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

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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. 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 incomes, race and ethnicity, and other socio-demographic indicators in response to floods, hurricanes, and extreme temperatures (Sheldon and Zhan, 2022; Fan et al., 2016), as well as in response to changes in risk levels for these events (Bakkensen and Ma, 2020; Fan and Bakkensen, 2022). These natural disasters can impact many different types of communities, but tend to be more concentrated in coastal regions and so the results should be interpreted in this context. Rural and agricultural regions may respond differently to changes in natural disaster risk. In addition, these papers tend to ignore the role of risk preferences in the decision to migrate. 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.

This paper evaluates sorting on risk preferences and incomes in response to changes in 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] Unlike flooding and hurricane risk, rural and agricultural communities are disproportionately impacted by escalating wildfire risk because of their proximity to wildland areas. In California, the 8 largest, 12 of the 16 most destructive, and the single deadliest wildfire in recorded history have

[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.

happened since 2017 (CalFire, 2022).

To answer the question of sorting on incomes and risk preferences, I develop a simple conceptual framework in which individual utility is decreasing in wildfire risk and increasing and concave in income. I also assume that house prices are negatively related to wildfire risk; increases in wildfire risk causes house prices to fall.[2] This provides the mechanism for two intuitive predictions: an increase in wildfire risk leads to sorting on incomes and risk preferences, with lower income and less risk averse people choosing to expose themselves to increased risk. While these theoretical predictions are straightforward, bringing credible empirical evidence to test them is not. The challenges are threefold: first, finding a granular measure of wildfire risk that varies cross sectionally and over time, second, constructing a way to measure risk preferences, and third, accounting for potential omitted variable bias.

The first challenge is finding a measure of wildfire risk that varies cross-sectionally and temporally. Public wildfire risk data is not available at this level of granularity, however, I can observe the behavior of insurance companies. Insurers have an incentive to accurately estimate risk levels in order to remain competitive and solvent, and to keep this information private.[3] I infer their risk estimates by observing their behavior. Risk estimates should theoretically be revealed in insurance prices, but strict regulation prevents insurers from charging rates that fully reflect their expectations of risk. But insurers can 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

[2] It is well documented that house values are negatively related to natural disaster risk, including the risk of flooding, earthquakes, and wildfires (Bakkensen and Barrage, 2022; Koo and Liang, 2022).

[3] Risk estimates that are not high enough mean the company won't collect enough premiums to cover damages, and risk estimates that are too high will lead the company to lose market share to competitors that can more accurately estimate risks.

with FAIR Plan market share.

The second 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. Because driving risk is independent of wildfire risk, if a change in wildfire risk induces a change in car insurance purchasing behavior and capacity to mitigate risks remains the same, then underlying risk preferences must have changed. This method of measuring risk preferences works if risk preferences are stable over time and consistent for similar types of risks, which is generally supported in the literature (Soane and Chmiel, 2005; Einav et al., 2012).

The third challenge is eliminating the possibility that an unobserved variable is causing omitted variable bias in the empirical estimation. The main endogeneity concern is about local differences in the propensity to undertake private mitigation behaviors, such as clearing defensible space. These actions could negatively impact FAIR Plan market share (because insurance companies are more likely to cover homes that are better protected), but are also likely related to incomes and risk preferences. Therefore, I use an instrumental variable approach and instrument for wildfire risk with an exposure instrument that draws from the shift-share literature. My instrument interacts an exogenous cross-sectional measure of wildfire risk with aggregate, annual shocks to wildfire risk. The idea is that areas with higher baseline wildfire risk are more likely to experience larger effects 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 local variation in risk mitigation behavior is purged by aggregation, 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 county-by-year fixed effects to control for a wide range of possible confounders, including changing regulation about how wildfire risk is price (common across zip codes) and amenity values (constant over time).

The results show evidence of sorting over wildfire risk in incomes. I find that a one standard deviation increase in wildfire risk is associated with a population decline of 4%, and an increase in the number of migrants that move into a zip code of 20%. Further, I can distinguish these migrants by income group; I find that an increase in wildfire risk increases low-income in-migration and decreases high-income in-migration. 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, and lower income people moving towards wildfire risk. These results are consistent with findings from prior work, including Bakkensen and Ma (2020) who find that low income people are more likely to migrate into areas with high flood risk.

I also find that increases in wildfire risk are associated with a shift towards a less risk averse population. A one standard deviation increase in wildfire risk corresponds to a 21% increase in the proportion of car insurance policies that exceed basic requirements, and the size of this effect is not impacted by the inclusion of income controls. This is consistent with Bakkensen and Barrage (2022) who establish that individuals sort on risk preferences in response to flood risk, but builds on it by using observational rather than survey data.

Finally, I provide preliminary evidence that sorting on incomes and risk preferences are caused by changes in housing costs. Because people are generally risk averse (as opposed to risk loving), they cannot be drawn to wildfire risky areas by the wildfire risk itself. Instead, lower income and less risk averse people likely migrate into risky areas because of lower housing costs. I empirically test if increases in wildfire risk are associated with decreases in housing costs, and find that a one standard deviation increase in wildfire risk reduces typical housing values by $13.5 thousand.

This paper contributes to the broad economics literature on natural disasters and adaptation to climate change (Smith et al., 2006; Gandhi et al., 2022; Botzen et al., 2019; Kousky, 2014). Wildfires have been understudied in this literature, and are different from other disasters because private mitigation behavior and public fire fighting effort can dramatically impact damages. This paper also contributes to the growing literature on environmental sorting (Bakkensen and Barrage, 2022; Bakkensen and Ma, 2020; Fan and Bakkensen, 2022; Sheldon and Zhan, 2022; Fan et al., 2016), but distinguishes itself by focusing on rural and agricultural communities that are vulnerable to wildfire risk. Understanding who exposes themselves to natural disaster risk is critical to understand recovery capacity and for achieving environmental justice goals. Finally, this paper contributes to the literature on insurance markets and risk preferences (Barseghyan et al., 2013; Schildberg-Hörisch, 2018). Risk preferences are often ignored because they are unobservable, but they are an important input into the decision making process, and heterogeneity in these preferences can contribute to observing a wide range of risk mitigating behaviors.

This paper proceeds as follows: section 2 provides relevant background on wildfire risk and the California insurance market, section 3 outlines the conceptual framework, 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). These impacts are heavily felt in rural areas: from 2000 to 2020 the burned area was over three times greater for rural compared to urban regions (Masri et al., 2021). 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.[4]

[4]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,

Figure 1 shows the total area burned from 1989 to 2022 and FHSZ designations. These maps show that fire risk is primarily a concern in mountainous or hilly regions, and that most fires burn in areas of low population density. The area burned appears to track the FHSZ map well with some discrepancies, likely caused by spatial variation in fire-fighting effort. 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.

To reduce exposure to wildfire risk, individuals can purchase insurance or engage in home hardening activities (Meldrum et al., 2019; Brenkert-Smith et al., 2012). The goal of home hardening is to reduce the chance of damage during a wildfire and can include clearing defensible space, building with ignition and fire resistant materials, and covering all vent openings. Constructing a new home to optimum wildfire resistance can increase costs by $18,200-$27,100 compared to constructing a new home that just meets current building regulations (Barrett et al., 2022). Home hardening can be so effective at reducing wildfire risk that it can impact whether or not insurers choose to offer coverage to a property. In California, a new regulation that forces insurers to provide discounts to homeowners that engage in home hardening activities was passed in 2022 (CDI, 2022).

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.[5] 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

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).

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

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 doubt on the continued ability of insurance companies to absorb fire-related losses (Issler et al., 2020).[6]

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.

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

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.[7] 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 **??** shows how FAIR Plan market share has evolved over time in each zip code in my estimation sample. In most zip codes, FAIR Plan market share increased from 2009-2020, with the largest increases coming in 2019 and 2020.

3 Conceptual Framework

In this section, I develop a simple theoretical model of how changes wildfire risk impact household utility that results in two testable hypotheses. Households maximize utility by choosing between locations that experience differential shocks in wildfire risk. For simplicity, consider two locations in which all amenities other than wildfire risk remain constant over time; $l = 0$ has low and constant wildfire risk while $l = 1$ experiences positive shocks to wildfire risk. Assume that all households are risk averse or risk neutral, and that the utility of household i choosing location l in year t is,

$$U_{ilt} = V^*_{ilt}(X_i, r_{lt}, Y_{ilt}) + \varepsilon_{ilt}, \tag{1}$$

where, $V^*_{ilt}(X_i, r_{lt}, Y_{ilt})$ is the highest utility household i can achieve with choice l in year t and

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

depends on household characteristics (X_i), wildfire risk level (r_{lt}), and disposable income (Y_{ilt}), and ε_{ilt} is an independently and identically distributed error term. I assume V^*_{ilt} is increasing and concave in disposable income (Y_{ilt}), and is decreasing in wildfire risk (r_{lt}), as show in equation 2.

$$\frac{\partial V^*_{ilt}}{\partial Y_{ilt}} > 0 \qquad \frac{\partial V^{*\,2}_{ilt}}{\partial^2 Y_{ilt}} < 0 \qquad \frac{\partial V^*_{ilt}}{\partial r_{lt}} < 0 \tag{2}$$

I model disposable income as a function of total household income (I_i) and housing costs in location l and year t $(h_{lt}(r_{lt}))$,

$$Y_{ilt} = I_i - h_{lt}(r_{lt}). \tag{3}$$

Housing is a composite good made up of housing and location characteristics, including risk levels for potential disasters. Therefore, housing costs in location l reflect the willingness to pay to live in location l of the households that live there. Increases in risk will reduce the expected value of living in location l, and therefore all households will experience a decrease in utility following an increase in risk. I expect this decrease in utility to be reflected in housing costs, and that housing costs in location l and year t will fall if wildfire risk increases in location l and year t,

$$\frac{\partial h_{lt}}{\partial r_{lt}} < 0 \tag{4}$$

The size of the relationship in equation 4 will depend on general equilibrium effects, but can be treated as exogenous to the individual household.

Equation 5 shows how utility for household i in location l and time t changes when wildfire risk changes. I decompose the change into the amenity effect, which directly measures the change in utility from an increase in risk, and the income effect, which measures the change in utility arising from a change in disposable incomes resulting from a change in housing costs. These effects work in opposite directions; an increase in wildfire risk causes a negative amenity effect and a positive income effect (through the channel of reduced housing costs).

$$\frac{\partial U_{ilt}}{\partial r_{lt}} = \underbrace{\frac{\partial V^*_{ilt}}{\partial r_{lt}}}_{\text{amenity effect} < 0} + \underbrace{\frac{\partial V^*_{ilt}}{\partial Y_{ilt}} * \frac{\partial Y_{ilt}}{\partial h_{lt}} * \frac{\partial h_{lt}}{\partial r_{lt}}}_{\text{income effect} > 0} \tag{5}$$

Assume an individual is indifferent between $l = 0$ and $l = 1$. Now assume that there is an increase in wildfire risk in $l = 1$, but not in $l = 0$. If the income effect is larger than the amenity effect, the household will choose to stay or move to $l = 1$, but if the amenity effect is larger than the income effect the household will prefer $l = 0$. Therefore, heterogeneity in the size of these effects across households will impact the migration decisions of those households.

Income heterogeneity

I assume that the amenity effect is independent of income levels. That is, household income is not associated with the size of the amenity effect. Therefore, income heterogeneity will only impact the income effect. Because utility is concave in incomes, higher income households will experience a smaller utility gain from the same increase in income than lower income households. Therefore, the income effect will be greater for lower income households. This yields the first hypothesis.

> **Hypothesis 1:** Lower income households are less likely to migrate away from and more likely to migrate towards areas that experience increases in wildfire risk.

Risk Preference Heterogeneity

Risk preferences measure how much a household cares about risk. In this model they are captured by the amenity effect. I restrict the amenity effect to be negative and allow it to vary by household, but assume the distribution is independent of income. Households that are more risk averse will have a larger amenity effect (more negative) than households that are relatively less risk averse, holding income constant. Therefore, more risk averse households will experience a larger drop in utility from an increase in wildfire risk. This yields hypothesis 2.

Hypothesis 2: Less risk averse households are less likely to migrate away from and more likely to migrate towards areas that experience increases in wildfire risk.

In the empirical portion of this paper I test hypotheses 1 and 2, and show evidence that housing costs fall in response to an increase in wildfire risk.

4 Data

The primary data comprise annual zip code migration and population, income, car liability insurance purchases, FAIR Plan market share, wildfire risk, and home values 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. Summary statistics are shown in Table 1.

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 2009 represents everyone who responded to the survey from 2009-2013).[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

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

$<$ 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. I focus on bodily injury coverage because it is required by the state.

I car liability insurance purchases to measure risk preferences. 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. After controlling for zip code and year fixed effects, driving risk will be unrelated to wildfire risk, so, if changes in wildfire risk induce changes in driving risk mitigation behavior, risk preferences must have changed.

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).

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.

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 of each pixel located within each zip code boundary. This data represent a snapshot of wildfire conditions at the end of 2014. Figure 2 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 3 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.

Home value data come from the Zillow Home Value Index (ZHVI). This represents the typical home value for a region and is calculated as a weighted average of homes in the 35^{th} to 65^{th} percentile range. The data are reported at the zip code month level, and I average over each calendar year to obtain an annual estimate. This data span 2009-2020, with some missing zip code years.

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 Empirical Strategy

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

[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.

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,

$$Y_{it} = \beta r_{it} + \phi_i + \psi_{ct} + \varepsilon_{it}. \tag{6}$$

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 unobserved variation that is constant over time, ψ_{ct} are county-by-year fixed effects that control for unobserved variation that is constant within a county but changes over time, 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, and risk preferences (measured by the proportion of automobile insurance policies that are 'basic limits'). Additionally I use typical house values as a dependent variable to test the mechanism that sorting on incomes and risk preferences is caused by lower house values falling in risk areas. β retrieves the change in Y_{it} for a one percentage point increase in FAIR Plan market share.

5.2 Identification

5.2.1 Threats to identification

The main threat to identification is omitted variable bias. If there is an omitted variable that is related to FAIR Plan market share and also related to an outcome variable, the estimated coefficients will be biased. For example, defensive expenditures are negatively correlated with FAIR Plan market share and also likely to be related to an outcome variable. As defensive expenditures increase, private insurers will be more likely to offer a policy thereby reducing FAIR Plan market share, holding all else constant. Defensive expenditures are also likely to be related to incomes; people with higher incomes are more likely to protect their homes because they can afford to do so.

Defensive expenditures are not the only possible omitted variable that could cause bias, for example, amenity values are correlated with wildfire risk and incomes. The wide range of outcome variables I use means that there is a greater potential for at least one of them to be correlated with an unobserved variable that is also related to wildfire risk. It is clear that some outcome variables will suffer from this problem (such as risk preferences and incomes as illustrated above), but less clear others will (such as population and migration flows). To overcome this potential identification concern, I use an exposure instrument.

5.2.2 An exposure instrument for wildfire risk

To circumvent potential omitted variable bias, I construct an exposure instrument for wildfire risk that draws from the shift-share literature. Shift-share instruments are typically constructed by interacting starting local industry employment shares (constant over time) with aggregate industry shocks (constant over location), and then summing across industries. This is done to avoid bias caused by omitted variables such as local productivity. The idea is that localities with higher exposure to a certain industry (a higher beginning local industry employment share) will experience a larger effect from a common shock to that industry. Goldsmith-Pinkham et al. (2020) demonstrate that identification using a shift-share instrument comes from independence of the starting local industry shares and the outcome variables, while Borusyak et al. (2021) show identification can also be achieved if aggregate shocks are independent across industries.

I construct my exposure instrument, Z_{it}, in equation 7 by using statewide changes in FAIR Plan market share (FP_t) as aggregate shocks and a baseline measure of wildfire risk, RPS_i, as my local industry shares. The idea is that zip codes with a higher baseline wildfire risk will be more exposed to aggregate shocks in wildfire risk. This differs from traditional shift-share instruments because the local industry shares do not sum to one, and I rely on a single aggregate shock rather than multiple, independent shocks.

$$Z_{it} = RPS_i * FP_t \tag{7}$$

The identifying assumption is that Z_{it} must not impact the outcome variables through any path other than FAIR Plan market share. The main confounders I am worried about are local differences in how FAIR Plan market share reflects wildfire risk. These same local variations are purged when I aggregate FAIR Plan market share to the state level. In addition, zip code and county-by-year fixed effects control for a wide range of cross-sectional and temporal variation.

Despite this, it is still possible a violation may occur. A violation will occur if zip code characteristics that affect outcomes (and vary with aggregate shocks) are also systematically correlated with zip code wildfire risk. For example, I may be concerned that building codes could be correlated with 2014 wildfire risk, and aggregate shocks to wildfire risk could disproportionately impact these building codes in a pattern related to baseline wildfire risk. However, in California, building codes are determined at the state level. There are stricter building codes in Fire Hazard Severity Zones, but this designation doesn't change over time, so it will be absorbed by zip code fixed effects.

To evaluate the strength of my instrument, I run the first stage regression given by,

$$r_{it} = \beta_1 Z_{it} + \phi_i + \psi_{ct} + \varepsilon_{it}, \tag{8}$$

where notation is consistent with equations 6 and 7. 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 8) is 3.33.

6 Estimation Results and Discussion

In this section, I report and discuss the estimation results from equation 6 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. When comparing wildfire risk in 2014 to FAIR Plan market share in 2014, a one standard deviation increase in wildfire risk (as measured by risk to potential structures) is related to a 10.25 percentage point increase in FAIR Plan market share. Therefore, the impact of a one standard deviation increase in 2014 cross sectional wildfire risk on population, migration, incomes, and risk preferences, is equal to the estimated coefficients multiplied by 10.25.

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

The results showing population and migration responses to changes in FAIR Plan market share are shown in Table 5. I use county-by-year fixed effects and show the naive specifications (columns 1-3) and the instrumental variable specifications (columns 4-6). The naive estimates show that a one percentage point increase in FAIR Plan market share today results in changes over the next five years of, a 49 person drop in population, a 33 person increase in the number of movers, and a 34 person increase in the number of local movers. If I inflate these estimates to correspond to a one standard deviation increase in wildfire risk, the population will decline by 507 people, the number of in-migrants will increase by 333, and the number of local in-migrants will increase by 347. These number correspond to an average decrease in population of 4%, an increase in the number of movers of 20%, and an increase in the number of local movers of 34%.

The instrumental variable estimates are similar to the naive estimates, but imprecisely estimated. The direction is consistent for population, movers, and local movers, and the size is consistent for movers and local movers, indicating there is no omitted variables biasing these results. The population estimate may suffer from omitted variable bias caused by defensive expenditures. People are more likely to undertake defensive expenditures if the population is low because they cannot rely on community firefighting efforts to protect their homes. Defensive expenditures are also likely to be negatively correlated with FAIR Plan market share, resulting in a positive omitted variable bias.

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.

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

In this section, I decompose migrants into different incomes groups. The results are shown in Table 5. I classify low income movers as migrants with incomes less than \$25,000 and high income movers as migrants with incomes more than \$65,000. Using the 2SLS specification, I find that a one percentage point increase in FAIR Plan market share increases the number of low-income migrants by 41.5 and decreases the number of high-income migrants by 58. If I inflate these estimates to correspond to a one standard deviation increase in wildfire risk, the number of low income movers increases by 425 (or 78% on average) and the number of high income movers decreases by 591 (or 219% on average).

These results indicate that as wildfire risk increases, the migrants into a zip code shift towards being low-income. This means that wildfire risk is concentrating on people with the fewest resources to recover following a disaster. 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?

I estimate risk preference sorting over wildfire risk by using the proportion of car insurance policies that are 'basic limits' as my dependent variable. The estimation results are shown in Table 6. County-by-year fixed effects over fit the model, so I use year fixed effects instead. 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.[10] First, I recognize that although wildfire risk impacts the migration decisions of low income and high income people differently, these effects are economically small. Therefore I expect the omitted variable bias caused by excluding incomes will be small and unimportant. This is exactly what I find; the coefficients on FAIR Plan market share are not biased by excluding income controls. My preferred specification (column 3) shows that a one percentage point increase in FAIR Plan market share corresponds to a 0.24 percentage point increase in the proportion of car insurance policies that are basic limits (or approximately a 2% increase). Said differently, a one standard deviation increase in wildfire risk causes a 21% increase in the proportion of car insurance policies that are basic limits. This suggests an increase in wildfire risk induces the population to be less risk averse. I assume this is caused by a population reshuffle, because risk preferences are relatively stable over time (Einav et al., 2012).

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). 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.

These results are one of the first attempts to quantify sorting on wildfire risk with observational

[10]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.

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.

6.4 Mechanism: House Values

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 costs. I empirically test if typical house values are lower in areas of higher wildfire risk, and the results are shown in Table 7. As expected, the coefficients in all of the estimated models are negative, indicating that housing costs are inversely related to wildfire risk. This provides preliminary evidence that housing costs are the driver of the sorting results.

7 Conclusions

This paper measures sorting on wildfire risk in incomes and risk preferences. I develop a conceptual model that predicts lower income and less risk averse people migrate into risky areas. I empirically test these predictions with an exposure research design that draws from the shift-share literature. I also develop a new way to measure wildfire risk and risk preferences 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, potentially caused by lower housing costs. These results are consistent with prior studies that analyze sorting on natural disaster risk.

Sorting on incomes has important implications for policy makers. If indeed lower income people migrate towards and higher income people migrate away from risky areas, then natural disaster risk is concentrating on people with the fewest resources to recover following a disaster. This increases the need for recovery assistance from government and non-governmental organizations. Furthermore, sorting on risk preferences indicates that it may become increasing difficult to incentivize people to undertake private risk mitigation behavior. Less risk averse individuals are more difficult to incentivize to undertake private risk mitigation behaviors, and therefore, government programs designed to help homeowners take action may need to become more aggressive.

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8 Tables

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
Local Movers	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
House Value	4,234	301,676.4	248,199.7	29,253.8	150,834.4	227,545.4	361,099.6	2,342,286.0

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 (ACS).
Movers is the 5-year estimate for total in-migration from the 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.
House Value comes from the Zillow Home Value Index (ZHVI) and reflects the typical value for homes in the 35th to 65th percentiles for a calendar year.

Table 2: Total Population and Migration

	Dependent variable:					
	Population	Movers	Local Movers	Population	Movers	Local Movers
	(1)	(2)	(3)	(4)	(5)	(6)
FP Mktshr	-49.45^{**}	32.51^{***}	33.83^{***}			
	(20.20)	(8.08)	(7.72)			
FP Mktshr (IV)				-168.37	31.61	23.50
				(130.62)	(66.19)	(54.48)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,506	7,466	7,466	7,506	7,466	7,466
R^2	1.00	0.99	0.98	1.00	0.99	0.98
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 3: Proportion of Population by Income Group with Year Fixed Effects

	Dependent variable:					
	Inc<50	50<Inc<100	100<Inc	Inc<50	50<Inc<100	100<Inc
	(1)	(2)	(3)	(4)	(5)	(6)
FP Mktshr	0.02	0.04	-0.06			
	(0.03)	(0.05)	(0.05)			
FP Mktshr (IV)				0.87^{**}	0.15	-1.02^{**}
				(0.36)	(0.30)	(0.45)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	No	No	No	No	No	No
Observations	8,885	8,885	8,885	8,885	8,885	8,885
R^2	0.95	0.67	0.97	0.94	0.67	0.96
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 4: Proportion of Population by Income Group with County-by-Year Fixed Effects

	Dependent variable:					
	Inc<50	50<Inc<100	100<Inc	Inc<50	50<Inc<100	100<Inc
	(1)	(2)	(3)	(4)	(5)	(6)
FP Mktshr	−0.03	0.12*	−0.09			
	(0.03)	(0.07)	(0.07)			
FP Mktshr (IV)				0.05	0.22	−0.27
				(0.10)	(0.16)	(0.17)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,885	8,885	8,885	8,885	8,885	8,885
R^2	0.96	0.73	0.98	0.96	0.73	0.98
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 5: Migration by Income Group

	Income<\$25,000	Income>\$65,000	Income<\$25,000	Income>\$65,000
	(1)	(2)	(3)	(4)
FP Mktshr	26.56***	−17.55***		
	(3.36)	(3.12)		
FP Mktshr (IV)			41.50*	−57.64**
			(22.31)	(21.74)
Zipcode FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Observations	7.466	7.466	7.466	7.466
R^2	0.73	0.97	0.73	0.97
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: Risk Preferences

	Dependent variable:					
	Proportion BL					
	(1)	(2)	(3)	(4)	(5)	(6)
FP Mktshr	0.03*	0.04***				
	(0.02)	(0.01)				
Inc<25		0.18***		0.12**		
		(0.03)		(0.05)		
25<Inc<50		0.15***		0.11***		
		(0.02)		(0.04)		
50<Inc<75		0.15***		0.11***		
		(0.02)		(0.04)		
75<Inc<100		0.15***		0.11**		
		(0.02)		(0.04)		
100<Inc<200		0.15***		0.10**		
		(0.02)		(0.04)		
FP Mktshr (IV)			0.24*	0.24	0.24	0.15*
			(0.13)	(0.16)	(0.24)	(0.08)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	No	No	No	No	No	No
Observations	11,042	8,885	11,042	8,885	2,462	2,110
R^2	0.92	0.97	0.91	0.96	0.95	0.98

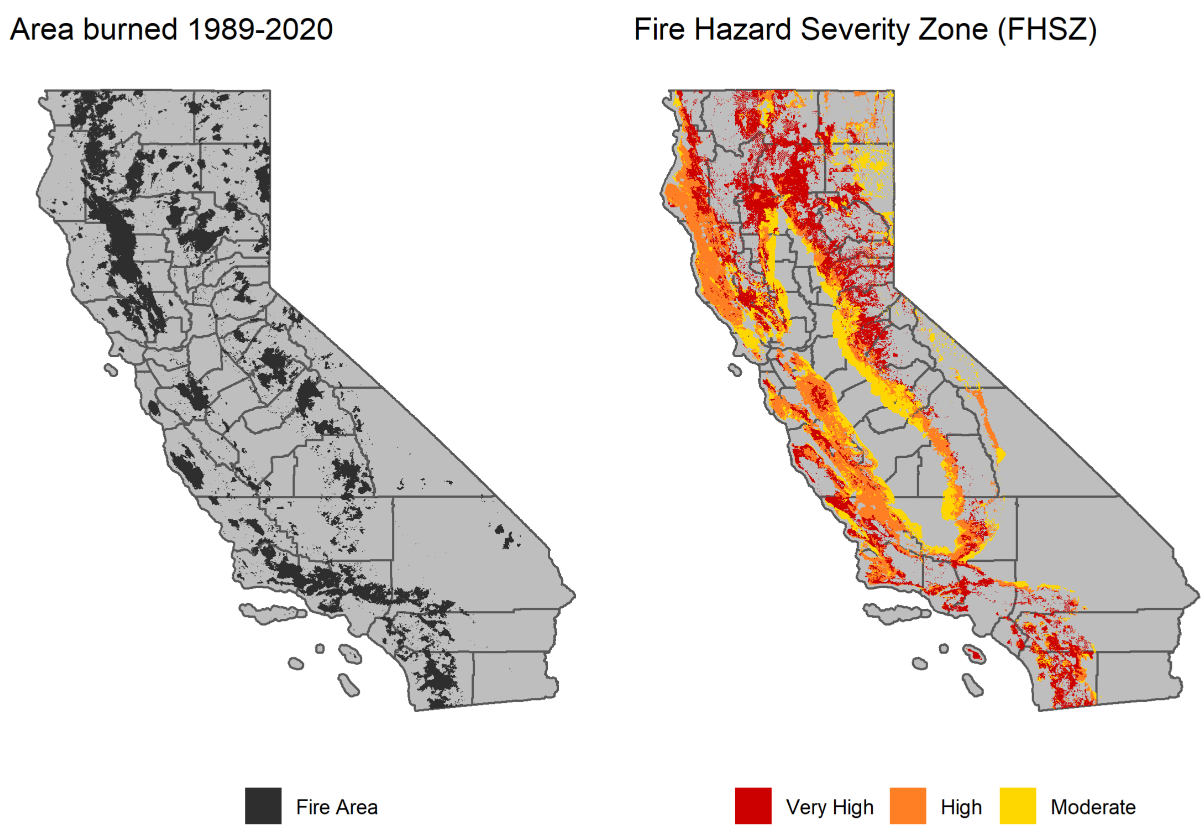
Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Typical House Values

	Dependent variable:	
	house_value	
	(1)	(2)
FP Mktshr	−415.53	
	(1,112.36)	
FP Mktshr (IV)		−13,531.07*
		(7,059.02)
Zipcode FE	Yes	Yes
Year FE	Yes	Yes
County-Year FE	No	No
Observations	4,234	4,234
R^2	0.94	0.93
Note:	*p<0.1; **p<0.05; ***p<0.01	

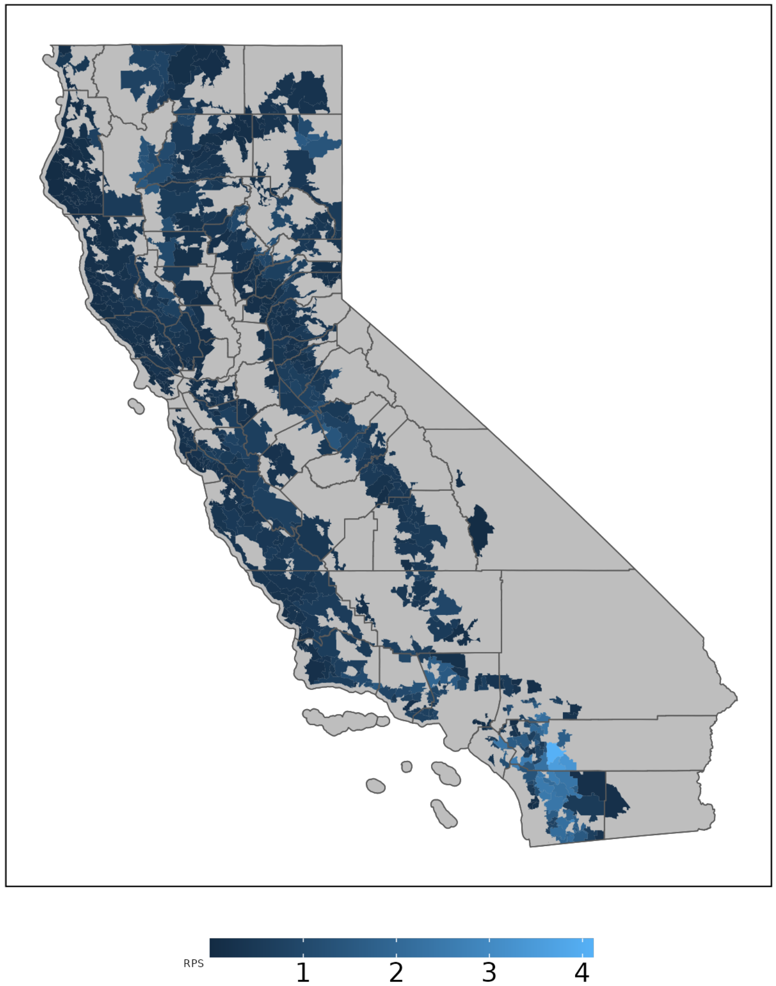
9 Figures

Figure 1: California Wildfires and Fire Hazard Severity Zones



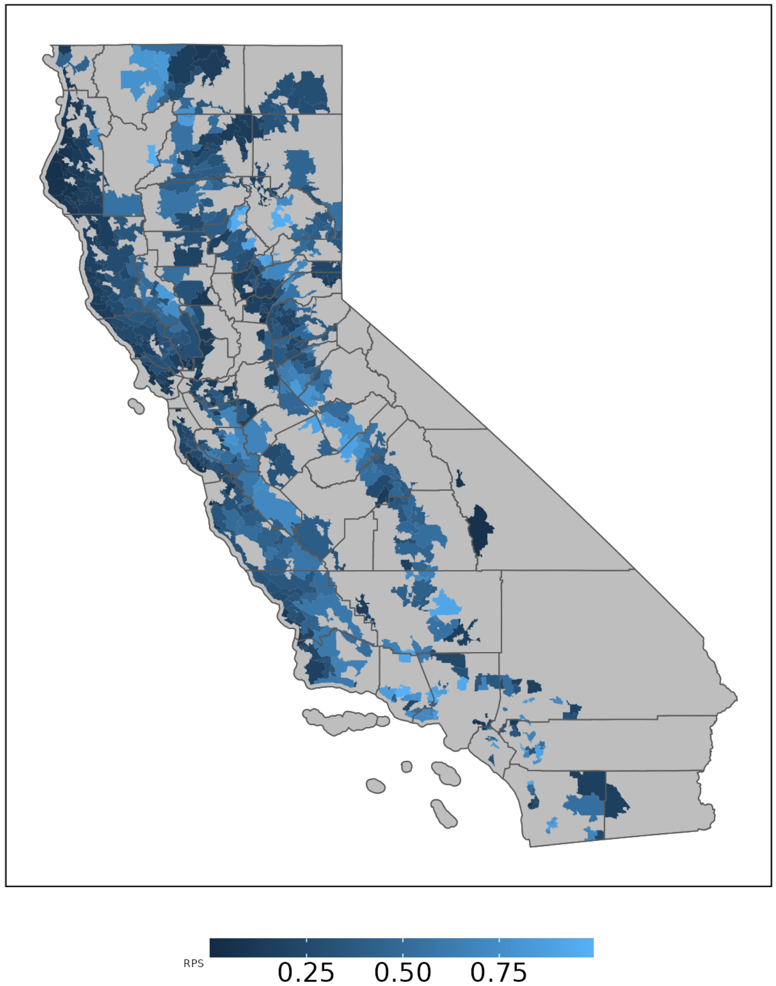
Wildfire and Fire Hazard Severity Zone boundaries come from CAL FIRE. The wildfire boundaries include all timber fires 10 acres or greater, brush fires 30 acres or greater, and grass fires 300 acres or greater. The FHSZ map was created from 2007 and reflects wildfire risk at that time.

Figure 2: 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 3: 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.

10 Appendix A: Additional Results Tables

Table 8: Total Population and Migration Results with Year Fixed Effects

	Dependent variable:					
	Population	Movers	Local Movers	Population	Movers	Local Movers
	(1)	(2)	(3)	(4)	(5)	(6)
FP Mktshr	-43.04^{***}	24.14^{***}	20.78^{***}			
	(11.59)	(5.12)	(4.35)			
FP Mktshr (IV)				198.06	-34.59	-63.08
				(122.76)	(52.75)	(47.95)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	No	No	No	No	No	No
Observations	7,506	7,466	7,466	7,506	7,466	7,466
R^2	1.00	0.99	0.98	1.00	0.99	0.98
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 9: Proportion of Population by Income Group with Year Fixed Effects

	Dependent variable:					
	Inc<50	50<Inc<100	100<Inc	Inc<50	50<Inc<100	100<Inc
	(1)	(2)	(3)	(4)	(5)	(6)
FP Mktshr	0.02	0.04	-0.06			
	(0.03)	(0.05)	(0.05)			
FP Mktshr (IV)				0.87^{**}	0.15	-1.02^{**}
				(0.36)	(0.30)	(0.45)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	No	No	No	No	No	No
Observations	8,885	8,885	8,885	8,885	8,885	8,885
R^2	0.95	0.67	0.97	0.94	0.67	0.96
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 10: Proportion of Population by Income Group with County-by-Year Fixed Effects

	Dependent variable:					
	Inc<50	50<Inc<100	100<Inc	Inc<50	50<Inc<100	100<Inc
	(1)	(2)	(3)	(4)	(5)	(6)
FP Mktshr	−0.03	0.12*	−0.09			
	(0.03)	(0.07)	(0.07)			
FP Mktshr (IV)				0.05	0.22	−0.27
				(0.10)	(0.16)	(0.17)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,885	8,885	8,885	8,885	8,885	8,885
R^2	0.96	0.73	0.98	0.96	0.73	0.98
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 11: In-Migration by Income Group

	Dependent variable:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FP Mktshr	12.26***	5.40***	6.10***	0.43	0.66	0.40	−1.09**	−11.14***
	(2.33)	(1.00)	(1.12)	(0.72)	(0.64)	(0.76)	(0.48)	(1.60)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	No	No	No	No	No	No	No	No
Observations	7,112	7,068	7,160	7,098	7,068	6,896	6,412	7,096
R^2	0.97	0.95	0.95	0.95	0.95	0.94	0.86	0.96

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

*p<0.1; **p<0.05; ***p<0.01

Table 12: In-Migration by Income Group

	Dependent variable:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FP Mktshr	15.31***	8.06***	7.69***	0.63	0.67	−0.07	−1.39*	−11.89***
	(2.85)	(1.91)	(1.98)	(1.02)	(1.04)	(1.21)	(0.75)	(2.38)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
County-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	0.97	0.95	0.96	0.96	0.95	0.94	0.87	0.97

Dependent Variables: (1) Movers with income < \$10,000 — *p<0.1; **p<0.05; ***p<0.01
(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 13: In-Migration by Income Group

	Dependent variable:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FP Mktshr (IV)	−12.65	−21.23*	−5.48	0.09	−0.94	0.27	−5.75	12.85
	(14.50)	(11.81)	(9.22)	(5.87)	(7.18)	(6.32)	(4.66)	(14.43)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	No	No	No	No	No	No	No	No
Observations	7,112	7,068	7,160	7,098	7,068	6,896	6,412	7,096
R^2	0.97	0.94	0.95	0.95	0.95	0.94	0.86	0.96

Dependent Variables: (1) Movers with income < \$10,000 — *p<0.1; **p<0.05; ***p<0.01
(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 14: In-Migration by Income Group

	Dependent variable:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FP Mktshr (IV)	12.97	-15.82	29.99^{**}	-5.45	11.68	-0.33	-13.50^{*}	-37.63^{**}
	(18.28)	(12.92)	(13.28)	(9.42)	(10.87)	(9.06)	(7.02)	(16.64)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
County-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	0.97	0.95	0.95	0.96	0.95	0.94	0.87	0.97

Dependent Variables: (1) Movers with income $<$ \$10,000 *p$<$0.1; **p$<$0.05; ***p$<$0.01

(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 15: Risk Preferences

	Dependent variable:					
	Proportion BL					
	(1)	(2)	(3)	(4)	(5)	(6)
FP Mktshr	0.02	0.02				
	(0.02)	(0.02)				
Inc<25		0.14^{***}		0.12^{***}		
		(0.03)		(0.04)		
25<Inc<50		0.12^{***}		0.10^{***}		
		(0.03)		(0.03)		
50<Inc<75		0.11^{***}		0.09^{***}		
		(0.03)		(0.03)		
75<Inc<100		0.10^{***}		0.08^{**}		
		(0.03)		(0.03)		
100<Inc<200		0.10^{***}		0.08^{***}		
		(0.03)		(0.03)		
FP Mktshr (IV)			0.11	0.10	-0.07	0.11^{***}
			(0.08)	(0.08)	(0.12)	(0.04)
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,042	8,885	11,042	8,885	2,462	2,110
R^2	0.93	0.97	0.93	0.97	0.97	0.99

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

Table 16: Typical House Values

	Dependent variable:	
	house_value	
	(1)	(2)
FP Mktshr	−153.14	
	(1,051.01)	
FP Mktshr (IV)		−3,287.18
		(4,259.56)
Zipcode FE	Yes	Yes
Year FE	No	No
County-Year FE	Yes	Yes
Observations	4,234	4,234
R^2	0.98	0.98
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	