Welfare Impacts of Climate Risk Classification*

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Abstract

Insured losses from natural disasters are rising, prompting insurers to adopt increasingly sophisticated approaches to modeling and classifying this catastrophe risk. We study the efficiency and equity implications of catastrophe risk classification in property insurance markets. In a theoretical model, insurers segment households by hazard exposure to support more granular risk pricing. We show how aligning premiums with expected losses can strengthen incentives to invest in cost effective risk mitigation. At the same time, more granular risk information exposes households to classification risk. Depending on the nature of the correlation between risk exposure and wealth, risk classification can exacerbate or mitigate pre-existing wealth inequality. We investigate these efficiency and distributional implications empirically using data from California's homeowners insurance market. Focusing on wildfire risk, we document the extent to which more granular risk classification, and an associated mean preserving increase in pricing granularity, increases insurance costs for properties in the right tail of the hazard distribution. While more granular risk classification strengthens incentives for private investments in wildfire risk mitigation in high risk areas, calibrated investment cost estimates suggest limited behavioral response. We further show that wildfire risk is negatively correlated with household income in California. This implies that more granular risk classification shifts more insurance costs onto lower income households. Our findings highlight trade-offs between efficiency and equity in catastrophe insurance pricing and inform the policy conversation around the use of catastrophe models in insurance pricing.

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1 Introduction

Climate change is increasing the frequency and severity of extreme weather events. In the United States, the number of weather-related disasters with at least $1 billion in losses has grown from 3.3 events annually in the 1980's to 23 events annually over the past 5 years (2020–2024).[1] These natural disasters can have severe and lasting impacts on households and communities. As new housing expands into high-hazard areas –i.e. floodplains and the wildland–urban interface — there are more U.S. households living in harm's way than ever before (Radeloff et al. 2018).

Insurance helps households manage these risks by offering financial protection against catastrophic losses. In exchange for paying an annual premium, policyholders gain access to recovery funding that can help them rebuild after a disaster. Past research has found that post-disaster recovery is faster and more complete in communities where a larger share of households are adequately insured (Kousky and You 2023). Insurance can be especially important in lower-income communities, where households often lack access to alternative sources of recovery capital such as savings, home equity, or low-interest credit (Ratcliffe et al. 2019).

To price catastrophe risk fairly and adequately, insurers must first estimate the likelihood that a disaster will impact a location and then assess the property damages that would be sustained in the event of a catastrophe. Insurers use available risk information to group insureds into classes that face probabilistically similar expected losses. More granular information can uncover economically meaningful differences in risk exposure, improving the alignment between premiums and expected losses. However, as granularity increases, the signal-to-noise ratio may worsen such that price differences are driven more by statistical noise than meaningful variation in risk exposure. More granular pricing can also raise equity concerns if high-risk areas disproportionately overlap with low-income communities or historically marginalized regions. In sum, finer risk classification need not deliver improved outcomes in practice. This paper investigates the efficiency and distributional implications of catastrophe risk classification in theory and practice.

A rich literature in economics has explored the welfare implications of risk-classification in insurance markets. The earlier literature focused on voluntary insurance markets with private information (e.g. health and auto insurance). In these contexts, more refined risk classification can improve market efficiency by mitigating the adverse selection problems that can arise when insureds hold private information about their risk profile (Rothschild and Stiglitz 1976; Crocker, Rothschild, and Snow 2025). Hoy 1982 shows that while risk classification can reduce average price discrimination against low-risk insureds, it may also worsen wealth inequality when income and risk exposure are negatively correlated.

More recently, researchers have begun to study risk classification in property insurance markets where insurers are better informed than property owners about catastrophe risk. Advances in data availability and analytics have transformed catastrophe modeling and risk

1. These numbers summarize inflation-adjusted losses. Source: NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2025). https://www.ncei.noaa.gov/access/billions/, DOI: 10.25921/stkw-7w73

classification, enabling insurers to assess natural hazard exposure with increasing sophistication. In contrast, homeowners struggle to assess their own risk exposure. Catastrophic events are rare, risk information can be confusing, and cognitive biases can lead households to under-invest in risk assessment. In this kind of setting, the efficiency case for more granular risk classification is less about mitigating adverse selection and more about strengthening incentives for private investments in risk reduction.

Recent reforms to the National Flood Insurance Program (NFIP) offer an opportunity to examine these incentive effects. Historically, NFIP premiums were based on coarse flood zone classifications and limited property attributes—an approach criticized for cross-subsidizing high-risk development and weakening incentives to reduce risk. In 2021, FEMA introduced a new pricing methodology that uses simulation-based catastrophe models and historical claims data to determine property-specific premiums. Fabian 2024 presents evidence that suggests flood insurance pricing reforms are steering development away from hazard-prone locations. Mulder 2024 shows how this flood risk rating reform has made risks more salient and strengthened financial incentives to reduce exposure.

Overall, new evidence from the NFIP suggests that flood insurance pricing reforms are changing adaptation behaviors through some combination of risk information and financial incentives. But it has been challenging to separate the effects of increasing the average level of insurance premiums (to more accurately reflect the assessed level of flood risk) from the effects of increasing the granularity of risk pricing (to capture how assessed risk exposure varies across properties). In this paper, we focus in particular on the efficiency and distributional implications of more granular catastrophe risk classification in markets for property insurance.

We use a stylized theoretical model to elucidate the channels through which more granular risk classification can coordinate more efficient investments in risk reduction and alter the distribution of catastrophe insurance costs. The model highlights the importance of three key factors: the degree of heterogeneity in assessed catastrophe risk exposure; the correlation between risk exposure and pre-existing social inequalities; and the cross-price elasticity of private investments in risk reduction. The relationships and equilibrium conditions we derive using our theoretical model provide a conceptual framework for our empirical analysis.

We use detailed data on wildfire risk and insurance in 400 California codes to evaluate how more granular risk classification impacts private mitigation investments and the distribution of insurance cost burdens. We document an economically significant negative relationship between household income and wildfire risk exposure; households in our sample whose income falls in the top 10% of the national distribution face approximately half the wildfire risk experienced by individuals in the bottom four deciles. Thus, a move to more granular risk classification lowers insurance costs for the wealthiest households and increases costs for lower income households. To assess the potential for efficiency improvements, we consider a suite of private investments that households can make to reduce the vulnerability of their homes in the event of wildfire. Under the strong assumption that households will adopt cost-effective risk mitigation measures, we assess the incentive value of more granular risk pricing. We find that more granular pricing does increase the level of investment in defensible space upgrades among the top two deciles of high risk homes.

The remainder of this paper is organized as follows. Section 2 provides some background on catastrophe risk classification in property insurance markets. Section 3 develops the theoretical framework that guides the empirical analysis. Section 4 summarizes the data elements we use in our analysis. Section 5 presents our empirical analysis of how increasing the granularity of wildfire risk classification in California impacts the distribution of risk costs and the level of investment in cost-effective risk mitigation measures. Section 6 concludes.

2 Catastrophe risk classification in property insurance markets

Managing natural catastrophe risk is substantially more costly and more complex than other insurable risks such as automobile accidents, health shocks, or unemployment. It is more costly because extreme weather events can cause massive damages that are correlated across space and time. To remain solvent following such events, insurers must be prepared to pay out many large claims simultaneously. This requires maintaining substantial capital reserves or purchasing costly reinsurance, both of which raise the overall cost of providing coverage.

Assessing catastrophe risk is also more difficult. Traditional actuarial methods that rely on historical claims data are poorly suited to rare, high-severity events. Climate change further complicates this exercise insofar as historical experience underestimates future risk exposure. In response to these challenges, insurers are increasingly turning to catastrophe (CAT) models—probabilistic tools that integrate geophysical hazard data (such as flood maps or wildfire spread simulations), property-level characteristics (such as elevation, structure type, or roof material), and assumptions about the frequency and severity of extreme events. These models enable more granular risk classification and pricing than was previously possible.

The growing use of catastrophe risk classification — using proprietary CAT models or publicly available data—has sparked controversy in property insurance markets. In the flood context, revised FEMA floodplain maps have drawn sharp backlash from homeowners reclassified into high-risk zones and facing steep premium hikes. Similar tensions have emerged around wildfire insurance pricing. As catastrophic losses have mounted, insurers argue that more sophisticated models improve their ability to anticipate losses and price risk more accurately. Consumer advocates raise concerns about the opacity of proprietary models and the potential for them to justify unaffordable or unfair premium increases.

These issues are becoming particularly salient in California's homeowners insurance market. As catastrophic wildfire losses escalate in California, insurers are developing more sophisticated wildfire risk classification strategies (Boomhower et al. 2024). New regulatory reforms aim to expand the use of CAT models in wildfire risk classification and property insurance pricing. Proponents of these reforms emphasize the efficiency benefits of aligning premiums with risk exposure while critics warn of reduced transparency and rising costs for high-risk households. Ongoing policy discussions focus on how to harness the incentive value of improved risk models while ensuring fairness and affordability.

3 Theoretical Framework

A stylized theoretical model helps to elucidate the potential efficiency and distributional implications of catastrophe risk classification in homeowners' insurance markets. We build on the seminal work of Rothschild and Stiglitz (1976) and Hoy (2006) to define our baseline model wherein both insurers and households are symmetrically uninformed about the probability that a property will suffer an insurable loss. We then extend the model to consider the efficiency and distributional properties of catastrophe risk classification when households can make private investments in self-protection that reduce their vulnerability in the event of catastrophe. Results derived in this section provide a conceptual foundation for our empirical analysis.

3.1 Baseline model: Symmetrically uninformed agents

The catastrophe risk faced by the owner of property i is the product of the degree of "hazard" (i.e. the likelihood and the intensity or magnitude of the catastrophic event) and the level of 'vulnerability' (i.e. the physical and environmental factors that determine the susceptibility of the structure to damage in the event of a catastrophe). To simplify the analysis, we consider only two states of the world: a catastrophic loss state (denoted L) and a no loss state (denoted NL). The probability that a catastrophe will impact property i is denoted p_i. We use D_i to denote the damages sustained in the loss state such that the catastrophe risk faced by a household is $p_i \cdot D_i$.[2]

In the baseline case, we assume that insurers and households cannot access information about property-specific hazard rates. Only the average probability of catastrophe in the population, $\overline{p}$, is known. We first consider a case in which the expected value of the insurable loss in the event of catastrophe, D, is exogenously determined and does not vary across households. In this case, the expected loss for all properties is $\overline{p}D$.

Insurance contracts are defined by a premium ρ and the indemnification I that is paid to the homeowner in the event of a loss. Prior to the purchase of insurance, the representative household's wealth is W_0. The household's preferences are defined by a von Neumann-Morgenstern utility function $U(W)$ which is assumed to be strictly increasing and strictly concave in wealth to accommodate risk aversion. The household's expected utility under an insurance contract $C(\rho, I)$ is given by:

$$\begin{aligned} V(\rho, I) &= \overline{p}U(W_0 - D - \rho \cdot I + I) + (1-\overline{p})U(W_0 - \rho \cdot I) \\ &\equiv \overline{p}U(W_L) + (1-\overline{p})U(W_{NL}) \end{aligned}$$

where W_L denotes wealth in the loss state and W_{NL} denote wealth in the no loss state.

In a competitive insurance market with free entry and exit, insurers earn zero profit in equilibrium:

2. The expected value of damages sustained in the event of catastrophe can be formulated as the product of the vulnerability of the structure to damages and the cost of damages sustained. For ease of exposition, this product is represented by a single measure D. In a later section, we will introduce additional notation such that vulnerability and reconstruction costs are represented separately.

$$\pi(\overline{p}, \rho, I) = \rho \cdot I - \overline{p} \cdot I = 0 \tag{1}$$

Rearranging this zero profit condition implies $\rho = \overline{p}$. The insurance contract that maximizes expected utility (given risk aversion) smooths consumption across states: $U'(W_L) = U'(W_{NL})$. In other words, utility-maximizing households fully insure such that $I = D$.

3.2 Hazard classification with fixed vulnerability

Now consider a case in which both households and insurers can access information that can be used to classify properties into one of two risk classes. Let θ denote the share of households that face a high hazard probability p^H. Let 1-θ denote the share of households facing a low hazard probability p^L.

Once this risk classification information becomes available, any insurer who continues to offer the pooled contract risks attracting an adversely selected share of the market. In competitive equilibrium, two risk class-specific contracts are offered: $C^H(p^H, D)$ and $C^L(p^L, D)$. Under this actuarially fair pricing regime, income levels are state-independent but vary across risk classes. The adoption of more granular risk classification reduces welfare for households classified as high risk. In contrast, households classified as low risk pay less for full insurance when more granular risk information is used to set premiums.

To evaluate the welfare consequences of risk classification, we consider a hypothetical ex ante perspective in which households do not yet know their individual risk type. In this setting–often associated with the Rawlsian "veil of ignorance"–households are identical in all observable respects, and differ only in their probabilistic exposure to catastrophe risk, which is revealed only after the insurance contract is signed. Under risk pooling, expected utility is simply $U(W_0 - \overline{p} \cdot D)$. Under risk classification, insurers offer type-specific premiums. From an ex ante perspective, expected utility is given by:

$$V(\rho^H, \rho^L, I) = \theta U(W_0 - \rho^H \cdot D) + (1 - \theta) U(W_0 - \rho^L \cdot D)$$

Because utility is strictly concave in wealth, Jensen's inequality implies that the expected utility under the pooling contract exceeds that under the risk-classified regime. Thus, risk-averse households would ex ante prefer a pooled contract which insures against both the occurrence of a loss event and the risk of being classified as high risk.

This welfare dominance result depends in part on our assumptions that expected losses (D) are exogenous and that households are identical in terms of initial wealth (W_0). Releasing this last assumption, suppose that risk type is positively correlated with initial wealth such that $U'(W_0^L - \overline{p}D) < U'(W_0^H - \overline{p}D)$. Under this scenario, households may ex ante prefer risk classification over risk pooling because risk classification mitigates – or eliminates– wealth disparities across states. In contrast, if risk exposure is negatively correlated with wealth, risk classification will exacerbate pre-existing wealth inequalities making risk classification even less appealing from a welfare perspective.

3.3 Private investment in self-protection

Thus far, we have assumed that the damage caused in the event of a catastrophe is exogenously determined. In fact, there are private investments that homeowners can make to reduce their vulnerability to damages. In the case of flood risk, elevating foundations can reduce property damage(Hovekamp and Wagner 2023). In the case of wildfire, maintaining defensible space around the home and making structural modifications reduces vulnerability to wildfire (Calkin et al. 2011; Baylis and Boomhower 2024).[3]

To accommodate these endogenous investments in self-protection, we now define the damage sustained in the event of catastrophe as $D(r)$, $D'(r) < 0$, $D''(r) > 0$. We normalize the per-unit price of self-protection to $\$1/unit$. Returning to scenario in which only pooled insurance contracts are offered, households can now choose private investments r and identification I to maximize utility:

$$\begin{aligned}\max_{r,I;\overline{p}} V(r, I) &= \overline{p}U(W_0 - D(r) - \rho \cdot I + I - r) + (1 - \overline{p})U(W_0 - \rho \cdot I - r) \\ &= \overline{p}U(W_L) + (1 - \overline{p})U(W_{NL})\end{aligned}$$

The corresponding zero profit condition is:

$$\pi(\overline{p}, \rho, I) = \rho \cdot I(r) - \overline{p} \cdot I(r) = 0 \rightarrow \rho = \overline{p}$$

The first-order condition for the optimal choice of r^* is:

$$\underbrace{-D'(r)\overline{p}U'(W_L)}_{\text{marginal benefit}} = \underbrace{\overline{p}U'(W_L) + (1 - \overline{p})U'(W_{NL})}_{\text{marginal cost}}, \tag{2}$$

The marginal benefit argument captures the reduction in the cost of fully insuring damages that results from a marginal increase in r. The marginal cost argument represents the probability-weighted reduction in utility that results from an incremental increase in private risk-reduction, leaving less to spend on other consumption.

The utility maximizing choice of indemnity I equates marginal utility across the loss and no loss states. Thus, Equation (2) can be reformulated to yield $-D'(r)\overline{p} = 1$. Intuitively, households will invest in self-protection until the marginal cost of these investments equals the marginal reduction in full insurance costs. Under this risk pooling scenario, all households make the same mitigation decision such that $-D'(r^{pool}) = \frac{1}{\overline{p}}$. This risk mitigation level will be too high for low-risk households and too low for high-risk households.

Returning to the scenario in which both households and insurers can access to risk classification information, we note that differentiated risk premiums (ρ^H and ρ^L) provide differentiated

3. Households can also choose to move out of harm's way. However, in the United States, households have been moving in the opposite direction; high-fire-risk areas have been experiencing some of the fastest population growth (Radeloff et al. 2018). In what follows, we focus on private investments that reduce structure vulnerabilities.

incentives for private investments in risk reduction. Households classified as high hazard will set $-D'(r) = \frac{1}{p^H} \geq \frac{1}{\overline{p}}$. In contrast, households classified as low hazard will want to reduce their level of investment vis a vis the pooling contract: $\frac{1}{p^L} \leq \frac{1}{\overline{p}}$.

Figure 1 provides a stylized illustration of how levels of private investments in risk mitigation can respond to more granular risk classification and insurance pricing. Risk classification induces households classified as high risk to increase their level of investment from $r^*(\overline{p})$ to $r^*(p^H)$. The red area represents the reduction in expected damages (net of the additional investment costs) induced by more granular risk pricing. This represents the reduction in full insurance costs incurred by high risk households due to increased investment in r. Properties classified as low hazard reduce investments in self-protection from $r^*(\overline{p})$ (under the pooling contract) to $r^*(p^L)$. Cost savings enjoyed by a household classified as low risk are represented by the green area.

Overall, risk classification yields more efficient investment in self-protection. However, high-risk households do pay more for insurance (as compared to the risk pooling scenario) which leaves them with lower residual wealth under the risk classification regime. Ex ante expected utility is given by the weighted average:

$$V_{class}(r, I) = \theta U(W_H) + (1-\theta)U(W_L)$$
$$W_j = W_0 - \rho^j D(r_j^*) - r_j^*, j \in H, L$$

In contrast to the case where damages are exogenous, we cannot directly apply Jensen's inequality to establish that risk pooling ex ante welfare dominates risk classification. It is still the case that risk classification introduces classification risk, but it can also improve efficiency (and reduce costs) by aligning private mitigation incentives with underlying risk. The net effect on welfare depends on the magnitude of this efficiency gain relative to the value of risk cost smoothing across types. From a policy perspective, this result highlights the importance of weighing the informational gains from risk classification against the insurance value of pooled arrangements.

3.4 Risk load

Thus far, we have ignored the costs of holding capital reserves, or purchasing reinsurance, that insurers must incur so they can be prepared to pay out many large claims in the event of a natural catastrophe. In practice, insurers add a 'risk load' to catastrophe insurance premiums to ensure that revenues collected cover all expected costs. We extend the model to incorporate this risk load in a stylized way. We assume that insurers charge a premium equal to $\delta \cdot \rho$, where $\delta \geq 1$. This markup reflects insurers' costs beyond expected losses, including the cost of capital, tail risk, and possibly ambiguity aversion.

Homeowners are required to buy and hold multi-peril property insurance to qualify for a mortgage. If we assume that lenders require homeowners to fully insure such that $I = D(r)$, incorporating risk load does not impact the level of insurance. However, because risk load makes insurance more expensive, households now see greater savings from reducing $D(r)$.

Efficient levels of investment in r now satisfy $-D'(r) = \frac{1}{\delta \cdot \bar{p}}$. In other words, incentives to invest in risk reduction are increasing in δ.

If insurers can price discriminate across high and low risk types, the marginal benefit of mitigation will be scaled by δp_j for $j =, H, L$ respectively. Under this scenario, the risk load factor increases mitigation incentives for both types, but the increase is more significant for high risk types because the risk load premium is proportional to expected loss. Importantly, higher levels of investment in r need not imply that risk load induces over-investment in risk mitigation. To the extent that the costs of holding capital or purchasing reinsurance reflect real capital costs, these costs should be reflected in efficient insurance pricing.

3.5 Theoretical implications to take to the data

This theoretical framework highlights three important factors that determine the efficiency and distributional implications of catastrophe risk classification in insurance markets. First, the greater the variation in hazard rates that is revealed by more granular risk information, the larger the potential for efficiency and distributional impacts. Second, the distributional implications of more granular risk classification depend significantly on the nature of the correlation between parcel-level risk exposure and measures of household wealth. A negative (positive) correlation implies that more granular risk classification will lead to a regressive (progressive) redistribution of risk costs. Finally, the efficiency implications of more granular risk classification will depend on the cross-price elasticity of risk mitigation investments. If improvements in risk classification have limited effects on households' investment behaviors, the value added by risk classification will limited - or negative. In what follows, we evaluate these three factors empirically in the context of wildfire risk classification in California's property insurance market.

Before turning to the empirical analysis, we highlight some limitations of our theoretical framework with implications for the interpretation of our more data-driven findings.

Our theoretical analysis has assumes that households are fully informed about the relationship between private investments in r and the damage costs they can expect in the event of catastrophe D. An alternative interpretation of this assumption is that insurance premiums fully reflect and reward the risk reduction benefits of private investments in r. In fact, cognitive biases and information frictions make this relationship very challenging for homeowners to understand and act upon and insurance premiums do not fully reward homeowners for the risk mitigation measures they take. Thus, the incentive values we estimate below should be interpreted as measures of the *potential* efficiency gains from more granular insurance pricing.

Our model does not account for the positive externalities and spillovers that can be generated by private investments in risk reductions (Baylis and Boomhower 2024). Nor do we account for the fact that catastrophe risk levels are expected to escalate with climate change. A failure to account for these two factors will lead us to under-estimate the social value of private investments in risk mitigation. Finally, we abstract away from the considerable uncertainty in granular estimates of catastrophe risk exposure. As the granularity of risk classification increases, so does the degree of uncertainty around the average hazard rate in a risk class or category. Ignoring this uncertainty simplifies the analysis considerably. But this simplification abstracts away from important concerns about declining signal to noise ratios as classification strategies get more granular.

4 Data

This section describes the data that we use to understand tradeoffs in wildfire insurance pricing in California. Section 4.1 describes the key data sources and Section 4.2 explains how we construct the final analysis sample.

4.1 Data Sources

Parcel-level wildfire risk

We obtained parcel-level wildfire risk and property characteristics data for 100,000 single family homes in California from CoreLogic, Inc., a leading provider of property information and risk analytics. The sample includes 250 homes in each of 400 California zip codes that exhibit significant variation in assessed wildfire risk. For each sampled property, we obtained three types of information. First, we collect standard assessor's information such as the home address, geolocated coordinates, reconstruction cost, and the year of construction. In addition, we have information related to wildfire risk, such as the distance to high hazard vegetation, distance to a responding fire station, and a public protection classification that rates local fire departments.

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

Finally, Core Logic provided probabilistic catastrophe loss measures which are derived from CoreLogic's 2021 wildfire CAT model. This simulation-based model considers both landscape attributes and structure characteristics, such as construction material and year built. We obtain measures of yearly losses for each home in the data based on thousands of model simulations. The reported statistics for each home include the average annual loss (averaged across all model simulations for a given year), the standard deviation of modeled annual loss realizations, and aggregate exceedance probability losses over return periods of 50, 100, 250, and 500 years.

Income and Demographic Information

Our main source for income and demographic data is the Privacy-Protected Gridded Environmental Impacts Frame (Gridded EIF) from the United States Census Bureau (Voorheis et al. 2024). The Gridded EIF reports population counts for income, race, and age bins in grid cells defined by one degree of latitude and longitude (about 1.2 kilometers). In each grid cell we observe population counts in each decile of the nationwide household income distribution; in each of several mutually exclusive race/ethnicity categories; and in three age bins. The data also report intersected income and race/ethnicity bins (for example, number of people who are White Alone and in income decile 5).

We also draw on some variables from the 5-year American Community Survey (ACS) from the Census Bureau. In particular, we use the ACS-reported population share in single family homes at the Block Group level in the probabilistic assignment of homes to income deciles described in Section 4.2.

4.1.1 Private investments in wildfire risk reduction

Our main analysis focuses on a commonly-considered package of retrofit investments to reduce the vulnerability of already-constructed homes to wildfire damage. We consider a package of defensible space upgrades that remove flammable material in the so-called "zone zero" area that extends five feet outwards from the exterior walls. We model our intervention on the landscaping upgrades described in Barrett and Quarles (2024), which include replacing wood mulch with pea gravel and replacing a wood privacy fence with ignition-resistant fiber cement panels. Barrett and Quarles (2024) report detailed retrofit costs that include labor, overhead, materials, and dumping costs per square foot. We also draw on a companion report that describes the costs for making these same investments at the time of initial construction or doing an already-planned remodel (Barrett, Quarles, and Gorham 2022). The online appendix describes the exact data from these reports that we use to calculate the landscape retrofit cost for each home in the data. We emphasize, however, that our model intervention is a stylized hypothetical and that true costs and landscaping choices are likely to vary from home to home. Our ultimate interest in this paper is not in the precise costs of wildfire retrofits, but rather how the incentive to make these retrofits varies with risk classification methods in the insurance market.

To quantify the vulnerability reduction from defensible space, we draw on data from Syphard, Brennan, and Keeley (2014), which describe outcomes for homes exposed to catastrophic fires in San Diego County in 2003 and 2007. The data show a 12 percentage-point decrease in loss probability for homes with 8–15 feet of defensible space, compared to homes without defensible space. We assume that the landscape retrofit has a service life of 40 years so that the present value of the upgrade benefits is the discounted (at 5%) sum of 40 years of decreased vulnerability. We acknowledge again that these numbers are an inexact proxy for the true benefits of landscape retrofits, and that there may be important heterogeneity in those benefits according to regional and local-scale factors. Moreover, given the long assumed lifespan of the investment, future predicted increases in wildfire hazard will affect the return to making these investments today in a way that is not reflected in our calculations.

We focus our model investment on landscaping upgrades because these are achievable at relatively low cost for existing homes. Wildfire vulnerability can also be reduced through "structure hardening" investments that swap ignition-resistant for flammable construction materials. Baylis and Boomhower (2024) find that the full package of hardening investments required under California's wildfire building codes for new homes reduce vulnerability by about 22 percentage points. These investments represent important, cost-effective adaptation actions during new home construction or renovations in high-hazard areas. However, Baylis and Boomhower (2024) also show that these hardening investments are not cost-effective as retrofits except in a handful of extreme hazard areas.

4.2 Dataset Construction

We consider the population of single family homes in the 400 zip codes in the wildfire risk data as a hypothetical market for homeowners insurance. Appendix Table 1 shows that this market would include about 2.7 million homes – smaller than the 9.4 million single family homes in California, but larger than the markets in many other U.S. states. Moreover, the in-sample zip codes capture the majority of high wildfire hazard homes in California, including about 75 percent of all California homes with a wildfire risk score over 50.

Sample Weights

The original process used to sample 250 homes from each zip code overweighted high-hazard homes in each zip because of our interest in understanding wildfire risk. In this analysis, we re-weight the 250 homes in each zip code to reflect the population distribution of wildfire risk scores in the zip. We then resample using these weights to build a weighted analysis sample that is representative of the population of homes in these 400 zip codes. To do this, we draw on auxiliary data from CoreLogic that report zip code totals of single family homes and the distribution of homes across low (≤ 50), medium ($51-60$), high ($61-80$), and very high ($81-100$) wildfire score ranges in each zip code. Our main re-weighting approach defines 800 zip code $\times$ wildfire score range (above/below 50) bins. In each of these bins, we draw homes from that bin with replacement until we reach the total number of homes reported for that bin in the zip code totals data.[4] We repeat this resampling procedure 100 times. This produces a sample weight for each home that is equal to that home's average number of appearances across the 100 resampled datasets rounded to the nearest integer. The final weighted sample includes 95,500 unique homes and sample weights that total to 2.7 million single family homes across 382 zip codes.

Assigning Income and Demographics

Each home in the dataset is matched to the appropriate EIF grid cell based on geographic coordinates. This spatial merge identifies grid-level distributions of income and other variables for each home. We must then make an assumption about where our homes fall in these local distributions in order to assign specific income deciles, race/ethnicity categories, and age groups. A widely-used heuristic is to assign each home the median characteristics of the area containing it (e.g., Census block group median income). There are two problems with this approach. First, it compresses the distribution of assigned incomes by ignoring within-area variation, yielding too few observations in the lower and upper tails. Second, it is prone

4. This approach requires us to drop 18 zip codes where our data do not include any homes in one of the wildfire score range bins. We have also calculated weights using four wildfire score ranges in each zip code. These weights produce very similar empirical results but require that we drop more zip codes to ensure complete coverage of homes in each score range bin.

to an ecological fallacy. Our wildfire risk sample consists exclusively of single family homes, reflecting the policy and research focus on the homeowners insurance market.[5] Area-average outcomes will not correctly describe the occupants of homes in our sample if individuals in single family homes are systematically different from those in multifamily housing. Appendix Table 2 uses individual-level data from the ACS Public Use Microdata Sample to show that there are in fact large differences in average income between households in single-family vs. multifamily housing, even within Census geographic units.

Instead of using area-median income, we assign income and demographic characteristics by drawing homes from the distributions implied by the gridded EIF. This requires an assumption about the degree of sorting into single family homes within grid cells. In the spirit of Borenstein (2012), we examine results for two alternative assignment methods that plausibly bound the effect of within-grid sorting. The first method (hereafter, the "no-sorting" method) matches each home in our data to a randomly chosen individual from the EIF grid cell. This method would be correct if there were no sorting on income within grid cells. The second method (hereafter, the "complete sorting" method) samples only from the richest $X\%$ of homes in the EIF grid, where X is the share of the population living in single family homes in the relevant Census Block Group according to the ACS. This method would be correct in the extreme case of complete sorting (zero overlap in income between multifamily and single family homes). We implement both methods with a bootstrapping approach that repeats the assignment of homes to individuals in the EIF 1,000 times and averages over these iterations as described in the Results section.

Description of the Analysis Dataset

Table 1 describes the weighted analysis sample. The mean average annual loss due to wildfire is \$219 per home. Importantly, this is a highly skewed variable with a median of \$62 and a 90th percentile value of \$553. Regardless of which method we use to assign income, this group of zip codes is wealthier than the nation overall: the median household income in this group is in the 8th decile of the national distribution if we assume complete within-grid sorting on income and in the 7th decile if we assume no sorting. This group has a slightly lower share White Alone and higher share Hispanic or Latino than the U.S. population, again consistent with California. The distribution of age groups roughly matches the nationwide distribution.

5 Empirical analysis of wildfire risk classification

This section uses the constructed dataset to explore implications of granular property insurance pricing for distributional outcomes and for mitigation incentives. Section 5.1 describes variation in wildfire risk and covariance of expected wildfire losses with income and other variables. Section 5.2 explores the range of insurance prices that would prevail under a range of classification schemes. Finally, Section 5.3 explores the mitigation incentives created by these pricing schemes and the implications for expected losses, mitigation investment, and

5. Further study on climate risk in multifamily housing is a fruitful area for research.

overall wildfire-related costs.

5.1 Distribution of Wildfire Risk Across Individuals and Groups

The distributional implications of more granular risk classification depend in part on the correlation between wildfire risk exposure and demographic variables of interest. Figure 2 shows the average expected annual wildfire loss (plus 18% risk load) for homes in each decile of the nation-wide distribution of household income.[6] These values were calculated by repeating the probabilistic matching procedures in Section 4.2 1,000 times and averaging together the income decile means from each iteration. The figure shows the mean and 95% confidence interval from this procedure. The solid line shows results for the no-sorting method and the dashed line shows results for the complete-sorting method. The sizes of the circular markers report the fraction of homes in our data that fall into each decile of the national income distribution.

Panel A reports the expected loss per $100,000 of reconstruction cost. With either income assignment method, there is a clear decreasing gradient of wildfire risk in income. Households in the top 10% of the national income distribution face roughly half the risk experienced by individuals in the bottom four deciles of the national distribution. Estimates for the lower-income bins are noisy because our study population contains relatively few individuals in this range of the national income distribution. Panel B reports overall expected wildfire costs. The income gradient in this figure is less steep, reflecting the fact that wealthy individuals tend to live in homes with higher reconstruction costs.

In both panels, the difference in implied income gradients across the no-sorting and complete-sorting assignment methods for income is relatively limited. For the rest of the distributional analyses in this section, we focus on the complete-sorting assignment method and on expected cost per unit of reconstruction cost.

Figure 3 disaggregates expected wildfire costs by income and race/ethnicity. The results presented here use the complete-sorting method to assign income.[7] There is a clear correlation between wildfire risk exposure and race. American Indian and Alaska Native (AIAN) households face a substantially higher expected cost at all income levels, though these estimates are noisy due to the small AIAN share in the study population. White households also face relatively high expected costs, especially at lower income levels.

Figure 4 considers the relationship between expected wildfire cost and age. The oldest age group of 65+ year-olds face notably high wildfire costs.

5.2 Insurance premium changes induced by risk classification

Boomhower et al. (2024) use detailed rate cases filed by admitted market insurers in California to assess the wildfire risk classification strategies used by different firms in the market.

6. Throughout Section 5, we assume that the costs of insuring wildfire risk include an 18% risk load, following Boomhower et al. (2024).

7. We sort the EIF population bins in descending order of income and then randomly by race/ethnicity bin within income decile.

They find that some insurers classify risk on the basis of zip code-level territory factors, some use categorical wildfire risk scores, and the largest insurer (State Farm) divides the state into 1 kilometer grids and uses catastrophe modeling to calibrate risk rating factors in each grid cell. In the analysis that follows, we approximate these alternative approaches to risk classification by varying the level of aggregation we use to summarize AAL values. This approach assumes that insurers set premiums to reflect the average level of wildfire risk within each risk class they define. The coarsest classification strategy we consider, which pools parcels within county, defines 43 different risk segments. The most granular classification we consider varies wildfire risk pricing across 12,290 fine grid cells.

Appendix Table 3 reports the R^2 values from regressions of property-level average annual loss on segment dummies in the various classification schemes. Because the more granular segmentation variables explain a substantially larger fraction of parcel-level wildfire risk, they introduce more separation in rates between consumers.

Table 2 reports distributions of wildfire risk premiums, expressed as a price per $\$100,000$ of reconstruction cost, under the alternative risk classification schemes we consider. For each classification scheme and each point in the distribution, we report the difference from the uniform statewide price that would prevail with no risk classification. That uniform statewide price is about $48 (the $41 sample average cost from Table 1 multiplied by 1.18 to reflect risk load). All forms of risk classification reduce the premiums paid by lower risk homes and increase the premiums paid by higher risk homes. Pooling by county or wildfire risk score introduces noticeably less differentiation than pooling by zip code or Census block group. These differences are primarily noticeable at the very top of the risk distribution - e.g., above the 95th percentile. This fact reflects the skewed nature of wildfire risk, such that a small number of homes face an outsize risk of loss.

The bottom panel of Table 2 helps to contextualize these numbers by reporting total wildfire-related costs. Moving from no risk classification to CBG-level risk classification would lower risks for the lowest-risk 50% of households by about $200 per year, have a roughly neutral effect at the 75th percentile, and increase insurance costs at the 95th and 99th percentiles by $843 and $2,001 per year.

Figure 5 summarizes how changes in insurance costs induced by increases in the granularity of risk classification are distributed across households. To summarize these relationships, we repeat the probabilistic matching of homes to income deciles from Section 4.2. Granular segmentation methods tend to lower total prices for the wealthiest households by about $100 on average and increase them for poorer households by about $10. This pattern is consistent with the decreasing gradient of wildfire risk in income.

5.3 Incentive value and private investments in risk reduction

This section considers the potential incentive value of more granular wildfire pricing for encouraging appropriate investments in risk mitigation.

Figure 6 shows the degree to which progressively more granular classification schemes reduce the difference between the price faced by a homeowner and their individual-level expected loss. Shrinking these pricing "errors" is what drives incentive value from granular pricing. The skewed nature of wildfire risk is again highly salient in this figure. About 70% of homes (from roughly the 15th to the 85th percentiles) face prices that are close to their individual risk under any classification scheme. The left side of the figure shows that about 15% of homes face substantially lower prices under coarser pricing. In the tail, statewide pooling results in prices for some homes that are hundreds of dollars or more below their individual expected loss. The main incentive benefits of more granular pricing are concentrated in this group; moving to CBG-level or grid-level pricing flattens the error curve noticeably in this region. The right side of the figure shows that the accuracy gains from increasing prices to true high-cost homes granular pricing are partially offset by a smaller group of positive pricing errors where an individual home has lower expected cost than other homes in its segment.

Figure 7 shows how changes in pricing translate to assumed takeup of our hypothetical landscape retrofit investment. These calculations require a number of assumptions that we describe here before discussing the results (again emphasizing the illustrative and approximate nature of the exercise). We assume that households are fully attentive and responsive to investment incentives implied by insurance pricing. The private value of investing in mitigation is the discounted present value of annual insurance savings, which in turn are assumed to be changes in annual expected loss plus risk load. The change in annual expected loss from the hypothetical landscape upgrade is the property-specific wildfire hazard p times the reconstruction cost times the change in vulnerability v due to the investment, which we take as 12 percentage points as described in Section 4.1.1.

The AAL measures we use represent the product of annual wildfire hazard p, vulnerability v, and reconstruction cost. To isolate the hazard component for this calculation, we assume $p_i = \frac{AAL_i}{v_i \cdot TIV_i}$, where TIV denotes the total insured value (reconstruction cost) of the home, which is calculated by CoreLogic using a standard reconstruction cost estimator. We coarsely approximate v_i for each home as 0.4 for homes built prior to 1998, 0.32 for homes built between 1998 and 2008, and 0.25 for homes built after 2008 based on Baylis and Boomhower (2022).[8] Appendix Figure 2 plots the distribution of implied parcel-level hazard rates given these assumptions.

We calculate the expected private benefit from the landscape retrofit for each homeowner under each classification scheme as the discounted sum of reduced insurance premiums implied by the structure-specific reconstruction cost, a 12 percentage point vulnerability reduction, and the segment-average wildfire hazard $\bar{p}$ that determines insurance prices in each classification scheme. We assume full rationality of households, so that homeowners adopt these investments if and only if the discounted sum of private cost savings exceeds the up-front cost.

Figure 7 shows the results. Starting in the top panel, the brightest yellow line titled "individual" shows the adoption rate when the investment is done as a retrofit on an already-

8. These rough vulnerability numbers abstract away from structure-specific factors that affect the detailed vulnerability used in the wildfire catastrpohe mode, such as distance to nearest fire station. Our vintage-based approximations also simplify the actual application of building codes, which actually vary across state and local responsiblity areas in California as described in Baylis and Boomhower (2024).

constructed home and $\bar{p} = p_i$. The investment starts to be cost-effective for homes above about the 80th percentile of wildfire risk in our sample. This is the efficient level of retrofit investment (ignoring neighbor externalities and other important issues). The other bars in Figure **??** show how coarser risk rating changes takeup as a result of the change in the $\bar{p}$ applied to each home. Coarser pricing both decreases takeup for the highest-risk homes and also increases takeup for lower-risk homes where investment is not actually cost-effective. Pricing at the CBG or grid cell level get close to the efficient level of mitigation. At the other extreme, a single statewide risk class would essentially eliminate investment by high-risk homes (the black line basically traces the x-axis).

Figure 8 shows how the sum of expected wildfire costs and up-front mitigation costs changes due to the incentive value of more granular risk pricing. The yellow bars represent the present value of expected wildfire damages borne by homeowners as insurance premiums. Depending on the classification scheme, these are on the order of \$20 billion for the 2.7 million homes in our study. The red bars show up-front expenditures on the hypothetical landscape retrofit. Moving from a single statewide risk class to pricing by grid cell would spur investments that would reduce expected wildfire losses from \$21.1 billion to \$17.8 billion, at an up-front mitigation cost of \$1.7 billion.

One takeaway from Figure 8 is that granular pricing creates meaningful incentive value that appreciably lowers total wildfire-related costs. At the same time, the bulk of the expected losses persist even when households face individual-specific insurance prices. This fact reflects the nature of wildfire risk: much of this expected loss is contributed by the large number of households who each face a small loss risk, such that many possible investments in mitigation may not be cost-effective. The results reinforce the importance of cost considerations in mitigation, especially for the large stock of already-built homes in wildfire hazard areas.

6 Conclusion

Climate change is intensifying the risks facing households and insurers alike. In response, insurers are developing more granular tools to classify and price catastrophe risk. This paper evaluates the efficiency and equity implications of such risk classification, combining a theoretical framework with new empirical evidence from California's homeowners insurance market.

Our theoretical framework shows how more granular catastrophe risk classification can support more efficient private investments in risk mitigation as high-risk (low-risk) households have an incentive to increase (reduce) investments in risk mitigation. However, these potential efficiency gains come at a cost: more granular classification exposes households to classification risk and can redistribute insurance costs in regressive ways when risk exposure is negatively correlated with income.

These theoretical findings guide an empirical analysis of detailed data on wildfire risk and insurance pricing. Using data from California, we find that that more granular wildfire risk classification substantially increases insurance premiums for the most exposed homes—homes that, in our sample of California zip codes, are disproportionately occupied by lower-income households. These shifts do strengthen incentives for risk mitigation. The most granular classification schemes that we consider yield close to the efficient level of mitigation investment. At the same time, the absolute level of mitigation investment under granular pricing is still modest. Even under optimistic assumptions about cost-effectiveness and household behavior, only a small share of homes face a level of wildfire hazard that would make our model landscaping retrofit cost-effective. These facts reflect two broad challenges about wildfire risk mitigation for already-built homes: (1) dedicated wildfire retrofits tend to be expensive, and (2) the large overall expected losses from California wildfire are partly driven by many properties that each face a low event hazard, so that investments must be inexpensive to be cost-effective.

These findings highlight a fundamental trade-off in pricing of catastrophic risk insurance. More granular risk classification can improve efficiency, but in doing so, it may also worsen affordability for vulnerable populations. This underscores the importance of policy complements that can preserve the incentive value of risk-based pricing while protecting the households most exposed to both physical risk and financial strain. Premium subsidies, mitigation grants, and public investments in risk reduction may be critical to achieving both resilience and fairness in a climate-challenged insurance landscape.

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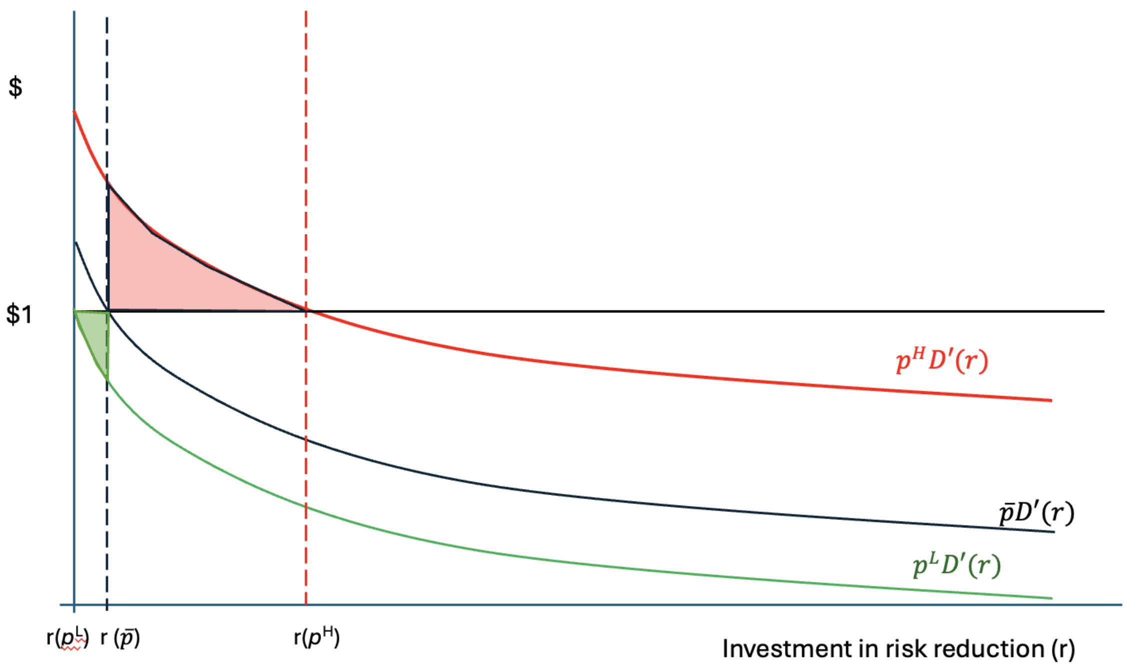
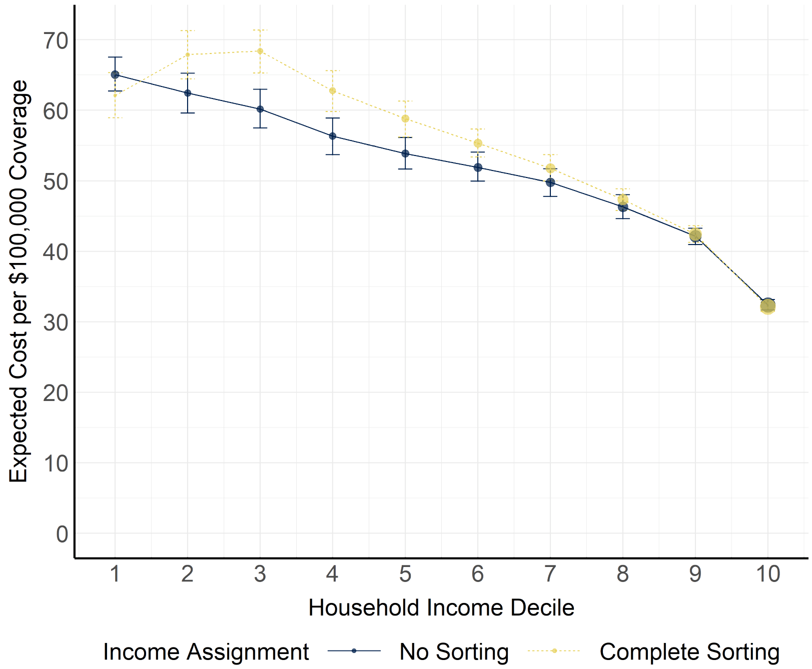
Figure 1: Risk Classification and Private Investments in Risk Reduction



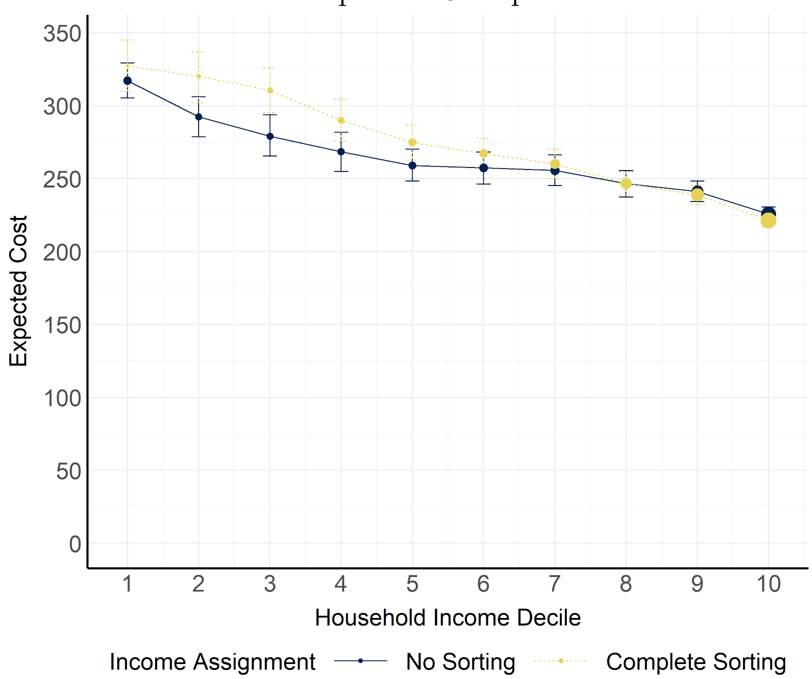
Notes: The figure illustrates how incentives for private investments in risk reduction vary with risk classification.

Figure 2: Average Annual Loss vs. Income

Panel A. Expected Cost per Coverage Amount

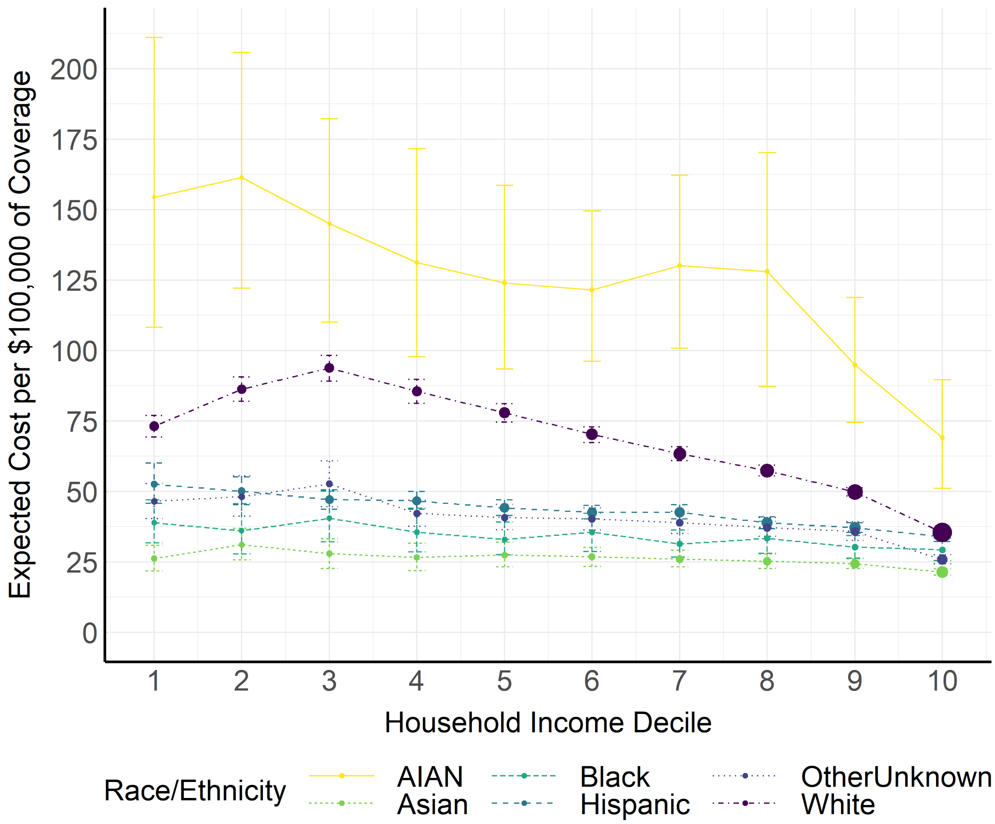


Panel B. Expected Cost per Home



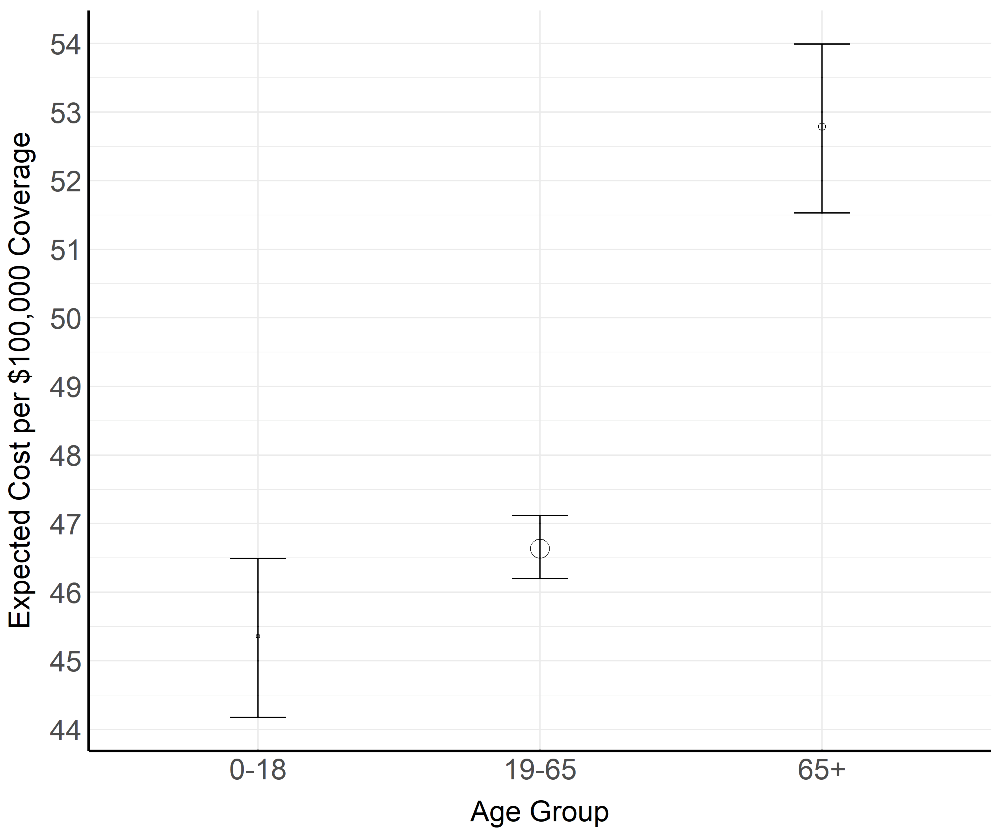
Notes: Expected cost and expected cost per $100,000 of coverage are calculated at the property level and include risk load. Income deciles are based on the U.S.-wide distribution of household income. Marker sizes indicate the share of homes in the analysis sample that fall into each decile group.

Figure 3: Average Annual Loss vs. Income by Race and Ethnicity



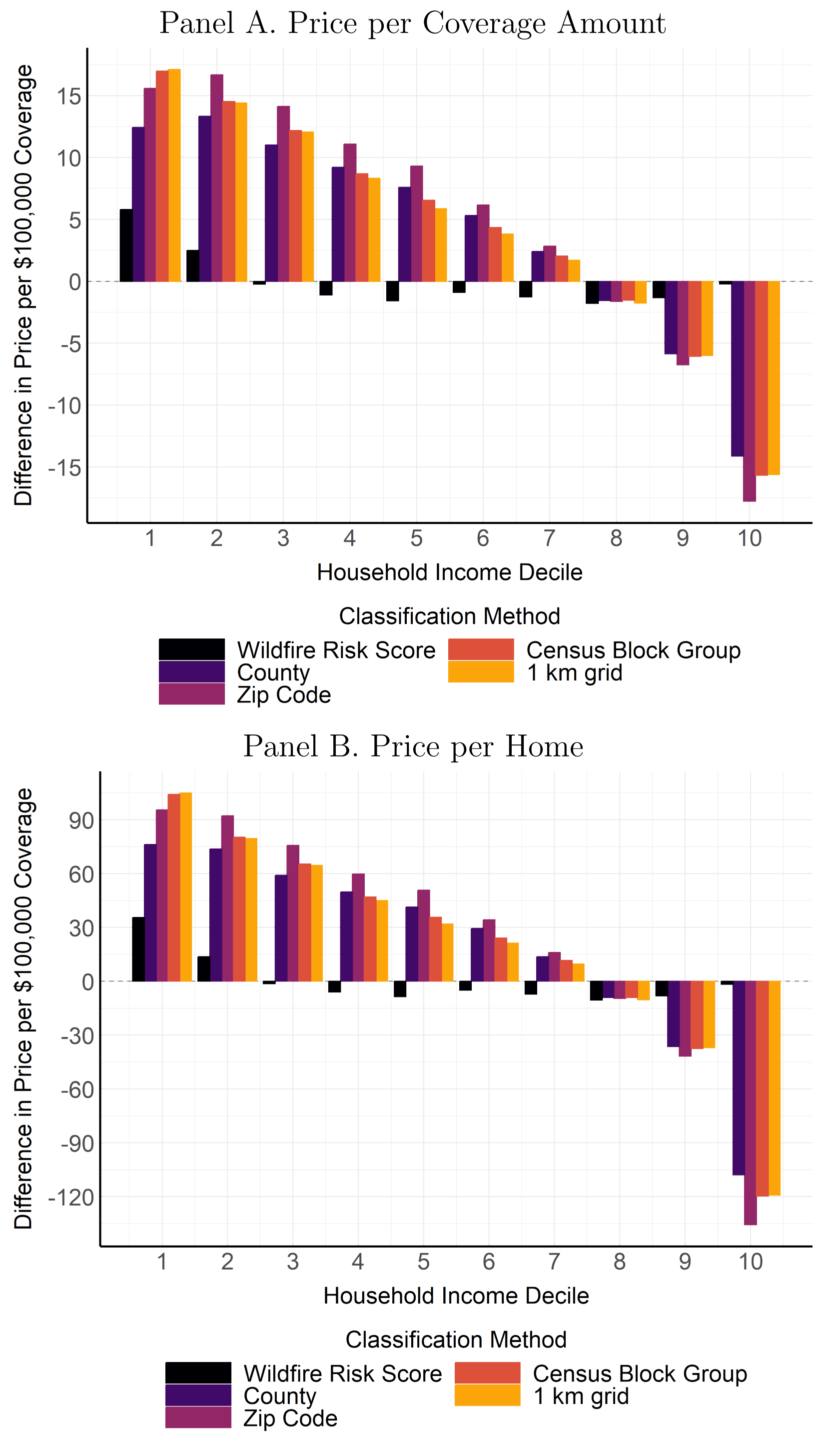
Notes: Expected cost per \$100,000 of coverage is calculated at the property level and includes risk load. Income deciles are based on the U.S.-wide distribution of household income. Allocation of homes to income bins assumes income-based sorting within grid cells. Marker sizes indicate the share of homes in the sample that fall into each income-by-race category.

Figure 4: Average Annual Loss vs. Age



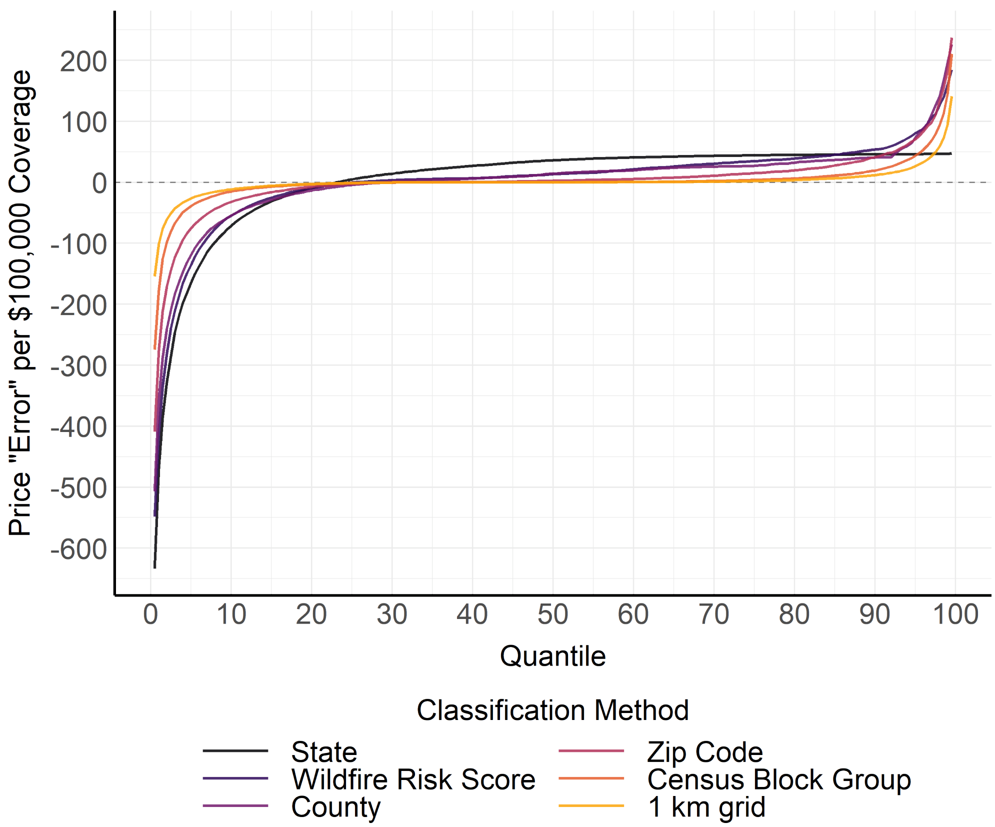
Notes: Expected cost per $100,000 of coverage is calculated at the property level and includes risk load. Income deciles are based on the U.S.-wide distribution of household income. Homes are allocated to age bins randomly within grid cells. Marker sizes indicate the share of homes in the sample that fall into each income-by-race category.

Figure 5: Premium Difference vs. Statewide Risk Classification, by Income Group



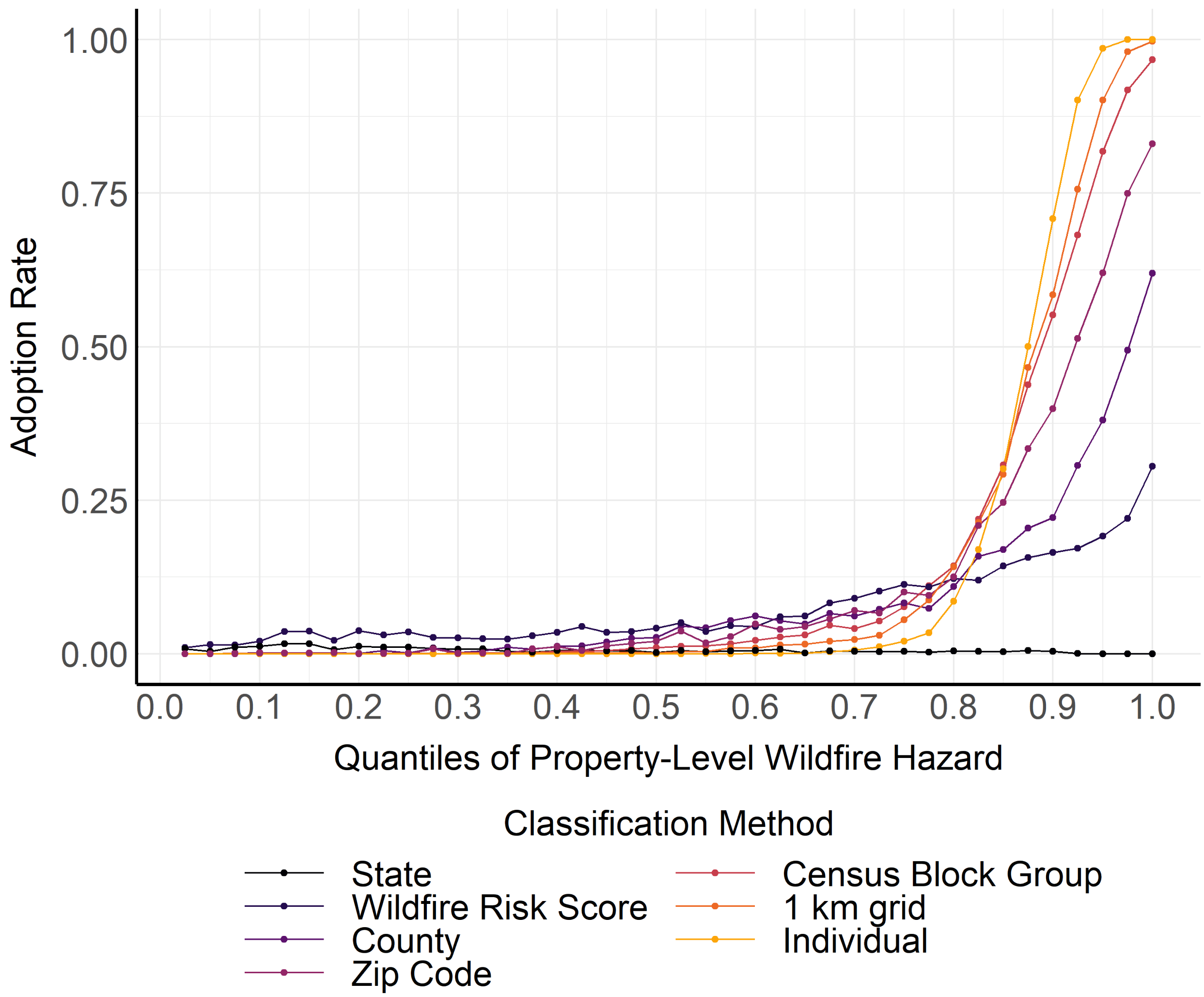
Notes: Each bar shows the difference in price relative to a scenario with a single statewide risk segment. Price and price per $100,000 of coverage are calculated by averaging expected cost including risk load at the segment level. Income deciles are based on the U.S.-wide distribution of household income.

Figure 6: Distribution of Pricing “Errors” Under Risk Classification



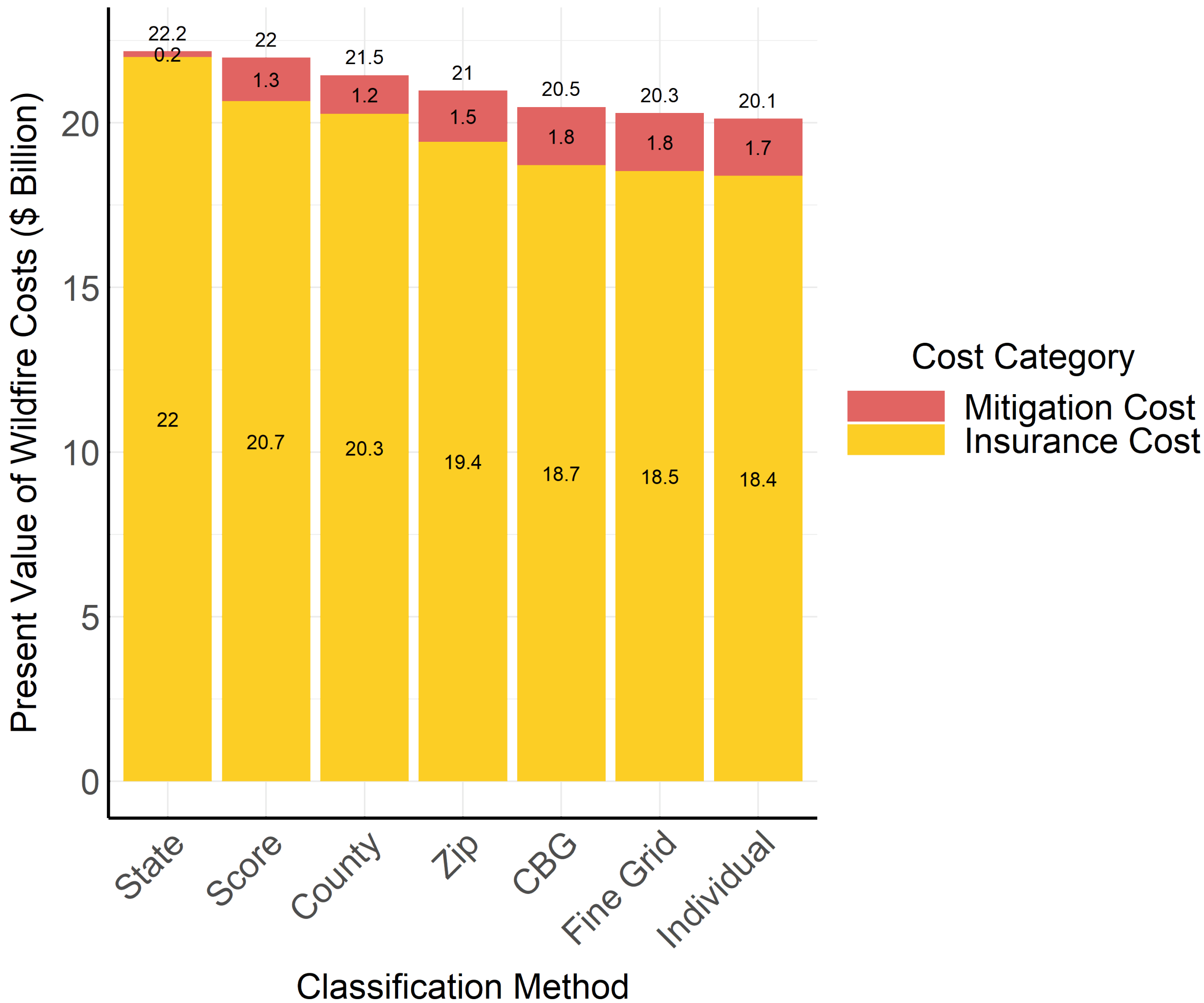
Notes: Figure shows quantiles of (price−expected cost), where expected cost is property-level average annual loss (including risk load) and price is the segment-level average of expected cost.

Figure 7: Adoption of Model Defensible Space Upgrade



Notes: Markers represent equal-observation bins containing 2.5% of homes in the weighted sample. Vertical axis reports the share of homes for which the model landscape retrofit would be cost-effective based on insurance prices and the assumptions about investment costs and vulnerability reduction described in the text.

Figure 8: Total Wildfire-related Costs vs. Classification Method



Notes:

Table 1: Summary Statistics for Analysis Sample

	Mean	p10	Median	p90
Property Data				
Reconstruction Cost ($)	620,303	325,650	546,369	1,017,834
Square Footage	2,176	1,127	1,987	3,467
Year Built	1978	1951	1980	2004
Average Annual Loss	217.66	10.13	59.38	548.06
Average Annual Loss per $100,000 Coverage	40.72	1.96	10.15	101.10
Income: Decile of Nationwide Distribution				
Income Decile With Complete Sorting	7.28	3.00	8.00	10.00
Income Decile Without Sorting	6.73	2.00	8.00	10.00
Race/Ethnicity				
White Alone	0.53			
Hispanic or Latino	0.22			
Other Race/Ethnicity	0.24			
Age				
18 and under	0.18			
19 to 65	0.61			
Over 65	0.21			

Notes: Statistics reflect the weighted analysis sample that represents 2.7 M California single family homes. Property Data are from CoreLogic Wildfire Risk Data. Income, Race/Ethnicity, and Age data come from the Gridded EIF and are matched probabilistically to the property data as described in the text.

Table 2: Effects of Granular Segmentation on the Distribution of Prices

		Price Relative to Statewide Mean Price								
Classification	Segments	p1	p5	p10	p25	p50	p75	p90	p95	p99
Price Per $100,000 Coverage										
County	43	-43.84	-41.28	-37.44	-25.35	-16.03	-5.07	55.06	165.27	274.52
Score	94	-40.30	-40.30	-40.30	-30.48	-9.53	8.93	48.65	100.99	171.20
Zip	362	-47.27	-46.40	-45.83	-41.33	-25.15	1.02	66.76	167.39	318.06
CBG	4,955	-47.34	-46.72	-46.39	-44.42	-33.92	-0.10	77.60	172.76	412.57
Fine Grid	12,290	-47.33	-46.76	-46.39	-44.54	-34.63	-3.45	74.45	165.80	445.46
Total Price										
County	43	-237.36	-217.43	-193.67	-144.81	-81.08	19.22	282.85	579.59	1,284.98
Score	94	-233.30	-222.37	-209.54	-152.45	-48.33	108.74	376.15	651.02	1,537.18
Zip	362	-252.43	-246.77	-240.51	-215.92	-127.57	25.10	353.27	709.41	1,604.91
CBG	4,955	-253.13	-249.61	-246.43	-232.36	-171.74	11.48	422.54	842.65	2,000.79
Fine Grid	12,290	-253.20	-249.61	-246.46	-233.61	-177.88	-5.00	405.89	859.20	2,196.48

Notes: Panel A reports the change in price per thousand dollars of coverage relative to statewide pooling at various points in the risk distribution. Panel B reports the change in total wildfire premium relative to statewide pooling.

Online Appendix to: Welfare Impacts of Climate Risk Classification

Judson Boomhower and Meredith Fowlie

1 Hypothetical landscape retrofit costs

The benchmark costs for our hypothetical landscape retrofit come from Barrett and Quarles (2024).

Replacing wood mulch: The reported all-in cost (including labor and overhead) of removing mulch within five feet of the structure and replacing it with pea gravel to a depth of 3 inches is \$463 per cubic yard of installed gravel. Assuming a square building footprint, the number of cubic yards required is,

$$[4 \times 5 \times \sqrt{(}FootprintArea) + 4 * 5 * 5] \times (1/4) \times (1/27)$$

where FootprintArea is the building footprint in square feet and noting that there are 27 cubic feet in a cubic yard. We calculate the footprint area for homes in our sample by dividing the square footage of the home by the number of stories. For a small number of homes with zero reported square footage, we imput square footage with the sample mean.

Replacing wooden fence: We assume that the homeowner replaces ten linear feet of wooden fence with a height of six feet. The reported all-in cost of demolition, disposal, new materials, and construction of a fiber cement fence is reported to be \$60.44 per square foot of new fence, yielding a fence upgrade cost of \$3,626.

Appendix Table 1: Analysis Sample vs. All California Zip Codes

	In-sample Zip Codes	All California Zip Codes
Total Single Family Homes	2,811,425	9,446,995
Wildfire Risk Scores		
Share ≤ 50	0.61	0.84
Share 51−60	0.12	0.04
Share 61−80	0.15	0.05
Share 81−100	0.12	0.06

Notes: Left column includes 400 zip codes in the wildfire risk dataset. Right column includes all California zip codes.

Appendix Table 2: Demographic Differences for Occupants of Single Family Homes

	Household Income (1)	Homeowner (2)	White (3)	Hispanic or Latino (4)	Limited English (5)
Single Family Detached Home	72,749.1***	0.531***	0.089***	-0.068***	-0.050***
	(2,237.7)	(0.006)	(0.005)	(0.005)	(0.003)
PUMA FE	✓	✓	✓	✓	✓
Observations	13,699,816	13,699,816	13,699,816	13,699,816	13,699,816
Dependent variable mean	132,195.6	0.56	0.47	0.31	0.08
R^2	0.15	0.34	0.16	0.18	0.05

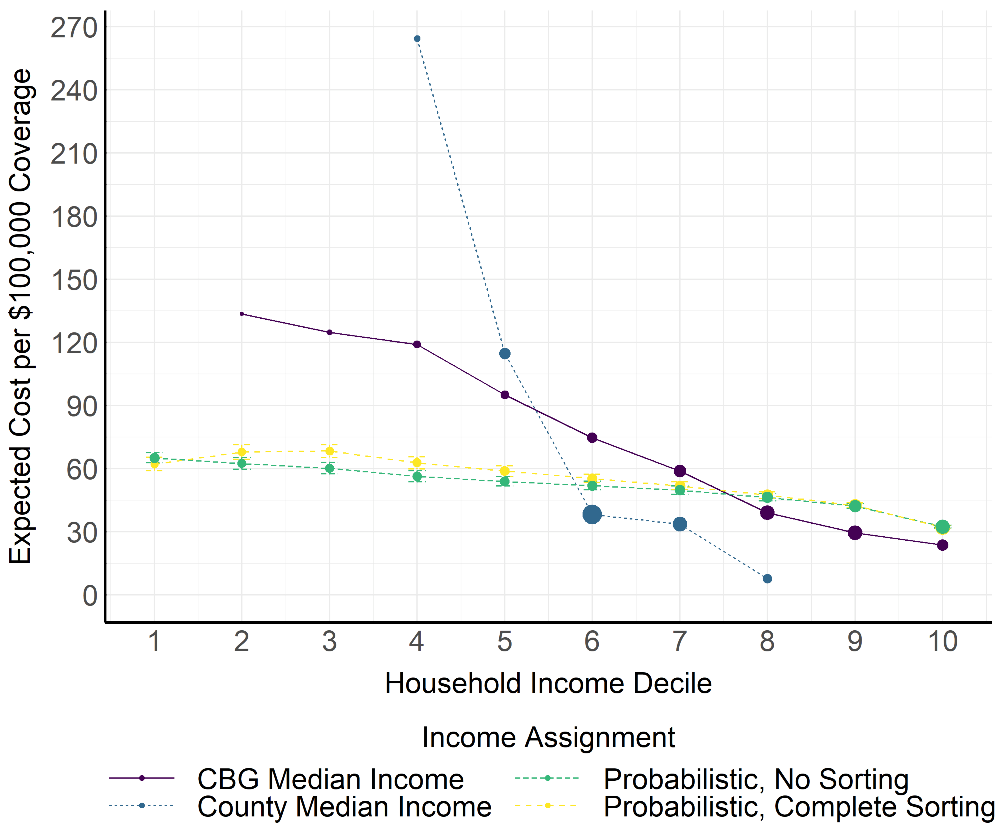
Notes: Table reports five separate OLS regressions of household characteristics on an indicator variable for single family detached home. Data come from the 2023 ACS Public Use Microdata Sample (PUMS) for California. All regressions include Public Use Microdata Area (PUMA) fixed effects. "White" and "Hispanic or Latino" are indicators for whether the householder is White Alone or Hispanic/Latino, respectively. "Limited English" is an indicator for whether any member of the household has limited English-speaking ability.

Appendix Table 3: R^2 for various Wildfire Risk Variables

Risk Variable	R^2
Wildfire Risk Score	0.15
County	0.31
Zip Code	0.50
Census Block Group	0.74
1 km grid	0.90

Notes: Table reports overall R^2 values from separate OLS regressions of average annual wildfire losses per $100,000 of coverage on risk class dummies using different classification methods.

Appendix Figure 1: Income Assignment Based on Area Median Income



Notes: Figure compares the methods used to assign income to homes in our data to results from assigning each home its CBG-median or county-median income.

Appendix Figure 2: Distribution of Annual Wildfire Probabilities