific insurers. Robust standard errors in parentheses. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$.

| | (1) | (2) | (3) |
|---|---|---|---|
| Premium per unit Coverage ($\alpha^F$) | 0.317 | 0.253 | -0.223 |
| | (0.517) | (0.724) | (0.686) |
| Total Premium ($\alpha^N$) | -0.0589*** | -0.0539** | -0.0661*** |
| | (0.0134) | (0.0167) | (0.0189) |
| High Income X Premium per unit Coverage | -0.133 | | |
| | (0.577) | | |
| High Income X Total Premium | 0.00437 | | |
| | (0.00961) | | |
| Mortgage X Premium per unit Coverage | | -0.0332 | |
| | | (0.733) | |
| Mortgage X Total Premium | | -0.00287 | |
| | | (0.0133) | |
| $N$ | 43246 | 43246 | 19656 |
| Insurer Fixed Effects | Y | Y | Y |
| Insurer × Policyholder Characteristics | Y | Y | Y |

# 7 FIGURES

Figure 1: The Distribution of Underinsurance Pre- and Post-Fire

The top panel shows the distribution of pre-fire coverage ratios, calculated as policyholders' coverage A limits divided by pre-fire replacement costs. The bottom panel plots the same distribution post-fire, adding extended coverage provisions to coverage A and post-fire replacement cost inflation to the denominator. The bottom panel excludes the 6.9% of policyholders with guaranteed replacement cost coverage who would cluster at a coverage ratio of 1.

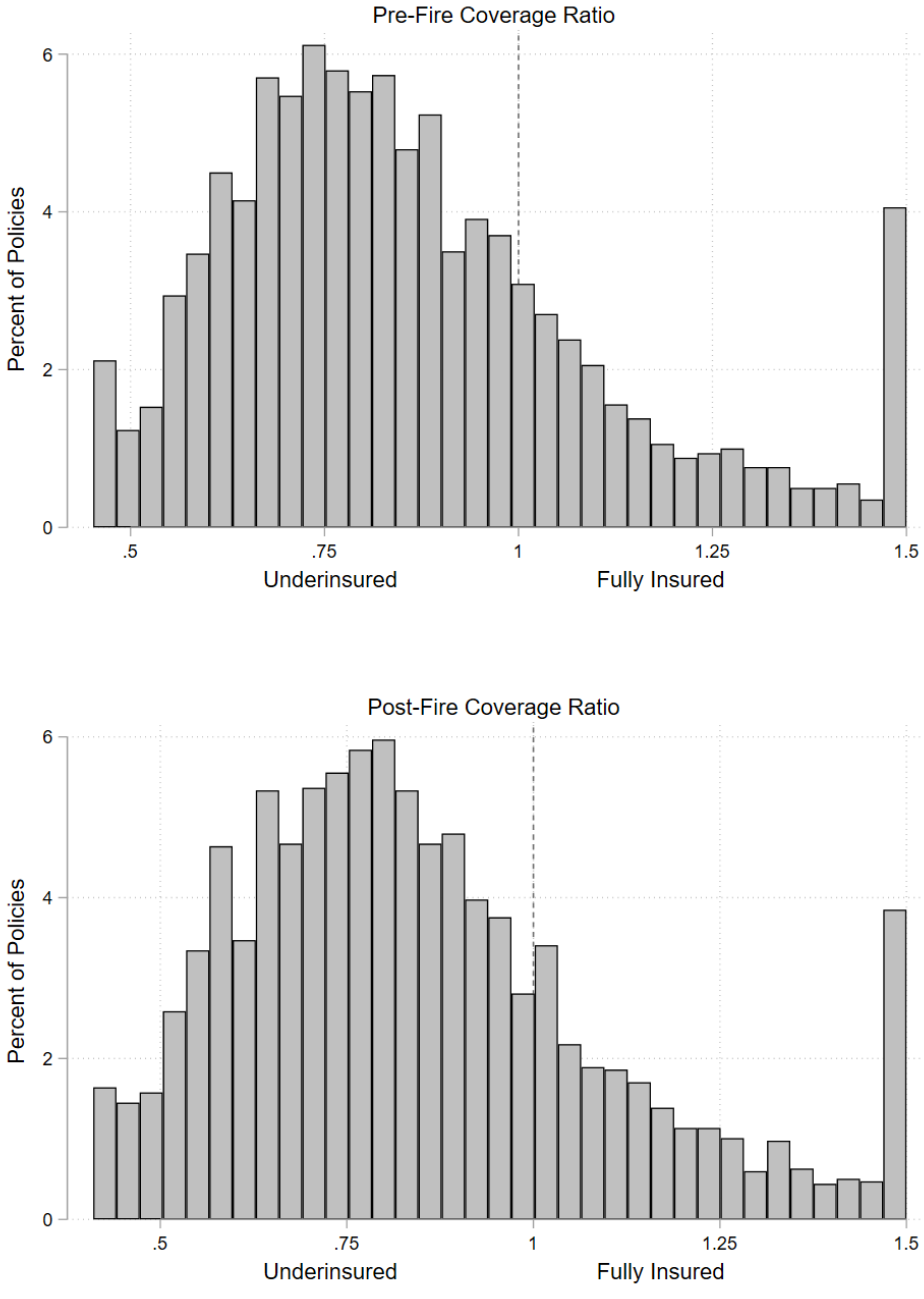
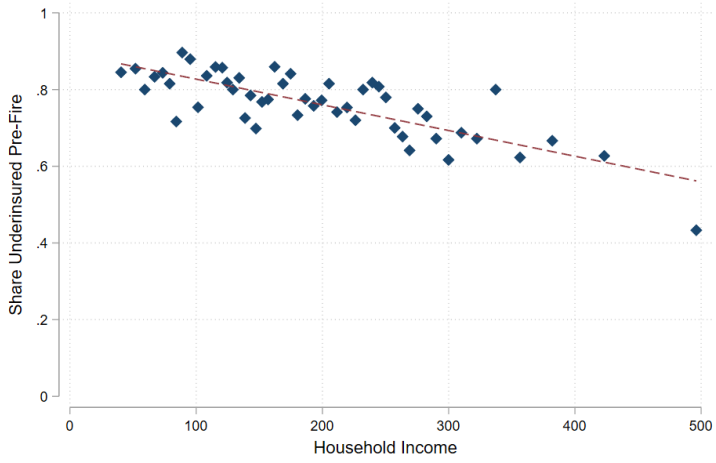
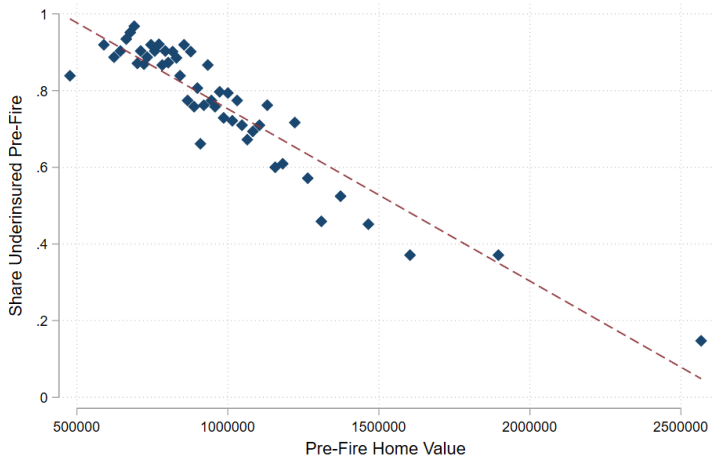


Figure 2: Underinsurance Varies by Policyholder Characteristics

This figure plots the share of policyholders who are underinsuranced according to the pre-fire coverage ratio by 50 quantiles of household income (top), home value (middle) and credit score (bottom).




(a)




(b)

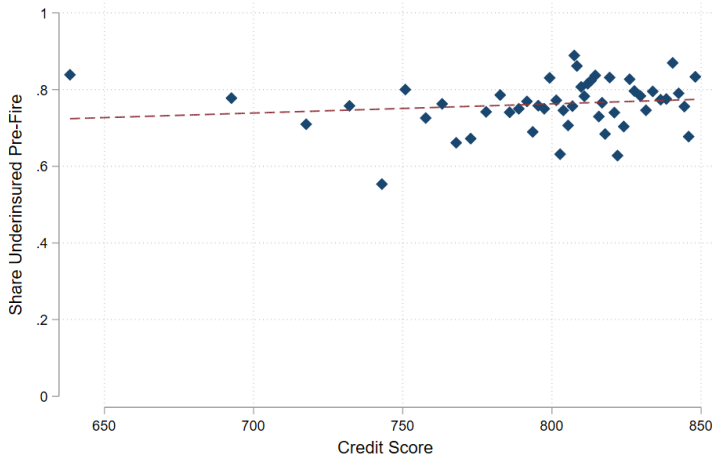


Figure 3: Older Policies are not more Likely to be Underinsured

This figure plots the share of policyholders underinsured pre-fire by the year when they bought their homeowners insurance policy, pooling policyholders who bought on or before 1990.

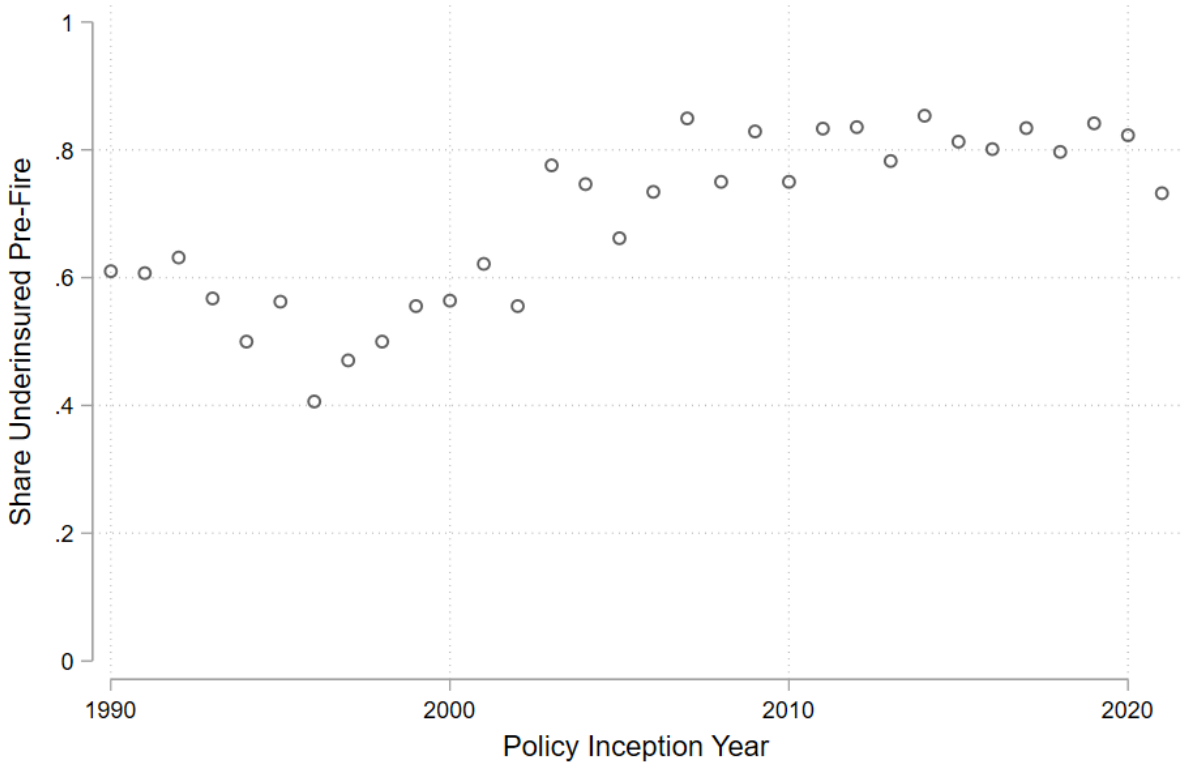


Figure 4: Wide Heterogeneity in Average Coverage Ratios Across Insurers

Shows the number of insurers by bins of policyholder average pre-fire coverage ratios.

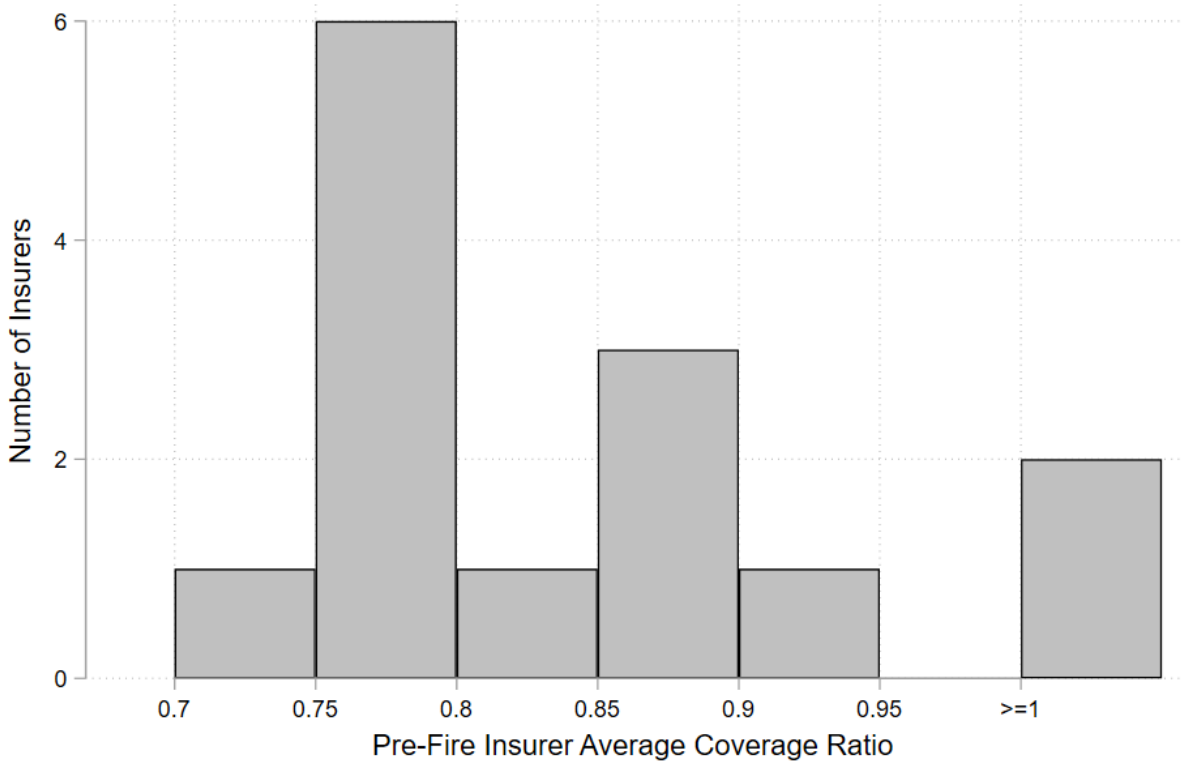
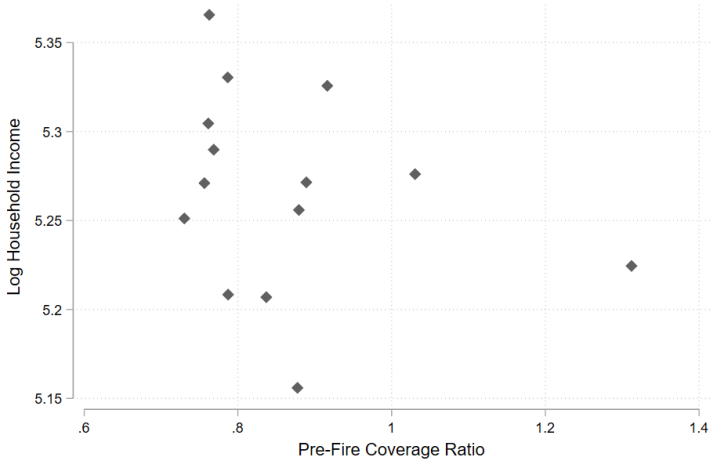
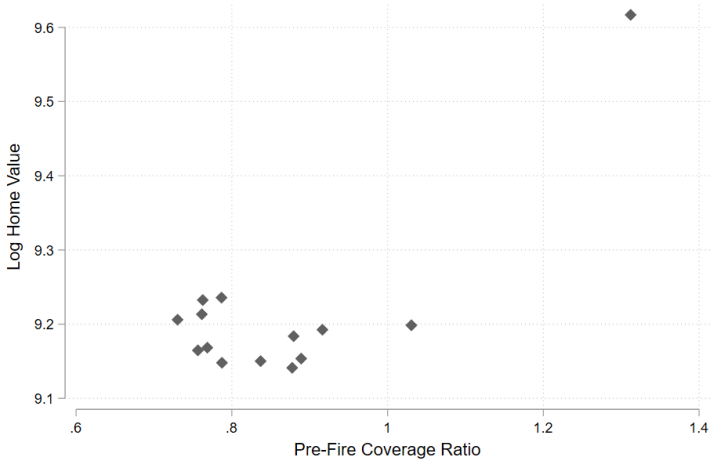


Figure 5: Average Policyholder Characteristics are Uncorrelated with Average Insurer Coverage Ratios

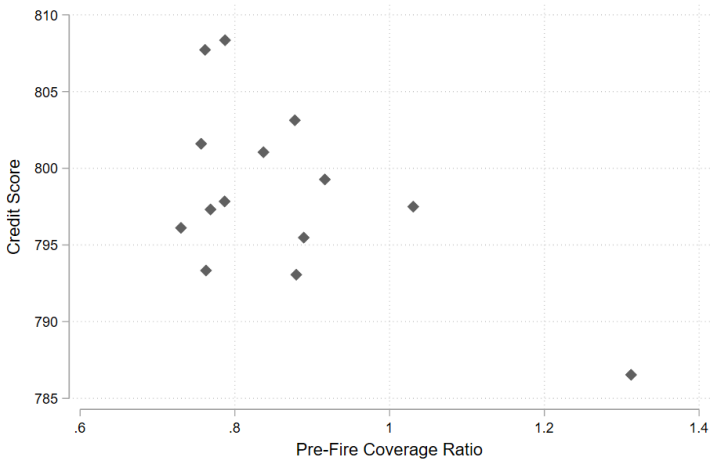
Plots average policyholder pre-fire coverage ratios (x-axis) by insurer against average policyholder incomes (top), home values (middle), and credit scores (bottom) along the y-axis.




(a)




(b)




(c)

Figure 6: Differences in Coverage Across Insurers Are Robust to Controlling for Policyholder Characteristics

This figure shows insurer pre-fire coverage ratio fixed effects estimated without any controls for policyholder characteristics (red) and with controls policyholder characteristics (blue). The fixed effect for insurer 8 is omitted with a coefficient of zero.

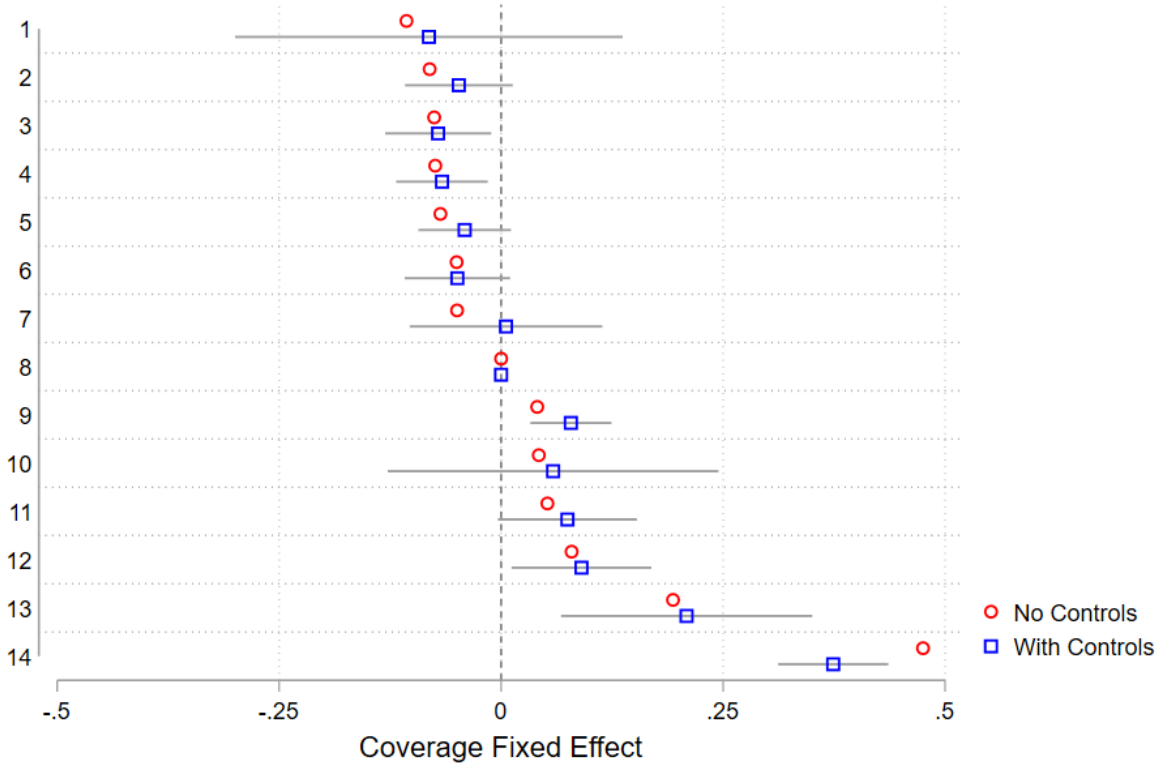


Figure 7: Consumer Welfare Improves without Coverage Neglect.

Distribution of welfare gains under the uniform coverage counterfactual relative to the baseline. Vertical line indicates the average welfare gain. Values above $1,500 are grouped together.

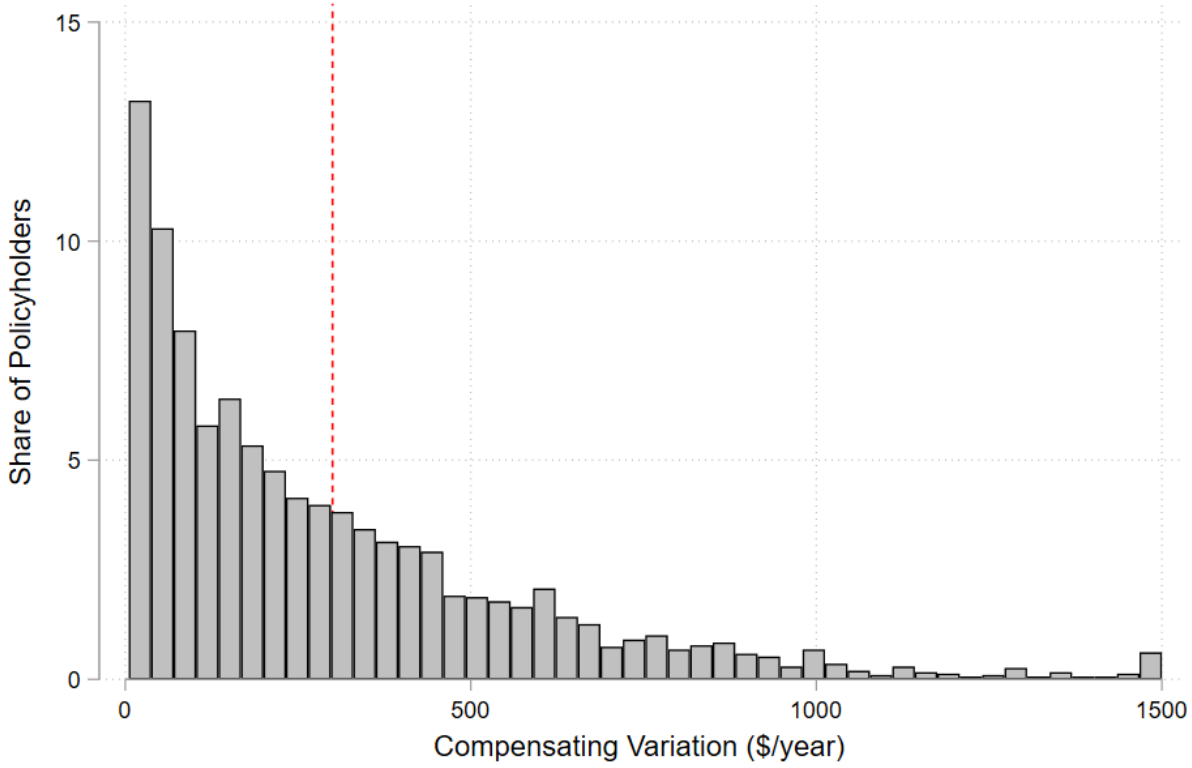
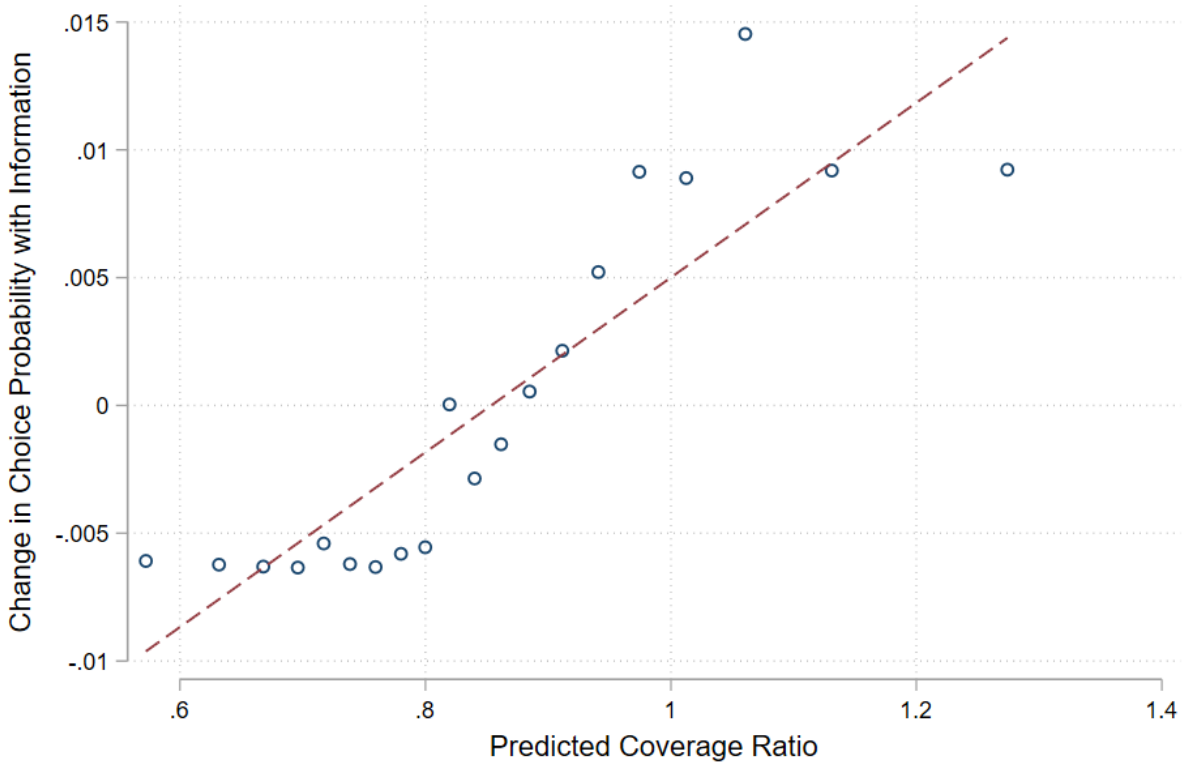


Figure 8: Removing Coverage Neglect Makes Consumers Less Likely to Choose Insurers with Lower Coverage Ratios.

Plots the average change in the choice probability for a given insurer (y-axis) by twenty quintiles of the predicted pre-fire coverage ratio (x-axis).



# A Appendix Tables

| VARIABLES | (1) Coverage Ratio | (2) Coverage Ratio |
|---|---|---|
| log Income | | 0.053*** |
| | | (0.009) |
| Credit Score (z) | | -0.007 |
| | | (0.005) |
| Log Zestimate | | 0.552*** |
| | | (0.102) |
| Mortgage | | -0.012 |
| | | (0.013) |
| Log Replacement Value | | -0.759*** |
| | | (0.058) |
| Home Purchased Age | | 0.002 |
| | | (0.002) |
| Home Purchased Age$^2$ | | 0.000 |
| | | (0.000) |
| Home Built Age | | -0.010*** |
| | | (0.002) |
| Home Built Age$^2$ | | 0.000*** |
| | | (0.000) |
| Premium per $100 Coverage | | -0.036 |
| | | (0.109) |
| Square Footage | | 0.000* |
| | | (0.000) |
| Square Footage$^2$ | | -0.000 |
| | | (0.000) |
| Observations | 3,089 | 3,089 |
| R-squared | 0.164 | 0.472 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A1: Results from regressing pre-fire coverage ratios over insurer fixed effects without controls (column 1) and with controls (column 2). The insurer fixed effect coefficients are plotted in Figure 6.

| VARIABLES | Coverage Ratio |
|---|---|
| Av. Coverage Ratio (LOO) | 0.824*** |
| | (0.113) |
| Log Income | 0.063** |
| | (0.023) |
| Log Zestimate | 0.458*** |
| | (0.091) |
| Credit Score (z) | -0.008 |
| | (0.006) |
| Mortgage = 1 | -0.019 |
| | (0.028) |
| Purchase Age | 0.002 |
| | (0.004) |
| c.sale_age#c.sale_age | 0.000 |
| | (0.000) |
| Home Age | -0.007** |
| | (0.003) |
| Home Age$^2$ | 0.000** |
| | (0.000) |
| Sqft | -0.000* |
| | (0.000) |
| Sqft$^2$ | 0.000* |
| | (0.000) |
| Constant | -6.093*** |
| | (1.118) |
| Observations | 758 |
| F-stat | 175.19 |
| R-squared | 0.359 |

Standard errors clustered by insurer
*** p<0.01, ** p<0.05, * p<0.1

Table A2: First stage estimation results of regressing post-fire coverage ratios over leave-one-out insurer average post-fire coverage ratios.

# B MEASURING PREMIUMS

As described in Section 2, we estimate the premium schedule for four insurers who do not appear in the Quadrant data but reported their premiums in the Colorado Department of Insurance data call. We estimate the premium schedule:

$$p_{ij} = \lambda_j + \gamma^j(Cov_i + Cov_i^2) + \alpha^j X_i + \epsilon_{ij}, \tag{A1}$$

The dependent variable is the annual premium. We include insurer fixed effects, a quadratic of the amount of coverage purchased, and property and household characteristics (quadratic square footage, log zestimate, standardized credit score, log income, extended replacement cost coverage provisions, building condition rating, home age, and quadratic of policy years from inception). We use the leave-one-out fitted values from Equations A1 as the estimated premium for a given policy $i$ at coverage $Cov_i$.

We have three insurers who both appear in Quadrant and reported their premiums in the data call. We use this overlapping sample to assess the quality of our premium estimates. Reassuringly, the quadrant premiums and our estimated premium schedules all have correlations coefficients between 0.7 and 0.8 for each of the three insurers.