Running from Wildfires: The Role of Risk Preferences in Natural Disaster Sorting

PRELIMINARY AND INCOMPLETE – PLEASE DO NOT CIRCULATE

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Abstract

Migration is one of the most common and effective ways to avoid natural disaster risk. This paper examines the impacts of wildfire risk on migration and isolates the role of risk preferences on spatial sorting. I develop a new measure of wildfire risk by exploiting the existence of a residual market for homeowners insurance in California, and construct a shift-share instrument to distinguish the impacts of wildfire risk from unobserved variables. My instrument interacts zip code level variation in baseline wildfire risk with aggregate shocks to wildfire risk. I test for changing risk preferences by examining risk reduction behaviors for risks that remain constant when wildfire risk changes: automobile liability insurance purchases. Results suggest that an increase in wildfire risk is associated with a mild reshuffling of the population where lower income and less risk averse people disproportionately migrate into risky areas. This has important implications for policy design; less risk averse people are more difficult to incentivize to undertake private risk reduction behaviors, and lower income people have fewer resources to recover following a disaster.

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1 Introduction

One of the most effective ways to reduce the risk of experiencing a natural disaster is also one of the most obvious: relocate to an area where natural disasters are less likely to occur. Migration can reduce the costs of increasingly frequent and severe natural disasters resulting from climate change by reducing populations in areas that are likely to experience damages. It is well established that households migrate in response to environmental dis-amenities such as extreme temperatures and precipitation volatility (Mueller et al., 2014; Bohra-Mishra et al., 2014). However, as more people make the decision to relocate out of risky areas, an opportunity opens for others to migrate in. Existing literature highlights sorting on income, race and ethnicity, and other socio-demographic indicators in response to natural disasters and natural disaster risk (Fan and Bakkensen, 2022; Bakkensen and Ma, 2020; Sheldon and Zhan, 2022; Fan et al., 2016). Less well understood is impact of risk preferences on the decision to take on natural disaster risk. Knowing the risk preferences of people that expose themselves to natural disaster risk is critical for policy design because it informs the types of policies that will incentivize climate change mitigation and adaptation behaviors. It is costlier to convince a less risk averse person to harden their home than to convince a more risk averse person to engage in the same behavior.

This paper evaluates sorting on risk preferences and incomes in the context of wildfire risk in California. Wildfires are the fastest growing economic climate risk, with more than 150 billion USD in damages predicted in the United States for 2020-2029 – almost triple the amount from 2010-2019 (NOAA, 2020; FSF, 2021; Kearns et al., 2022). A major contributing factor to this trend is people exposing themselves to higher wildfire risk by choosing to live in wildfire risky areas.[1] Rural communities and some agricultural areas are disproportionately impacted by escalating wildfire risk because of their exposure to wildland areas. In California, the 8 largest, 12 of the 16 most destructive, and the single deadliest wildfire in recorded history have happened since

[1]The wildland urban interface (WUI) is the area where houses and wildland vegetation meet or intermingle, and where wildfire problems are most pronounced. From 1990-2010, the WUI grew by 41% in the number of houses and by 33% in land area (Radeloff et al., 2018). Burke et al. (2021) estimate that nearly 50 million homes are currently in the WUI, and the number is increasing by 1 million every 3 years.

2017 (CalFire, 2022).

To answer the question of sorting on risk preferences, I develop a simple theoretical framework in which households differ in risk preferences and trade off between migration and other risk mitigation behaviors to manage changing wildfire risk. This model reveals that as wildfire risk increases, more risk averse households migrate out, and less risk averse households migrate in. While these theoretical predictions are straightforward, bringing credible evidence to test them is challenging. The primary obstacle is capturing a measure of wildfire risk that is separate from local differences in wildfire risk mitigation behaviors.

The first challenge is measuring risk preferences, which are inherently unobservable. I measure risk preferences by looking at changes in voluntary, mitigating behavior for risks unrelated to wildfires: observed automobile liability insurance purchases. If a change in wildfire risk induces a change in mitigating behavior for risks unrelated to wildfire and capacity to mitigate risks remains the same, then underlying risk preferences must have changed.

The second challenge is measuring wildfire risk. There is no publicly available wildfire risk data that varies cross-sectionally and temporally. However, insurers have an incentive to accurately estimate risk levels in order to remain competitive and solvent, and to keep this information private. But by observing firm behavior, I infer their risk estimates. Risk estimates should be revealed in insurance prices, but strict regulation prevents insurers from charging rates that fully reflect their expectations of risk. However, insurers are allowed to select which customers they offer policies to, and simply refuse to insure anyone whose risk level exceeds the threshold needed to remain profitable, forcing these risky customers to purchase from California's insurer of last resort, the California Fair Access to Insurance Requirement (FAIR) Plan. The FAIR Plan is mandated to provide basic fire insurance to people that are not able to find coverage on the traditional market because their risk level is too high. The size of the FAIR Plan in any local market represents the wedge between insurers' expectations of wildfire risk and price regulation. I measure wildfire risk in each zip code and year in California with FAIR Plan market share.

The third challenge is eliminating the possibility that an unobserved variable is correlated with

FAIR Plan market share and the dependent variables (in-migration numbers, incomes, and risk preferences). For example, wildfire risk may be solely determined by ecological and climatic conditions, but FAIR Plan market share could be influenced by private risk mitigation behavior, which may also be correlated with incomes and risk preferences. Therefore, I use an instrumental variable approach and instrument for wildfire risk with a Bartik share-shift instrument. My instrument interacts an exogenous cross-sectional measure of wildfire risk with aggregate, annual shocks to wildfire risk. The idea is that areas with a higher baseline wildfire risk are more likely to experience stronger impacts from an aggregate change in wildfire risk. Because baseline wildfire risk is unrelated to private risk mitigation behavior (it measures only environmental risk and ignores any human impacts on wildfire risk) and differences in local trends in risk mitigation do not impact aggregate wildfire risk, this instrument isolates the portion of FAIR Plan market share in each zip code that is driven by wildfire risk. In my estimation I additionally include zip code and year fixed effects, controlling for all unobservable confounders that do not vary differentially over time in different zip codes. This accounts for changing regulation about how wildfire risk is priced (common across zip codes) and amenity values (constant over time).

I find that increases in wildfire risk are associated with a shift towards a less risk averse population. If risk preferences are stable over time, this result suggests that households sort on risk preferences over wildfire risk. This is consistent with Bakkensen and Barrage (2022) who establish that individuals sort on risk preferences in response to flood risk using survey data.

I also find evidence of sorting over wildfire risk in incomes. In this case I directly link incomes to migration decisions. In a zip code, increasing wildfire risk is associated with more in-migration of low-income people, less in-migration of high-income people, and an overall decline in incomes. This is consistent with results from Bakkensen and Ma (2020) who find that low income people are more likely to migrate into areas with high flood risk.

Lower income and less risk averse people are likely drawn to areas of higher wildfire risk because of lower house prices. Wildfire risk is a disamenity for almost everyone, and therefore increases in wildfire risk will likely cause house prices to fall.

I assume that there are no risk-loving people, which means people are not seeking wildfire risk.

This paper proceeds as follows: section 2 provides relevant background on wildfire risk and the California insurance market, section 3 outlines an expected utility model of sorting on risk preferences, section 4 describes the data, section 5 puts forth the empirical strategy, the results are in section 6, and section 7 concludes.

2 Institutional Background

2.1 Wildfire risk in California

In California, a transition to a more arid climate combined with decades of fire suppression policy is causing more frequent and larger wildfires (Schweizer. et al., 2019). In addition, development in high fire risk areas puts more structures at risk, making these fires more devastating. From 2005 to 2020, wildfires destroyed 89,210 structures, with 2017, 2018, and 2020 accounting for 62% of those losses (Barrett, 2020). The 8 largest, 12 of the 16 most destructive, and the deadliest wildfire in California recorded history happened since 2017 (CalFire, 2022). Moving forward, wildfire risk in California is expected continue increasing.

Structures at highest risk for wildfire damage are located in fire hazard severity zones (FHSZ), which were created by the Government of California and represent conditions as of 2007-2011.[2] Figure 1 shows the total area burned from 1989 to 2022 and FHSZ designations. In this paper, I restrict my estimation sample to zip codes that are at least 25% contained within a FHSZ, because these are the regions where wildfire risk is a relevant consideration.

Beyond insurance, individuals can reduce their individual exposure to wildfire risk by engaging

[2]A preliminary update to the FHSZ map was released in December 2022, but has not yet been formally adopted. Classification of a FHSZ is based on a combination of how a fire will behave and the probability of flames and embers threatening buildings. Each area gets a score for flame length, embers, and the likelihood of the area burning. The elements that determine the FHSZ designation are vegetation (fire hazard considers the potential vegetation over a 30-50 year time horizon), topography (fire typically burns more quickly and intensely up steep slopes), climate (fire moves faster and is more intense under hot, dry, and windy conditions), crown fire potential (under extreme conditions, fires burn to the top of trees and tall brush), ember production and movement (burning embers, known as firebrands, spread fire ahead of the flame front and can ignite buildings up to a mile away from the main fire), and fire history (past fire occurrence in an area over several decades).

in defensive behaviors, such as clearing defensible space Meldrum et al. (2019); Brenkert-Smith et al. (2012). In California, a new regulation that forces insurers to incorporate private risk reduction activities such as clearing defensible space and home hardening into insurance prices was passed in 2022 (CDI, 2022). Defensive behaviors can also impact whether insurance is available at all.

2.2 Regulation of Homeowners' Insurance

Insurance is an important and widely used tool to mitigate potential financial damages from a wide range of risks. General homeowner policies usually cover losses from theft and vandalism, storms (eg. hail damage), and wildfires and smoke. Most mortgage lenders require homeowners to purchase insurance, which contributes to a high uptake of homeowners insurance.[3] Losses from other natural disasters, such as floods and earthquakes, are usually not included in a general homeowners policy.

Most jurisdictions require that insurance rates be approved by a regulator before they can be implemented. In general, insurers justify rates using specific attributes of risk that predict loss, including catastrophe modeling. Catastrophe modeling allows insurers to evaluate and manage catastrophe risk from perils ranging from earthquakes and hurricanes to floods and wildfires, and is the most accurate, stable, and flexible way to predict expected losses. However, in California, the use of catastrophe modeling to justify rates is prohibited.

Instead of catastrophe modelling, insurers must use at least the last 20 years of observed loss history to justify rate changes. This is especially problematic for risks that may change quickly such as wildfire risk, and has resulted in many situations where the regulated price lies below the actuarially fair premium. From 2003-2022 (the past 20 years) on average approximately 1 million acres per year burned, but from 2017-2022 (the past 5 years) on average approximately 1.8 million acres per year burned. This highlights how a 20-year average loss history does not accurately measure expectations about current losses. Recent large losses and strict price regulation cast

[3] According to the National Association of Insurance Commissioners, about 90% of homeowners have insurance.

doubt on the continued ability of insurance companies to absorb fire-related losses (Issler et al., 2020).[4]

Although insurers cannot use catastrophe modeling to justify rates, they can use it to select which risks they want to insure. For example, if wildfire risk for a customer increases, an insurer may not be allowed to increase the premium charged, but they will be allowed to drop the policy. In 2019, insurers in California dropped 235,274 homeowner policies, a 61% increase from 2018 (CDI, 2021), with most dropped policies coming from areas of moderate to high fire risk (Bikales, 2020). This strategy can allow an insurer to remain profitable under changing wildfire risks and restrictive price regulation, but leaves homeowners with fewer insurance providers to purchase from. If a homeowner cannot find insurance on the traditional market because they are deemed too risky, they can turn to the insurer of last resort in California, the Fair Access to Insurance Requirement (FAIR) Plan.

2.3 The California FAIR Plan

The California FAIR Plan was established as the insurer of last resort in August 1968 following the riots and fires of the 1960s. Its purpose is to provide temporary, basic fire insurance when traditional insurance is not available. FAIR Plan insurance is generally more expensive and provides less coverage than traditional insurance; it only provides coverage for wildfire, internal explosion, and smoke, and there is a maximum coverage limit that is binding for many homeowners.[5] The FAIR Plan is mandated to operate at zero economic profits, and receives no government funding.

Californians have had to increasingly rely on FAIR Plan coverage in wildfire risky areas as wildfire risk has increased, because insurers are unwilling to cover them. Figure 8 shows how FAIR Plan market share has evolved over time in each zip code in my estimation sample.

[4]Insurers lost almost $25 billion from the 2017 and 2018 wildfire seasons.

[5]Anecdotally there are reports of people paying 2-3 times as much for FAIR Plan insurance than they were paying for traditional insurance.

3 Conceptual Framework

In this section, I develop a simple theoretical model of the trade-off between insurance purchases, clearing defensible space, and the decision to migrate from wildfire risk in response to changes in natural disaster risk.[6] I begin by modelling how defensible space impacts the probability of loss, premiums, and the availability of traditional insurance in a hazardous location (H) that experiences a positive probability of wildfire each year. I then model the decision to migrate and show that as individuals become more risk averse, they are more likely to migrate to a safe location (S).

I assume that individuals behave according to the utility function,

$$U = (\alpha_j + Y)^r, \tag{1}$$

where, α_j are amenity values in location j, $j \in (H, S)$ represents the hazardous and safe locations, $0 < r < 1$ represents risk preferences, and Y is disposable income after accounting for insurance and defensible space costs and wildfire losses. I assume that wildfire risk is positively correlated with amenity values such that $\alpha_H > \alpha_S$.

3.1 Optimal Choice of Defensible Space in Location H

In this section, I model how defensible space impacts the probability of loss, premiums, and whether traditional insurance is available in location H.

Let $p(\rho, DS)$ be a function that represents the probability of loss for a household. This depends on an external measure of wildfire risk (ρ) and the quantity of defensible space (DS). $p(\rho, DS)$ is increasing in ρ and decreasing in DS. Let $c(DS)$ be an increasing, convex function that represents the total cost of defensible space, and γ be the potential losses from a wildfire.

In the traditional market, I require insurers to charge actuarially fair prices such that the price

[6] The model can readily be expanded to account for the effects of income that differs by location on the decision to migrate.

per unit of coverage is equal to the probability of loss.[7] I also impose a price ceiling, $\bar{p}$, but allow insurers to drop policies that are unprofitable. Customers whose probability of loss exceeds the price ceiling ($p(\rho, DS) > \bar{p}$) will not be offered a policy in the traditional market, and must purchase from the FAIR Plan. In the FAIR Plan, I restrict prices to be actuarially fair, but I do not impose a price ceiling. However, I assume that the FAIR Plan will only cover a fraction of the potential losses, represented by θ.

The utility from participating in the traditional market is,

$$U_{trad}(DS) = (\alpha_H + y - p(\rho, DS)\gamma - c(DS))^r, \quad \text{if} \quad \bar{p} \geq p(\rho, DS), \tag{2}$$

where, y is disposable income before insurance and defensible space costs are accounted for. Individuals mitigate all potential losses through insurance purchases, The optimal DS is given by DS^{trad}, such that $\frac{\partial U_{trad}(DS)}{\partial DS} = 0$. The first-order condition defining this solution is,

$$\frac{\partial U_{trad}(DS)}{\partial DS} = (\alpha_h + y - p(\rho, DS)\gamma - c(DS))^r(-p'(DS)\gamma - c'(DS)) = 0, \tag{3}$$

where, $p'(DS)$ is the marginal change in the probability of loss from a change in DS and $c'(DS)$ is the marginal cost of DS.

If $\bar{p} > p(\rho, DS)$, an individual will purchase from the FAIR Plan and gain utility,

$$\begin{aligned} U_{FAIR}(DS) = p(\rho, DS)(\alpha_H + Y - p(\rho, DS)\theta\gamma - c(DS) - (1-\theta)\gamma)^r + \dots \\ \dots + (1 - p(\rho, DS))(\alpha_H + Y - p(\rho, DS)\theta\gamma - c(DS))^r. \end{aligned} \tag{4}$$

The optimal DS if purchasing from the FAIR Plan is given by DS^{FAIR}, such that $\frac{\partial U_{FAIR}(DS)}{\partial DS} = 0$.

If $p(\rho, DS^{FAIR}) > \bar{p}$ and mitigation costs are continuous, it may still be optimal to invest in additional defensible space in order to lower the probability of loss so that traditional insurance is

[7] Because prices are actuarially fair and individuals are risk averse, they will always choose to purchase a full coverage policy if it is offered to them.

available. Individuals will prefer traditional insurance because it offers full coverage rather than partial coverage, and therefore there is a range where people will over invest in *DS* in order to purchase traditional insurance. If $U_{trad}(p^{-1}(\bar{p})) > U_{FAIR}(DS^{FAIR})$, where, $p^{-1}(\bar{p})$ is the amount of defensible space required to reduce the probability of loss to $\bar{p}$, an individual will adapt in order to qualify for traditional insurance.

3.2 Migration from Hazardous Location (H) to Safe Location (S)

Now assume the individual has the choice to move to a location where there is no wildfire risk, so they do not need to purchase wildfire insurance or invest in defensible space. Also assume there are no moving costs. If the utility gained in the hazardous location at optimal *DS* (resulting in the individual purchasing from the traditional market or the FAIR Plan) is less than the utility of living in location *S*, this individual will choose to migrate.

3.3 Risk Preferences

Figure 8 illustrates how risk preferences influence migration in a graphical framework. The y-axis is utility and the x-axis is the probability of loss. The black lines represent an individual that is more risk averse (r is closer to 0), and the blue lines represent an individual that is less risk averse (r is closer to 1). U_{safe} shows the utility from living in the safe location, $U_{trad}(DS^{trad})$ is the utility from living in the hazardous location and participating in the traditional market, and $U_{FAIR}(DS^{FAIR})$ is the utility from living in the hazardous location and participating in the FAIR Plan. The traditional market will refuse to insure any properties with a probability of loss greater than $\bar{p}$.

Under the baseline scenario (black lines), and individual will migrate to the safe location if the probability of loss exceed p^3. If the probability of loss is between $\bar{p}$ and p^2, they will over-invest in defensible space to be eligible for traditional insurance. If the probability of loss is less than $\bar{p}$ or greater than p^2 but less than p^3, this individual will invest the optimal amount in defensive expenditures.

Now consider an individual that is less risk averse (r is closer to 1), shown in figure 8 by the blue lines. Utility increases in the safe location (U_{safe}) and in the traditional market $U_{trad}(DS^{trad})$. In both of these markets individuals don't face any risk, because it either doesn't exist or is completely mitigated by insurance. In the FAIR Plan ($U_{FAIR}(DS^{FAIR})$), utility increases by a larger amount because all losses are not covered by insurance. This changes the range over which individuals are willing to migrate to the safe location from $p > p^3$ to $p > p^4$. This simple example illustrates how individuals sort on risk preferences.

As individuals become less risk averse they are also less willing to adapt in order to be eligible for traditional insurance. This is shown in figure 8 by the difference between p^1 and p^2.

4 Data

The primary data comprise annual zip code migration and population, income, car liability insurance purchases, FAIR Plan market share, and wildfire risk spanning 2009-2020. I only include zip codes that are at least 25% contained within a FHSZ, because these are the regions where wildfire problems are most relevant.

I assemble a panel data set at the zip code level for California. Summary statistics are shown in Table 1. I only include zip codes that are at least 25% contained within a FHSZ, because these are the regions where wildfire risk is most relevant. My study period is from 2009-2020.

Migration and population data come from the American Community Survey (ACS). To measure migration, I use the five-year average of the number of movers, local movers, and movers in different income groups as my dependent variables. A mover is someone who changed addresses less than one year before they answered the survey and a local mover is someone whose previous address was in the same county as their current address. Movers are grouped into 8 income groups; income $<$ \$10 000, \$10 000 $<$ income $<$ \$15 000, \$15 000 $<$ income $<$ \$25 000, \$25 000 $<$ income $<$ \$35 000, \$35 000 $<$ income $<$ \$50 000, \$50 000 $<$ income $<$ \$65 000, \$65 000 $<$ income $<$ \$75 000, and \$75 000 $<$ income. Zip code-year level data points represent estimates for five years. For example, the number of movers in 2020 represents everyone who responded to the survey from 2016-2020).[8] This data covers 2011 to 2021, with some zip code-years missing due to confidentiality.

Income data from 2009 to 2020 come from the Internal Revenue Service (IRS). The data give the number of tax returns filed in each zip code and year in each of the following income categories: income $<$ \$25 000, \$25 000 $<$ income $<$ \$50 000, \$50 000 $<$ income $<$ \$75 000, \$75 000 $<$ income $<$ \$100 000, \$100 000 $<$ income $<$ \$200 000, and income $>$ \$200 000. I use the proportion of tax returns in each category to construct my dependent variables.

Car liability insurance data come from the Survey on Auto Liability (SAL) from the CDI, spanning 2008 to 2021. I construct a variable that is the proportion of vehicle insurance policies that are "basic limits" to use as a dependent variable to measure risk preferences. "Basic limits" policies meet the minimum coverage requirement for automobile insurance and "above basic limits" policies exceed the minimum coverage requirements for automobile insurance. The idea is the more risk averse people are more likely to purchase "above basic limits" policies than less risk averse people, all else equal. I focus on bodily injury coverage because it is required by the state.

FAIR Plan market share comes from the Community Service Statement (CSS) from the CDI, which reports the number of exposure units (policy months) of coverage at the zip code-year level for each insurance company (including the FAIR Plan). From this I calculate FAIR Plan market share as the FAIR Plan exposure units divided by the total number of exposure units in a zip code and year. Figure 8 shows FAIR Plan market share for all zip codes in my estimation sample from 2009 to 2019.

Wildfire risk data come from the Risk to Potential Structures (RPS) data set, published by the Forest Service Research Data Archive (Scott et al., 2023). These data integrate wildfire likelihood and intensity with generalized consequences to a home on every 30m by 30m pixel for the United States. For every place on the landscape it poses the hypothetical question, "What would be the risk to a house if one existed here?" I aggregate to the zip code level by averaging the values

[8] County-year level data points from the same survey represent estimates for one year. In a robustness check I use county level estimates.

of each pixel located within each zip code boundary. This data represent a snapshot of wildfire conditions at the end of 2014. Figure 8 shows the RPS data aggregated to the zip code level for all zip codes in my estimation sample. A small number of zip codes have a high RPS value which makes it difficult to see the cross sectional variation. Figure 8 shows the RPS values for all zip codes in my estimation with an RPS less than 1. The RPS values represent the probability that a fire capable of causing damage to building burns each year.

I exclude from my data set any zip code directly impacted by a moratorium on cancellations and non-renewals in the year it was impacted and any following years because the moratorium distorts the ability of insurers to adjust who they offer insurance to and therefore will disrupt the ability of FAIR Plan market share to reflect wildfire risk.[9] This only impacts some zip codes for 2018, 2019, and 2020.

5 Estimation Strategy

This section sets forth an empirical strategy to test if households sort on income and risk preferences in response to changing wildfire risk.

5.1 Econometric Model

I estimate the impacts of wildfire risk on population, migration, incomes, and risk preferences using a two-way panel fixed effects model,

$$Y_{it} = \beta r_{it} + \phi_i + \psi_t + \varepsilon_{it}. \tag{5}$$

Zip codes are indexed by i, years are indexed by t, Y_{it} is the outcome of interest, r_{it} is wildfire risk level (measured by FAIR Plan market share), ϕ_i are zip code fixed effects that control for

[9]In 2018, the California legislature passed Senate Bill 824 that prohibits insurance companies from cancelling or refusing to renew a policy because of wildfire risk in any zip code either impacted by, or adjacent to, a wildfire that was declared a disaster by the state government (CDI, 2023). Each moratorium lasts one year, and begins on the day the disaster is declared.

unobserved variation that is constant over time, ψ_t are year fixed effects that control for unobserved variation that is constant across zip codes, and ε_{it} are unobservables. I cluster standard errors at the zip code level. I use a range of dependent variables to estimate my effects: total population, in-migration, local in-migration, in-migration by income group, proportion of tax returns in each income group, and risk preferences (measured by the proportion of automobile insurance policies that are 'basic limits'). β retrieves the change in Y_{it} for a one percentage point increase in FAIR Plan market share.

I use FAIR Plan market to measure wildfire risk. Strict price regulation restricts insurers ability to price changing wildfire risk, but insurers can select which risks to take on. FAIR Plan market share is the proportion of the market that traditional insurers have refused to insure due to high wildfire risk. While an insurer can drop a policy for a wide range of reasons, the FAIR Plan only covers losses from fire, internal explosion, and smoke damage, so the only reason to buy it is to insure from wildfire risk.

5.2 Measuring risk preferences

I measure risk preferences by examining how changes in wildfire risk impact automobile liability insurance purchases. After controlling for zip code and year fixed effects, driving risk will be unrelated to wildfire risk, so, any changes in mitigating behaviors for risks unrelated to wildfires indicates a change in risk preferences.

I assume that each person has a quantifiable risk preference, and that their risk reduction behavior is consistent for the financial risks that come from wildfire and from driving. This assumption is consistent with empirical evidence from the literature; individual risk preferences appear to be persistent and moderately stable over time (Soane and Chmiel, 2010), and individuals are more consistent in their risk preferences across related domains (such as different types of insurance) than across unrelated domains (such as personal finance and health) (Einav et al., 2012; Soane and Chmiel, 2005).

5.3 Identification

My identifying assumption is that there are no unobserved factors that vary differentially between zip codes over time that are correlated with wildfire risk and an outcome variable. There are two threats to this assumption stemming from supply and demand for FAIR Plan insurance. First, on the supply side, regulations about how insurers price wildfire risk impact how many households purchase from the FAIR Plan, and if these change differentially over time and are related to wildfire risk, my identifying assumption will fail. Correspondence with the CDI indicates that rate filings generally apply to the entire state, so pricing rules will be consistent across zip codes, and year fixed effect account for changes that are common across all zip codes.

The second threat to identification comes from the demand side. As highlighted in the conceptual framework, individuals can manipulate whether traditional insurance is available to them or not by investing in adaptations such as clearing defensible space. And, the likelihood an individual will undertake adaptations is also likely to be correlated with income and risk preferences, both of which are outcome variables. To illustrate the direction of the potential bias, consider income as the dependent variable. Incomes and adaptations will be positively correlated because people with higher incomes can afford defensive adaptations. In addition, I hypothesize that wildfire risk and incomes will be negatively related.[10] If this is the case, omitting adaptations will bias the effect of wildfire risk towards zero. The potential bias will also attenuate the coefficient when using risk preferences as the dependent variable; the proportion of basic limits policies is negatively correlated with adaptations and I hypothesize positively related to wildfire risk. Table 2 shows my hypotheses for the relationships between wildfire risk and my dependent variables, and the direction of the expected biases arising from omitting amenity values from these models.

I do not expect population or migration to be correlated with adaptations, and therefore do not expect these specifications to suffer from omitted variable bias.

[10]This comes from prior work on sorting over natural disaster risk in incomes. For example, Bakkensen and Ma (2020) find that flood risk is negatively related to incomes.

5.3.1 A shift-share instrument for Wildfire Risk

To circumvent the omitted variable bias present in the income and risk preference specifications, I construct a shift-share instrument for wildfire risk.

Shift-share instruments are used in exposure research designs and are typically constructed by interacting local industry employment shares with aggregate industry shocks to avoid bias caused by omitted variables such as local productivity. The idea is that localities with a higher exposure to a certain industry (a higher local industry employment share) will experience a larger effect from a common shock to that industry than localities with a lower employment share. Goldsmith-Pinkham et al. (2020) demonstrate that identification using a shift-share instrument comes from independence of the local industry shares from outcome variables.[11]

I construct my instrument, Z_{it}, in equation 6 by using statewide changes in FAIR Plan market share (FP_t) as my aggregate shocks and a baseline measure of wildfire risk, RPS_i, as my local industry shares. I argue that RPS_i are independent of all outcome variables because they are a reflection of physical wildfire conditions and are not affected by individual adaptations, outcome variables or arbitrary map boundaries (such as city or county limits). This instrument avoids the problem of omitted variable bias caused by adaptions because it is unrelated to both local differences in adaptations and to incomes and risk preferences.

$$Z_{it} = RPS_i * FP_t \tag{6}$$

The impacts of wildfire risk on incomes and risk preferences are obtained using standard two stage least squares. The first stage is given by,

$$r_{it} = \beta_1 Z_{it} + \phi_i + \psi_t + \varepsilon_{it}, \tag{7}$$

where notation is consistent with equations 5 and 6.

[11] Identification can also be achieved if the local industry shares are endogenous, but the aggregate shocks are exogenous (Borusyak et al., 2022).

6 Estimation Results and Discussion

In this section, I report and discuss the estimation results from equation 5 for a variety of outcome variables to determine the effects of wildfire risk on population, migration, incomes, and risk preferences. The coefficients are interpreted as the effects from a one percentage point increase in FAIR Plan market share. For most zip codes, an increase of one percentage point in FAIR Plan market share is large; 71% of zip codes have FAIR Plan market share less than one percent in the sample.

In many of the specifications I use a two-stage least squares design instrumenting for wildfire risk with my share-shift instrument. This instrument is strong; the R-squared value of the first stage is 0.71, the F statistic is 24.72, and the t-statistic on the coefficient for the instrument (β_1 in equation 7) is 3.33.

6.1 Do people migrate in response to changes in wildfire risk?

I use ordinary least squares with year and county-by-year fixed effects to estimate the effect of wildfire risk on population and migration, shown in Table 3.[12] Columns 1-3 use year fixed effects. These estimates show that a one percentage point increase in FAIR Plan market share today results in changes over the next five years of, a 43 person drop in population, a 25 person increase in the number of movers, and a 21 person increase in the number of local movers. Controlling for county-by-year fixed effects (columns 4-6) results in similar, but larger, estimates.

These results are consistent with a population reshuffle following a change in wildfire risk, with more people migrating out of a risky area than migrating in. In the following sections I investigate how incomes and risk preferences are related to these migration patterns.

[12]In a robustness check I instrument for wildfire risk. The results are much noisier, and I am not able to statistically detect any impacts of wildfire risk on population or migration.

6.2 Do incomes change in response to changes in wildfire risk?

I estimate income sorting on wildfire risk using two methods. First, I use ordinary least squares and standard two-stage least squares to estimate the effect of wildfire risk on incomes, shown in Table 4. These results show the short-term, one year response to changes in wildfire risk by using IRS income data reported at the zip code-year level. The standard regression results (columns 1-3) yield no significant impact of FAIR Plan market share on incomes. But, the instrumental variable design shows that a one percentage point increase in FAIR Plan market share results in a 0.9 percentage point increase in the proportion of people with income less than \$50,000 and a 1 percentage point decrease in the proportion of people with income more than \$100,000. These results are statistically significant, but economically small. These results also don't directly link migration to incomes; incomes could fall because lower income people migrate in, or in response to an income shock.[13] To clarify this question I use five year migration estimates by income group.

Table 5 show the results from an ordinary least squares regression of FAIR Plan market share on in-migration by income group for the following five years. An increase in FAIR Plan market share today increases the number of low income movers (incomes less than \$25,000) and decreases the number of higher income movers (incomes more than \$65,000) over the next five years. The number of movers with incomes more than \$25,000 and less than \$65,000 is unaffected by changes in FAIR Plan market share. When using these same specifications but instrumenting for wildfire risk, the coefficients are imprecisely estimated.

Taken together, these results indicate that incomes decrease following an increase in wildfire risk, and that this is caused, at least in part, by a population reshuffle. Results in Table 4 give the short-run impact of wildfire risk on incomes, but don't directly link changes in incomes to migration. Results in Table 5 directly link incomes and migration, but rely on data that represent 5 years into the future rather than one year. Both results support the hypothesis of sorting on incomes in response to wildfire risk. However, the size of the coefficients are economically small, indicating

[13] A natural disaster, such as a wildfire, could be a shock that reduces income in the area it happened. This may also be correlated with increases in wildfire risk. In a robustness check I remove all zip codes that touch a wildfire boundary from the time of the wildfire onward and find similar results.

a limited sorting response on incomes in response to changing wildfire risk.

This finding is consistent with Bakkensen and Ma (2020) who find clear evidence that low income residents are more likely to move into high risk flood zones, Strobl (2011) who find that wealthier people migrate out of places hit by a hurricane, and Boustan et al. (2020) who find that out-migration increases following severe disasters, and that incomes fall.

6.3 Do risk preferences change in response to changes in wildfire risk?

Table 4 reports the estimates of the impact of wildfire risk on risk preferences using ordinary least squares and two stage least squares. My outcome variable is the proportion of automobile insurance policies that are 'basic limits.' Columns 1 and 2 show the standard least squares results, columns 3 and 4 show the two stage least squares results, column 5 restricts the sample to zip codes with at least 40% of tax filings with gross income less than $25,000 (approximately 25% of the data), and column 6 restricts the sample to zip codes with at least 7% of tax filings with gross income more than $200,000 (approximately 25% of the data). Income controls are included as the proportion of people in each income category (excluding the category with incomes greater than $200,000) in columns 2 and 4.

The empirical challenge in estimating the impact of wildfire risk on risk preferences is twofold. Incomes are a bad control variable because they are also causally impacted by changes in wildfire risk (Cinelli et al., 2022), but, excluding incomes could result in omitted variable bias that exaggerates the coefficient if incomes also impact the decision to purchase basic or above basic limits car insurance.[14] First, I recognize that although the effect of wildfire risk on incomes is statistically significant, it is economically small. Therefore I expect the omitted variable bias caused by excluding incomes will be small and unimportant. Because of this, my preferred specification is column 3. Second, to reduce the potential for bias coming from changes in income, I restrict the estimation sample to the poorest zip codes (column 5) and the richest zip codes (column 6).

[14] Incomes are negatively related to wildfire risk and I expect them to be negatively correlated with the proportion of policies that are basic limits. I also anticipate finding a positive impact of wildfire risk on the proportion of policies that are basic limits. Therefore, omitting incomes could cause my estimate to be exaggerated.

Restricting the sample to include zip codes in a narrow income band reduces the possible impacts of FAIR Plan market share on income, and therefore reduces the bias. It also shows heterogeneity in sorting on risk preferences by income group; I cannot statistically detect an effect of FAIR Plan market share on the proportion of policies that are basic limits in the low income group, but I can in the high income group.

The results show that a one percentage point increase in FAIR Plan market share increases the proportion of individuals that purchase basic limits car insurance by 0.24%. As with the income results, this effect is statistically significant but economically small. I conclude that as wildfire risk increases, the population becomes less risk averse.

These results are one of the first attempts to quantify sorting on wildfire risk with observational data. Bakkensen and Barrage (2022) analyze the question of risk preference sorting on flood risk with a door-to-door survey, but ask hypothetical questions that are difficult to answer accurately. This paper uses observational data, but assumes that individuals and insurance companies have the same perceptions of risk, and that those perceptions are correct. Future research will refine the empirical method and expand this method to other settings.

7 Conclusions

This paper measures sorting on wildfire risk in incomes and risk preferences through an exposure design that uses a shift-share instrument to account for unobserved factors that may be correlated with wildfire risk. I also develop a new way to measure wildfire risk that varies by zip code over time.

Taken collectively, the results from the estimation tell a story that as wildfire risk increases in an area, there is a reshuffling of the population, with lower income and less risk averse people migrating in. However, the estimated coefficients are economically small, so it's important not to overstate the extent of sorting on wildfire risk. These results are consistent with prior studies that analyze sorting on natural disaster risk.

These results are informative for policy makers. Less risk averse individuals are more difficult to incentivize to undertake private risk mitigation behaviors, and lower income people have fewer resources to recover following a disaster.

It's important to note that the migration results depend on data that represent population and migration for five years, so they may not reflect a precise response. This data is not able to determine how quickly individuals respond to a change in wildfire risk or how this effect decays over time.

The conceptual model shows that extremely risk averse people will be less likely to migrate from environmental risk because they adapt such that the potential damages from a disaster are drastically reduced. At the same time, individuals that are close to risk neutral also won't migrate from wildfire risk, but they don't adapt. It is the individuals that are reasonably risk averse that don't fully mitigate damages from a disaster on the intensive margin but still risk averse enough to prefer to move out of a risky area. The fact that I am able to detect some evidence of sorting on wildfire risk indicates that there is some density in the distribution of risk preferences in the middle.

The role of home values in these results has not yet been explored. The vast majority of people are not risk seeking, and therefore are not drawn to wildfire risky areas by the wildfire risk itself. In fact, if all else is equal, most people would never choose to migrate into a risky area. There must be an additional factor that causes them to move. I hypothesize that this is lower housing prices. If wildfire risk puts downward pressure on home values, it could draw lower income and less risk averse people to migrate in. In future work I will empirically investigate this mechanism.

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8 Tables and Figures

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
FP Mktshr	11,044	1.5	4.0	0.0	0.02	0.3	1.1	50.0
Population	7,506	12,714.9	17,930.7	0	700	3,311	18,953	99,293
Movers	7,466	1,696.3	2,664.2	0.0	60.7	420.6	2,469.9	26,854.8
Movers (county)	7,466	1,014.5	1,684.5	0.0	25.6	215.5	1,297.3	15,181.3
Mov<10	7,112	254.7	672.9	0.0	8.1	64.0	305.3	12,204.9
10<Mov<15	7,068	123.8	217.9	0.0	0.0	36.0	156.3	2,853.5
15<Mov<25	7,160	167.0	280.9	0.0	3.0	44.5	214.1	3,268.8
25<Mov<35	7,098	134.1	213.6	0.0	0.0	35.2	175.3	2,155.6
35<Mov<50	7,068	136.0	204.2	0.0	0.0	37.9	194.0	1,251.3
50<Mov<65	6,896	105.4	159.4	0.0	0.0	26.0	153.6	1,126.6
65<Mov<75	6,412	50.1	77.6	0.0	0.0	13.0	69.9	556.0
75<Mov	7,096	220.3	382.4	0.0	0.0	40.1	283.9	4,015.4
Inc<50	8,885	58.1	13.3	21.9	49.6	58.4	67.0	100.0
50<Inc<100	8,885	23.0	5.1	0.0	20.5	23.3	25.6	50.0
100<Inc	8,885	18.9	12.9	0.0	9.8	16.5	25.5	67.5
Proportion BL	11,042	11.7	5.3	0.0	8.2	10.9	14.7	43.9

FP Mktshr is FAIR Plan market share from the California Department of Insurance (CDI)
Population is the 5-year population estimate from the American Community Survey
Movers is the 5-year estimate for total in-migration from the American Community Survey (ACS)
Movers (county) is the 5-year estimate for in-migration originating from the same county from the ACS
Mov<10 is the 5-year estimate for in-migration of people with less than $10,000
10<Mov<15 is the 5-year estimate for in-migration of people with incomes between, $10,000 and $15,000
15<Mov<25 is the 5-year estimate for in-migration of people with incomes between $15,000 and $25,000
25<Mov<35 is the 5-year estimate for in-migration of people with incomes between $25,000 and $35,000
35<Mov<50 is the 5-year estimate for in-migration of people with incomes between $35,000 and $50,000
50<Mov<65 is the 5-year estimate for in-migration of people with incomes between $50,000 and $65,000
65<Mov<75 is the 5-year estimate for in-migration of people with incomes between $65,000 and $75,000
75<Mov is the 5-year estimate for in-migration of people with incomes greater than $75,000
Inc<50 is the proportion of people with income less than $50,000, from the Internal Revenue Service (IRS)
50<Inc<100 is the proportion of people with income between $50,000 and $100,000, from the IRS
100<Inc is the proportion of people with income larger than $100,000, from the IRS
Proportion BL is the proportion of automobile insurance policies that are basic limits, from the CDI

Table 2: Bias from Omitting Adaptations

Outcome Variable	Expected Sign of Coefficient	Correlation with Adaptations	Direction of Bias
Population	negative	none	none
In-migration	positive	none	none
Income	negative	positive	attenuate
BL prop	positive	negative	attenuate

Table 3: Migration Results

	Dependent variable:					
	Population	Movers	Movers (county)	Population	Movers	Movers (county)
	(1)	(2)	(3)	(4)	(5)	(6)
FP Mktshr	-43.037^{***}	24.145^{***}	20.785^{***}	-49.452^{**}	32.511^{***}	33.834^{***}
	(11.592)	(5.122)	(4.353)	(20.204)	(8.083)	(7.723)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	No
County-by-year FE	No	No	No	Yes	Yes	Yes
Observations	7,506	7,466	7,466	7,506	7,466	7,466
R^2	0.998	0.986	0.978	0.999	0.987	0.981

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4: Income Results

	Dependent variable:					
	Inc<50	50<Inc<100	100<Inc	Inc<50	50<Inc<100	100<Inc
	(1)	(2)	(3)	(4)	(5)	(6)
FP Mktshr	0.018	0.042	−0.060			
	(0.026)	(0.050)	(0.054)			
FP Mktshr (IV)				0.870**	0.151	−1.021**
				(0.360)	(0.303)	(0.448)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
IV Model	No	No	No	Yes	Yes	Yes
Observations	8,885	8,885	8,885	8,885	8,885	8,885
R^2	0.951	0.669	0.974	0.940	0.668	0.958
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 5: Migration Results by Income Group

	Dependent variable:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FP Mktshr	12.260***	5.401***	6.100***	0.427	0.664	0.404	-1.085^{**}	-11.142^{***}
	(2.326)	(0.998)	(1.117)	(0.724)	(0.636)	(0.756)	(0.481)	(1.603)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,112	7,068	7,160	7,098	7,068	6,896	6,412	7,096
R^2	0.967	0.948	0.950	0.954	0.950	0.938	0.862	0.962

Note: *p<0.1; **p<0.05; ***p<0.01

Dependent Variables:
(1) Movers with income < \$10,000
(2) Movers with \$10,000 < income < \$15,000
(3) Movers with \$15,000 < income < \$25,000
(4) Movers with \$25,000 < income < \$35,000
(5) Movers with \$35,000 < income < \$50,000
(6) Movers with \$50,000 < income < \$65,000
(7) Movers with \$65,000 < income < \$75,000
(8) Movers with income > \$75,000

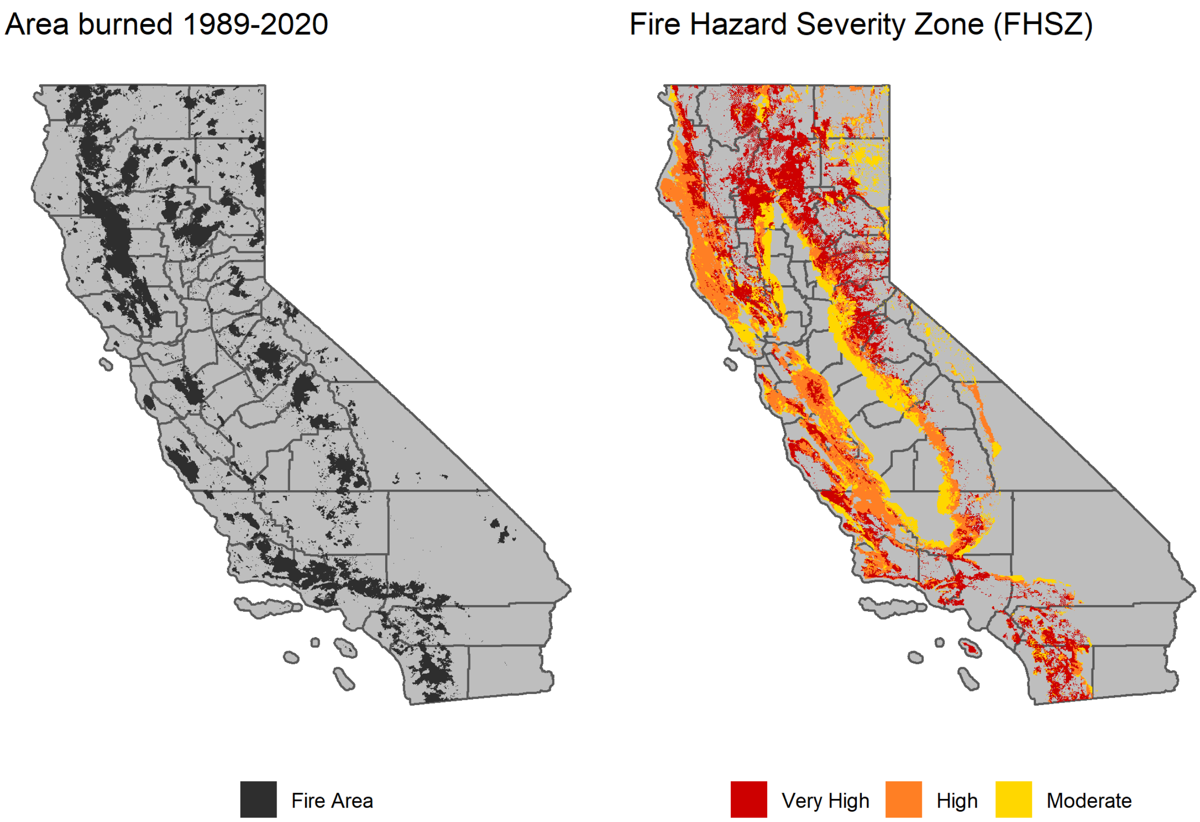
Table 6: Risk Preference Results

	Dependent variable:					
	Proportion BL					
	(1)	(2)	(3)	(4)	(5)	(6)
FP Mktshr	0.034*	0.038***				
	(0.018)	(0.014)				
Inc<25		0.175***		0.120**		
		(0.025)		(0.050)		
25<Inc<50		0.153***		0.112***		
		(0.022)		(0.039)		
50<Inc<75		0.150***		0.107***		
		(0.021)		(0.039)		
75<Inc<100		0.150***		0.105**		
		(0.023)		(0.041)		
100<Inc<200		0.146***		0.102**		
		(0.021)		(0.042)		
FP Mktshr (IV)			0.241*	0.242	0.240	0.149*
			(0.126)	(0.165)	(0.240)	(0.077)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
IV Model	No	No	Yes	Yes	Yes	Yes
Observations	11,042	8,885	11,042	8,885	2,462	2,110
R^2	0.916	0.965	0.910	0.961	0.951	0.979

Note: *p<0.1; **p<0.05; ***p<0.01

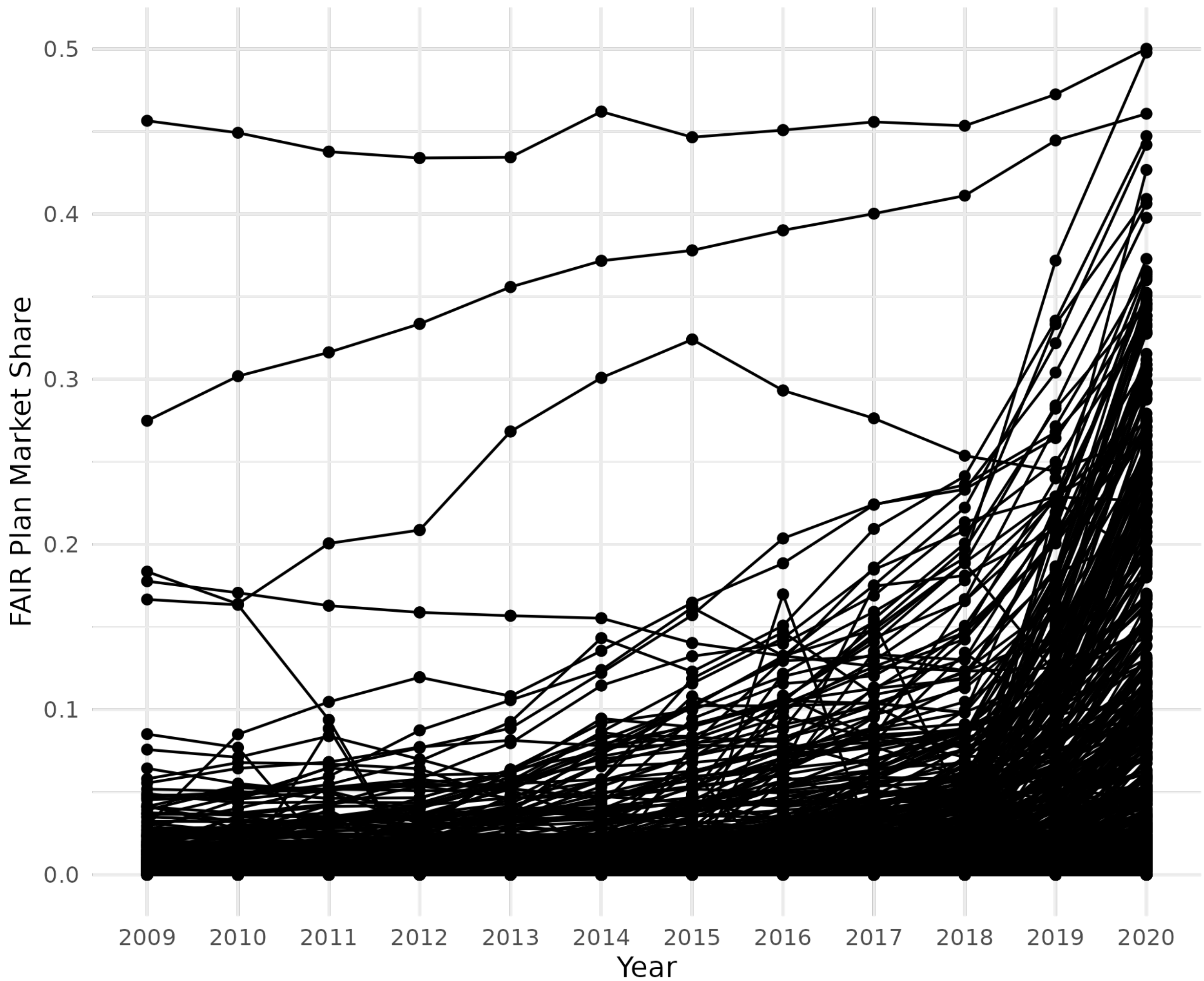
BL Prop is the proportion of automobile insurance policies that are basic limits. Column 5 restricts the sample to zip codes with at least 40% of tax filings with gross income less than $25,000 (approximately 25% of the data), and column 6 restricts the sample to zip codes with at least 7% of tax filings with gross income more than $200,000 (approximately 25% of the data). Income controls are included as the proportion of people in each income category (excluding the category with incomes greater than $200,000).

Figure 1: California Wildfires and FHSZ



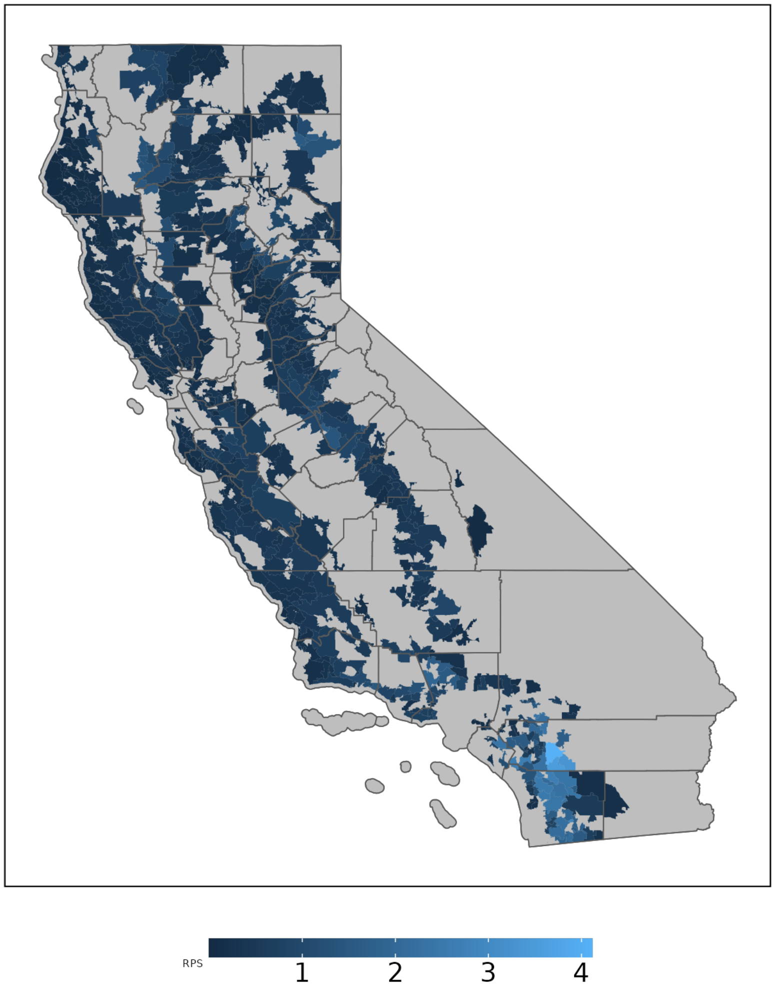
Wildfire and Fire Hazard Severity Zone boundaries come from CAL FIRE. The wildfire boundaries include all timber fires 10 acres or greater, brush fires 30 acres or greater, and grass fires 300 acres or greater. The FHSZ map was created from 2007 and reflects wildfire risk at that time.

Figure 2: FAIR Plan Market Share by Zip Code



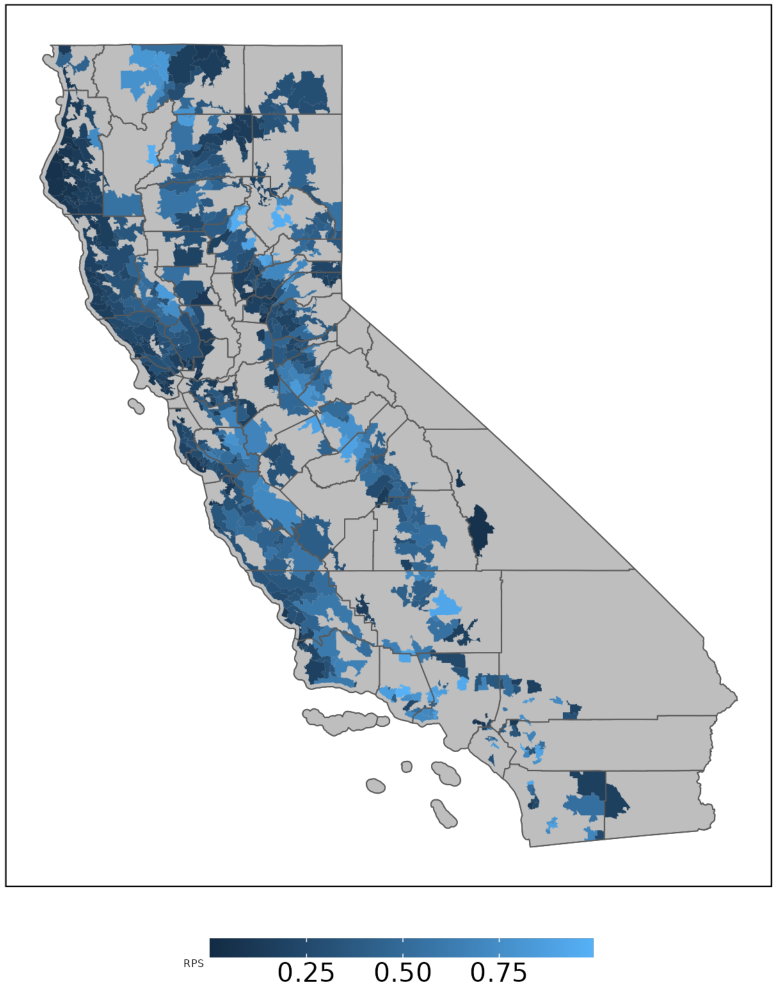
This chart shows FAIR Plan market share for every zip code that is in the estimation sample (at least 25% contained in a FHSZ by land area).

Figure 3: Risk to Potential Structures (RPS)



This map shows the average RPS values for each zip code in the estimation sample (at least 25% contained in a FHSZ by land area). RPS values represent the probability that a property experiences damage. RPS represents the percent chance that a fire capable of causing damage to a building burns in 2014.

Figure 4: Risk to Potential Structures (RPS) for Zip Codes with $RPS < 1$



This map shows the average RPS values for each zip code in the estimation sample (at least 25% contained in a FHSZ by land area) that has an RPS value less than 1. RPS values represent the probability that a property experiences damage. RPS represents the percent chance that a fire capable of causing damage to a building burns in 2014.

Figure 5: Conceptual Framework