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YSSP Report

**Young Scientist Summer Program**

# Building better: an analysis of the determinants of wildfire building code adoption in California

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This report represents the work completed by the author during the IIASA Young Scientists Summer Program (YSSP) with approval from the YSSP supervisor.

It was finished by Jennifer Richmond on September 29, 2021, and has not been altered or revised since.

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# ABSTRACT

Wildfires ravage communities, forests, and government budgets each year in the US. The risk of wildfires continues to evolve as climate change enables conditions that are hotter, drier, and conducive to more frequent and intense fires. It remains unclear to what extent public policy is nimble enough to respond effectively at the local, state, and federal levels. A patchy web of disaster resilience policies and building codes meant to "harden" structures, as a defense against wildfires, exist in some places to attempt to protect public safety, property, and forests. However, it is uncertain whether codes are enforced, if codes are enforced differently by local jurisdictions or states, and whether codes are effective at changing consumer behavior. Here we derive empirical evidence from multivariate binomial regression analysis to predict whether homeowners' adopt fire-resistant building materials following major policy changes and whether key spatial and socioeconomic characteristics help or hinder adoption as well. We find that homes built after California's comprehensive building code change in 2008 and homes located in Firewise communities or wildland urban intermix (WUI) areas all exhibit strong, positive effect sizes for adopting higher levels of fire-resistant home building materials. Findings from this study may help to identify where public policy is making strides in wildfire resilience and where improvement and investment are needed.

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## List of Abbreviations and Acronyms

Below is the list description of all abbreviations or acronyms used in the following text.

| Abbreviations/Acronym | Description |
|---|---|
| ACS | American Community Survey |
| CAL FIRE | California Department of Forestry and Fire Protection |
| GIS | Geographic Information Systems |
| LRA | Local Responsibility Area |
| MLS | Multiple Listing Service |
| NFPA | National Fire Protection Association |
| QGIS | Quantum Geographic Information Systems |
| SRA | State Responsibility Area |
| WUI | Wildland Urban Intermix or Interface |
| ZTRAX | Zillow Transaction and Assessment Dataset |

# 1 Introduction

From 2011-2020, there were an average of 62,805 wildfires annually in the US. These fires have burned an average of 7.5 million acres annually. In 2020 along, 58,950 wildfires burned 10.1 million acres, which was the second highest number of acres burned since 1960; of these 10.1 million acres burned in 2020, nearly 40% were in California [CRS, 2021]. Despite the imminent risk, 43 million homes are located in the most wildfire-prone areas, which are known as wildland-urban interface (WUI) zones. Although WUI areas continue to expand as development encroaches on these areas, WUI areas make up only about 10% of the US land area as of 2018. However, WUI areas are home to more than a third of houses [Kramer et al., 2018]. As risk and hazard models continue to indicate that wildfires will only become a greater threat in these areas, public policy can intervene to provide fire-fighting services and infrastructure, educational outreach and information regarding fire safety and risk, and protect lives and property through enforcement of preparedness regulations and fire-resistant building codes and standards. This work focuses mainly on the latter piece of the policy approach to evaluate building standards and codes that increase wildfire resilience.

The goal of this research is to better understand the empirical underpinnings of the relationship between building code adoption and higher classes of fire-resistant building materials being used in home construction throughout building code enforcement areas and non-enforcement areas. Building codes meant to harden homes are an important part of wildfire resilience because evidence suggests that codes and standards - though by no means foolproof - can be effective at protecting property while also preventing further spread of fires [Syphard and Keeley, 2019, Evans et al.]. Even a limited number of fire-resistant homes in a community has been shown to reduce the spread and threat of wildfires [Baylis and Boomhower, 2021].

California is the only state in the US that has instituted statewide building code regulations for fire-resistant housing materials in designated high-hazard areas. Similar to other states, California has mapped fire hazard severity zones, and it has also mapped state responsibility areas (SRAs) and local responsibility areas (LRAs), which are designations that determine official responsibility for wildfire suppression efforts. State authorities are in charge of fire suppression in SRAs and local authorities are in charge of fires in LRAs; if fires cross these boundaries, authorities negotiate or consolidate responsibility. In 1995, the California legislature passed a bill requiring that all houses built or re-roofed in all SRAs and certain LRAs adhere to an ignition-resistant roofing mandate. Roofing materials are classified on an ordinal scale of ignition resistance, including Class A, B, C, or unrated. The 1995 law required that roofs be at least Class B. In 1997, the law was amended to require that all houses in these areas install Class A ignition-resistant roofs, and then in 1999, unrated roofing materials were outlawed throughout the entire state. In 2008, the state passed the first statewide comprehensive wildfire building code requirement - known as Chapter 7A of the California Building Code - for all houses built in SRAs and certain LRAs. Chapter 7A includes specific fire-resistant requirements for many housing characteristics beyond just roofing, including decks, eaves, exterior walls, siding, landscaping, and other features. (As a note, the more comprehensive regulation for building standards in Chapter 7A does not necessarily correspond directly to a fire-resistant rating class system in the same way that roofing does.)

Here we plan to evaluate the empirical relationship of these policy changes on fire-resistant class ratings for housing in California using housing data and fire insurance classification data made available through Zillow. The Zillow Transaction and Assessment Dataset (ZTRAX) is the largest real estate database in the US. The ZTRAX database includes several rounds of updated data from recent years, but given that I will be using the construction year to evaluate changes over time, I will only be using a recent round from 2020 as a cross-sectional sample. Within the ZTRAX database, all homes evaluated in this study are rated using a five-letter fire-insurance rating system. The definitions provided for each class are defined by Zillow in the provided data dictionary and we present them here in Section 4. We use this classification as a categorical outcome variable to test the hypothesis that the policy changes in California starting with roofing in 1995 and then comprehensive housing requirements in 2008 have driven significantly higher fire-resistant home classifications among those homes built after the roofing code change in 1995 and even more significant effects among homes built in 2008 or later. To test this, we use a variable representing periods of time that correspond to a statewide policy absence, roofing requirements starting in 1995, and comprehensive housing requirements starting in 2008, i.e. 1) pre-1995 construction, 2) 1995-2007 construction, and 3) post-2007 construction. Using the construction year as an independent variable, the fire-resistant home classification as an outcome variable of the relative amount of adoption of higher levels of fire-resistant building materials, and a range of socioeconomic and spatial variables as covariates, we hope to estimate the the degree of change in adoption of these materials over time and changes to the regulations.

# 2 Background

The overlap between wildfires and the built environment continues to grow as human development increasingly moves into heavily wooded or wildland areas [Kramer et al., 2018, Brenkert-Smith et al., 2012, Renner et al., 2006]. This is happening relatively rapidly in many states, including California, where - among other drivers of development expansion - real estate prices near urban areas in much of the state are increasingly and prohibitively expensive. According to Kramer et al. [2018], the most *threatened* and most often *destroyed* buildings in the US are located in the wildland urban interface (WUI). Kramer et al. [2018] found that from 2000-2013 within the conterminous US, 59% of buildings that are threatened by wildfires and 69% of buildings that have been destroyed by wildfires are located in the WUI. Among states from 2000-2013, California experienced the most property destruction and also had the highest percentage of destroyed buildings within WUI areas. The encroachment on wildland areas is only projected to increase in coming decades. Mann et al. [2014] estimate that by 2050, California's exurban land classes will replace nearly 12 million acres of wild and agricultural lands, increasing the threat of wildfires and property destruction from wildfires.

For the growing number of homes located in high-risk areas, one strategy to protect properties and lives while potentially slowing the spread of wildfire is to require a certain standard of fire-resistant building quality. In a recent working paper, Baylis and Boomhower [2021] found that a 2010 or newer home in a building code-enforced area in California is about 15 percentage points (38%) less likely to be destroyed than a 1985 home. Not only did the authors discover positive direct impacts from building codes, but they also found significant indirect benefits for communities in which some homes adopt higher levels of fire-resistant building materials; they found that a home's likelihood of destruction during a wildfire falls by about 3 percentage points (8%) if its nearest neighbor was built under the modern wildfire codes.

Understanding that the use of fire-resistant building materials can lead to higher structure survival rates [Baylis and Boomhower, 2021, Syphard et al., 2017, Syphard and Keeley, 2019, Evans et al.], what are the barriers and the determinants of adoption of defensive building practices? Haines et al. [2008] conducted a study in 2008 finding that building code adoption and enforcement at the municipal level can encounter a number of key barriers. First, a community has to muster the political will and ability to allocate public funding for code implementation and enforcement. Evans et al. also point to political will as a main determinant for enforcement of regulations and motivation for wildfire preparedness and mitigation within communities. It is important to note that political will for these mitigation efforts may increase in the aftermath of a wildfire. The second major obstacle is apathy or even resistance from homeowners or homeowner organizations. The authors cite that Washington and Colorado tried unsuccessfully to pass legislation at the state level requiring stronger building requirements to combat property destruction from wildfires. However, there has been more success at the local level with suggesting voluntary guidelines for construction and defensible space around the home as well as offering assistance to aid implementation of mitigation efforts at local and county levels.

Paveglio et al. [2015] suggests it is imperative to consider the social complexities at local levels to understand why there is uptake or resistance to wildfire resilience and mitigation efforts. Paveglio et al. [2015] cite the following characteristics as those that should be considered when targeting resilience and mitigation programs or policies: (1) previous wildfire experience, (2) primary versus secondary home ownership, (3) formal versus informal outreach programs, (4) personal efficacy, (5) community identity, (6) demographics, and (7) income. Specific to the community level, the authors point to different community identities or archetypes that frame the approach to wildfire preparation, such as rural versus urban or libertarian versus more communal archetypal constructs that can heavily influence the form that response efforts take. This study and many others invoke key socioeconomic and spatial indicators as major determinants for adoption of key wildfire preparedness measures [Evans et al., Renner et al., 2006, Brenkert-Smith et al., 2012, Ergibi and Hesseln, 2020, Schulte and Miller, 2010, Wolters et al., 2017].

# 3 Methods

The main methodological approach of this study is to find empirical evidence based on multivariate regression analysis to support or negate the hypothesis that building code changes in California in 1995 and, especially, the more comprehensive code change in 2008 may have had an impact on the level of fire-resistant building class adoption throughout the state. We also evaluate which key spatial and socioeconomic variables may help to predict higher levels of fire-resistant building classes. These variables have been added to the analysis based on their relevance according to the literature, which is explained in greater detail in Section 2. To address these research goals, we rely on binomial multivariate logistic regression models that will be explained in more detail in this section and in Section 5. We have also run initial diagnostic tests and preliminary models that we will explain briefly in this section.

We first ran a diagnostic chi-squared test to evaluate whether there are significant differences to exploit between observed and expected values when comparing the dependent and independent variable categories. The outcomes of the chi-squared test are presented in Table 1. Observed values are the number of observations per category in the data. Expected values are calculated by multiplying row totals by column totals and dividing by the total number of observations in the twoway table. The construction year is represented by different time periods corresponding to building code changes in California, and $A$, $B$, $C$, $D$, and $S$ are listed along the top of each section of Table 1 to represent each fire-resistant home classification outcome. classifications $A$, $B$, and $C$ are at least somewhat to very fire-resistant, and $D$ and $S$ represent homes that are not fire-resistant at all. Classifications are explained in more detail in Seciton 4.

**Table 1:** Chi-squared = 4371.6, df = 8, p-value < 2.2e-16

| Observed values | | | | | |
|---|---|---|---|---|---|
| Construction year | A | B | C | D | S |
| 1995-2007 | 103 | 258 | 136 | 230969 | 22 |
| 2008-2020 | 199 | 416 | 209 | 72525 | 24 |
| Pre-1995 | 310 | 2343 | 12259 | 1005223 | 152 |
| **Expected values** | | | | | |
| Construction year | A | B | C | D | S |
| 1995-2007 | 106.91 | 527.03 | 2201.77 | 228617.69 | 34.59 |
| 2008-2020 | 33.89 | 167.05 | 697.88 | 72463.22 | 10.96 |
| Pre-1995 | 471.20 | 2322.91 | 9704.35 | 1007636.08 | 152.45 |
| **Residuals** | | | | | |
| Construction year | A | B | C | D | S |
| 1995-2007 | -0.378 | -11.719 | -44.025 | 4.918 | -2.140 |
| 2008-2020 | 28.364 | 19.261 | -18.506 | 0.229 | 3.937 |
| Pre-1995 | -7.426 | 0.417 | 25.933 | -2.404 | -0.036 |

Residuals are calculated by finding the difference between the observed and expected values and then dividing those values by the square root of the expected value. The residuals from the chi-squared test are presented in detail in Table 1 and are shown according to the magnitude of positive or negative deviation from the expected value in Figure 1. The size of the dot and the gradation of color indicate the magnitude of deviation for each categorical comparison. The most striking comparisons between observed and expected values are for the $C$ class in the 1995-2007 period where the observed value is much lower than is expected, the $A$ category in the 2008-2020 period where the value is much higher than expected, and the $C$ class in the pre-1995 period where the value is much higher than expected. Overall, the 2008-2020 shows the strongest deviations from expected values compared to other time periods, suggesting there is something about this time period that is creating a greater deviation.

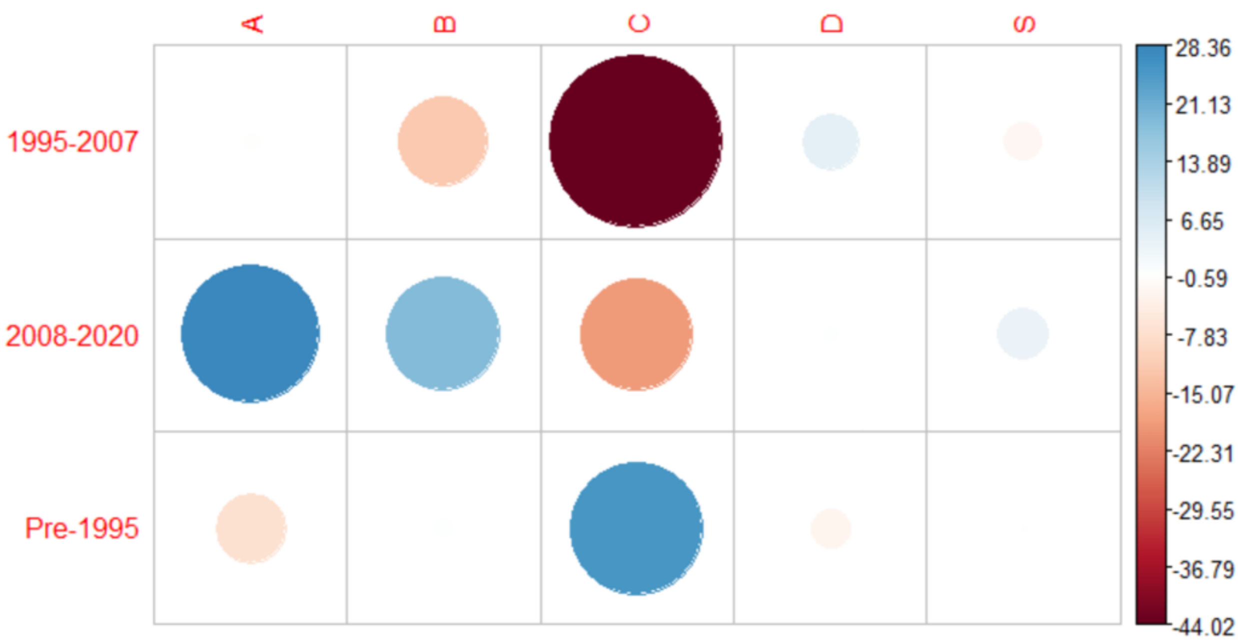


**Figure 1:** Chi-squared residuals plot (Note: Pearson chi-squared test was used)

After running an initial diagnostic evaluation with the chi-squared test, we then moved forward with regression analysis. Initially, we ran ordered logistic regression models using the building class variable and an ordered outcome variable since the $S$ and $D$ classes represent homes that are not built to be fire-resistant and the $C$, $B$, and $A$ classes represent homes that are progressively more fire-resistant, with class $A$ homes being the most fire-resistant.

The ordered logistic regression models yielded highly significant results; however, a major assumption of this model is the proportional odds assumption, which requires that the estimate coefficient in the model must apply to each category of the categorical outcome variable without significant deviation. In this case, the proportional odds assumption was not supported. We tested whether the proportional odds assumption holds in two ways. First, we ran a Brant test with the brant package in R, which basically evaluates whether the deviations from what are proportionally expected in the outcome categories of the dependent variable are greater than what could be attributed to chance. The null hypothesis of the Brant test is that the proportional odds assumption holds. In Table 2 below, the results suggest that the null hypothesis should be rejected, meaning that the model is invalid.

**Table 2:** Brant test of proportional odds assumption

| | X2 | df | probability |
|---|---|---|---|
| Omnibus | 3,844.094 | 6 | 0 |
| CodeYear.L | 3,021.456 | 3 | 0 |
| CodeYear.Q | 649.524 | 3 | 0 |

Although the Brant test is popularly applied to test the validity of the ordered logistic regression model, it is extremely conservative in its underlying assumptions. Therefore, it is helpful to accompany the Brant test with a more careful evaluation of the proportional odds assumption. Another method is to run binomial regression models between pairs of consecutive categories of the dependent variable to evaluate if the differences in coefficients are significant. In Table 3, the results of this test are presented as coefficients representing the difference between each pair for each period of the independent variable. It is clear that the coefficients are significantly different across categories of the dependent and independent variable, which supports the general findings from the Brant test that the model is invalid.

**Table 3:** Binomial comparison between categories of dependent variable

| IV category | Diff_AB | Diff_BC | Diff_CD | Diff_DS |
|---|---|---|---|---|
| Pre-1995 (Intercept) | -0.919 | 0.641 | -13.537 | 15.359 |
| CodeYearPre-1995 | -1.106 | -2.305 | 4.927 | -2.347 |
| CodeYear2008-2020 | 0.179 | 0.050 | 3.230 | -2.886 |

To relax the proportional odds assumption, we then ran multinomial regression models with a five-class categorical variable. The main difference between the ordered logistic model and the multinomial model is that there is no assumed order of the dependent variable. However, the sample size for certain categories, especially categories $A$ and $B$ in time periods 1995-2007 and 2008-2020, was relatively small. This made it difficult for the multinomial regression model to converge consistently in these categories.

In order to account for the small sample size in select categories, we collapsed the dependent variable into a binary outcome variable where *0* represents categories $D$ and $S$ and *1* represents categories $A$, $B$, and $C$. Categories $A$, $B$, and $C$ represent homes that are fire-resistant to at least some degree. Categories $D$ and $S$ represent homes that are not built to be fire-resistant at all.

The formal notation for the binomial regression model is presented in Equation 1 below. A binomial regression model calculates that log odds probability of an outcome from a binary variable. The right-hand side of the equation includes a set of predictor variables used to predict the log-odds probability.

$$log(\frac{\pi}{1-\pi}) = \beta_0 + \beta_1 x_1 + ...\beta_k xk \tag{1}$$

$Where:$
$\pi = probability$
$x = predictors$

Log-odds estimates are not intuitive for most audiences; therefore, results from binomial regression models are often reported in odds ratios, which are more straightforward to communicate. In Equation 2 below, the formal notation for calculating odds ratios is presented. Odds ratios represent the odds or probability that an outcome will occur given certain input parameters. Finally, we also calculated the predicted probabilities, which make a prediction based on the data that the outcome will equal one when a predictor variable increases by a unit while all other input variables are held constant at their means.

$$\theta = \frac{(\frac{\pi}{1-\pi})|x = x_1}{(\frac{\pi}{1-\pi})|x = x_2} \tag{2}$$

$Where:$
$\theta = odds\ ratio$
$\pi = probability$
$x = predictors$

# 4 Data

We evaluate the outcomes of fire-resistant class ratings for housing in California according to changes to the building code in 1995 and 2008 in California using multiple data sources; these include 1) housing data made available through Zillow, 2) socio-economic data from the US Census Bureau and election results data, and 3) GIS-derived data. The Venn diagram in Figure 2 below shows how parts of the Zillow dataset, GIS-derived variables based on intersections of homes with key perimeters of interest (e.g., WUI zones), and socioeconomic data from the US Census Bureau and election outcomes data all combine to form the full dataset used in this analysis. Not all parts of each data source overlap perfectly within one another, meaning that merging them together limits the overall number of observations to a small degree after dropping observations that do not have values for each variable to be used in the regression analysis.

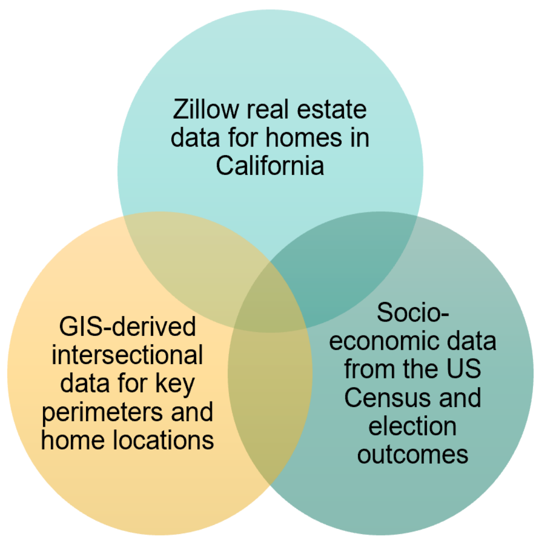


**Figure 2:** Parts of the Zillow dataset, socioeconomic data from US Census Bureau and voting outcomes from the 2020 presidential election in the US, and GIS-derived variables make up the full dataset used in this analysis.

The Zillow Transaction and Assessment Dataset (ZTRAX) is the country's largest real estate database. The ZTRAX database includes rounds from recent years, but given that we use the construction year to evaluate changes over time, we only include the latest panel as a cross-sectional sample. Within the ZTRAX database, all buildings are rated using a five-letter grading system used by California's home insurance rating system, which is outlined in Table 4. The definitions provided for each class are defined by Zillow in its provided data dictionary. We use this classification as an outcome variable to test the hypothesis that the policy changes in California starting with roofing in 1995 and then comprehensive housing requirements in 2008 have driven significantly higher fire ratings among homes built in 1995 and even higher ratings among homes built in 2008 or later. [1] To test this, we have included

[1]Note that this rating system is not a direct correlate to the changes of the building code in California. It

a main independent variable in the regression models, which is also constructed from Zillow's data, representing statewide policy absence, roofing requirements, and comprehensive housing requirements, i.e. 1) pre-1995 construction, 2) 1995-2007 construction, and 3) 2008-2020 construction.

| Building Class | |
|---|---|
| **Code** | **Description** |
| Class A | Buildings having fireproofed structural steel frames carrying all wall, floor and roof loads. Wall, floor and roof structures are built of non-combustible materials. |
| Class B | Buildings having fireproofed reinforced concrete frames carrying all wall floor and roof loads which are all non-combustible. |
| Class C | Buildings having exterior walls built of a non-combustible material such as brick, concrete, block or poured concrete. Interior partitions and roof structures are built of combustible materials. Floor may be concrete or wood frame. |
| Class D | Buildings having wood or wood and steel frames. |
| Class S | Specialized buildings that do not fit in any of the above categories. |

**Table 4:** Wildfire building code classifications used in the Zillow database

The Zillow dataset captures a large proportion of homes in California overall. However, when limiting the dataset to listed homes that have a reported year of construction (independent variable) and a reported wildfire building class (dependent variable), the dataset constricts significantly. Figure 3 below shows a narrowing of the Zillow sample size used in this analysis after restricting observations to those with construction years and wildfire building classifications. When socioeconomic variables are also merged into the dataset, this limits the data further to 1,048,149 total observations used in the final analysis.

The distribution of homes according to each outcome variable category, which in this case is each fire-resistant building class, is quite disproportionate. The majority of homes within each of the five counties represented by the Zillow data fall within the $C$ and $D$ classes. Table 5 shows the distribution of home observations across each building class category as well as the total number of homes represented in the data, the number of existing homes in each county according to 2019 Census data, and finally the percentage of existing homes that are represented by the data. A majority of homes in each county is captured in the analysis, but the Zillow database is not comprehensive. Homes that are sold directly by owners, homes that are sold at auction, or any other homes that are not included in the Multiple Listing Service (MLS) in the US are not included in Zillow's database.

is used in this study as a general indicator of the level of adoption of higher classes of fire-resistant building materials and not necessarily as a measure of proper code enforcement attached to homes meeting a certain

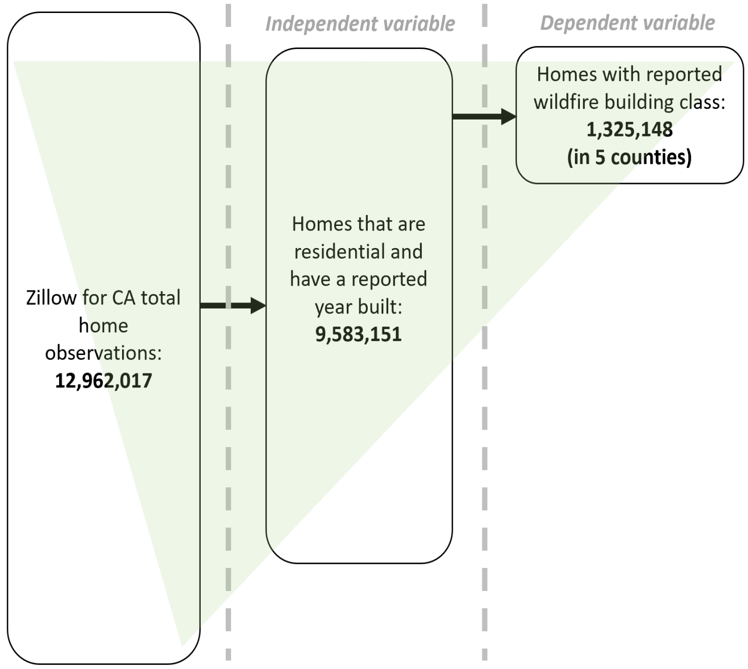


**Figure 3:** Zillow dataset sample size after restricting the sample to homes that have a reported year of construction and wildfire building class

**Table 5:** Homes observed when filtered on construction year and fire-resistant building class

| County | A | B | C | D | S | Total | Census | % |
|---|---|---|---|---|---|---|---|---|
| Alameda | 607 | 2,841 | 1,216 | 388,416 | 33 | 393,113 | 622,922 | 63% |
| Fresno | 1 | 3 | 2,374 | 232,674 | 74 | 235,126 | 336,473 | 70% |
| San Bernardino | 2 | 172 | 7,190 | 525,888 | 51 | 533,303 | 731,400 | 73% |
| Stanislaus | 2 | 1 | 1,488 | 137,555 | 39 | 139,085 | 182,978 | 76% |
| Sutter | 0 | 0 | 336 | 24,184 | 1 | 24,521 | 34,583 | 71% |
| Total | 612 | 3,017 | 12,604 | 1,308,717 | 198 | 1,325,148 | 1,908,356 | 70% |

In addition to the primary variables from the Zillow data, we also use socioeconomic data from the US Census Bureau for control variables in the regression models. This includes data on median household income, household retirement savings, percentage of the population living under the poverty line, and bachelor's degree attainment. All of these variables are aggregated at the Census tract level within counties corresponding to home observations in the Zillow data.

Political affiliation has also been associated with the adoption of progressive adaptive measures, such as using more fire-resistant home building materials. Therefore, we have also included a variable from the New York Times for the percentage of the Democratic lead within the boundary of each election precinct (within counties) during the 2020 presidential

class rating.

race. This is the most recent proxy for party affiliation (of the two dominant parties) available at a local scale in California. This variable is meant to give a general indication of party affiliation at the precinct level. Of course, political affiliation within geographic areas changes over time, but this is meant to be a general, recent indicator only.

Finally, several variables were derived using geographic perimeter data from the state of California's Department of Forestry and Fire Protection (CAL FIRE). We imported perimeter layers into QGIS for wildfires occurring within the previous 10 years, city boundaries for Firewise communities,[2] wildland urban intermix (WUI) areas, and wildland urban interface (WUI) areas.[3] Using these perimeters as polygons and homes' latitude and longitude locations as points, we were able to run intersectional geoprocessing for each perimeter layer to assign each home in the data to a dummy value (i.e. zero or one) to represent the home's location in or outside of each perimeter. The maps in Figure 4 show different polygon layers for wildland urban intermix (gold) and wildland urban interface (red) areas on the map on the left, historical wildfire perimeters (orange) dating back 10 years on the map in the center, homes located within Firewise communities (small blue triangles) on the map on the right, and homes located within counties (small brown triangles) included in the analysis (Sutter, Alameda, Stanislaus, Fresno, and San Bernardino) on the right as well.

Once all the variables were constructed, we merged all the data components together to form the full dataset. Each variable is summarized in Table 6 below. The *Class* variable is the dependent variable, which has been collapsed into a dummy variable where *0* is a combination of *D* and *S* class categories (which are not fire resistant) and *1* is a combination of *A*, *B*, or *C* classes (which all include some amount of fire-resistant materials). The rationale to collapse the categories into a binary variable will be explained in more detail in Section 3, but this generally increases the observations by outcome for regression analysis. The *CodeYear* variable is the independent variable, which is a factor variable corresponding to three time periods: 1) pre-1995, 2) 1995-2007, and 3) 2008-2020.

After the dependent and independent variables in Table 6, there are four GIS-derived dummy variables. *Fire10* is a dummy variable denoting whether a home is located in a historical wildfire perimeter from the previous 10 years. *Firewise* is a dummy variable indicating whether a home is located in a designated Firewise community. There are three cities or towns in San Bernardino county (Big Bear, Big Bear Lake, and Yucaipa) that are or were recently registered as Firewise communities according to the National Fire Protection Association. *WUI1* is a dummy variable for homes in wildland urban intermix areas, and *WUI2* is a dummy variable for homes in the wildland urban interface areas.

Finally, there are five socioeconomic variables, but not all are included in the regression models due to multicollinearity between income-related variables. *Income (ln)* is logged median household income by US Census tract. *Retirement* is logged mean household retirement savings by US Census tract. *Poverty* is the percentage living under the US poverty line by US Census tract. *Bachelors* is the percentage of bachelor's degree attainment at the US

[2]Firewise communities are those designated communities that choose to organize themselves voluntarily to be part of the National Fire Protection Association's Firewise program. This program helps communities to spread information about defensive and preparedness techniques that can be used to protect homes, individuals, and the local community from devastating effects of wildfires.

[3]Wildland urban intermix areas are where human development is adjacent or overlapping with forested areas. Wildland urban interface areas are where human development is located within forested areas.

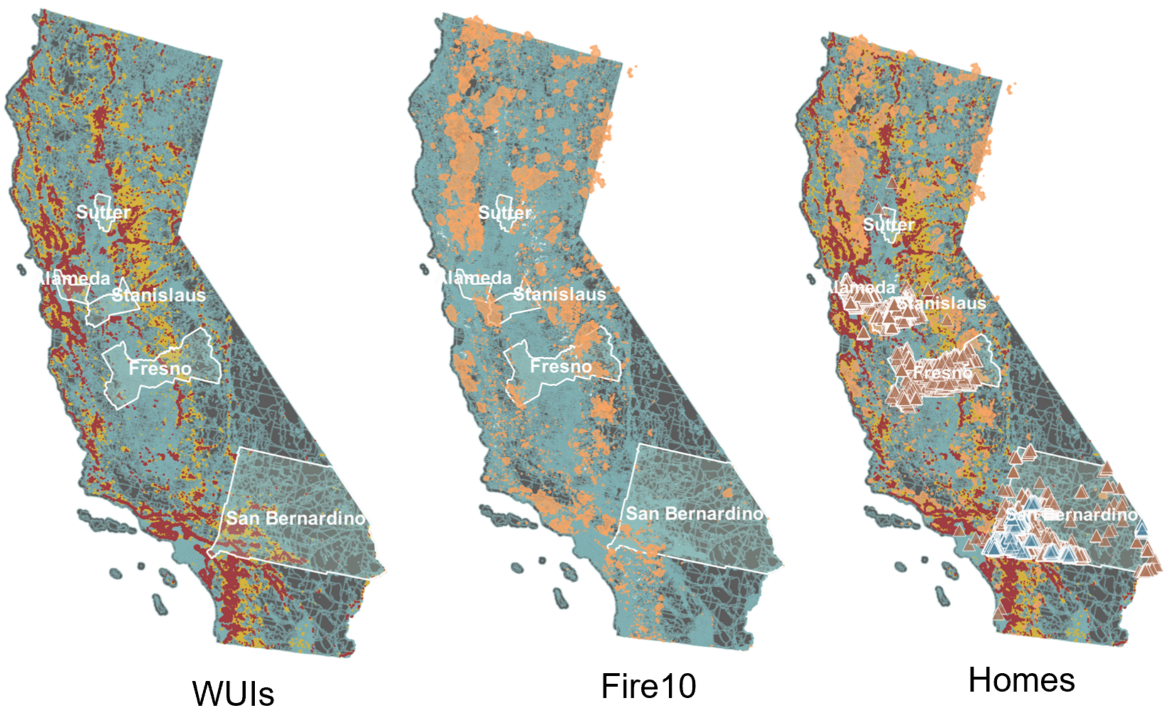


**Figure 4:** The map on the left shows wildland urban intermix areas in gold and wildland urban interface areas in red. The map in the center shows wildfire perimeters from the previous 10 years from 2020 in orange. The map on the right shows homes located within Firewise communities as blue triangles with white outlines; also shown are homes generally located within the five counties represented by the relevant Zillow data. These five counties are outlined and labeled in white in each map. The base layer (gray and turquoise is simply an administrative boundaries layer.)

Census tract level. All US Census variables are taken from the 2019 estimates of the latest American Community Survey (ACS), which we have accessed using the *tidycensus package* in R. The ACS is conducted annually by the US Census Bureau among a sample of the US population. Finally, *Democrats* is a variable indicating the percentage Democratic party lead during the 2020 US presidential election aggregated at the election precinct level. This variable is reported by The Upshot at the New York Times and is noted to be accurately tabulated for California. This variable can range from -100 to 100% because it indicates the Democratic lead, which could be negative.

**Table 6:** Summary statistics of full dataset

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Class | 1,047,739 | 0.013 | 0.113 | 0 | 0 | 0 | 1 |
| CodeYear | 1,047,739 | 1.340 | 0.717 | 1 | 1 | 1 | 3 |
| Fire10 | 1,047,739 | 0.001 | 0.032 | 0 | 0 | 0 | 1 |
| Firewise | 1,047,739 | 0.016 | 0.127 | 0 | 0 | 0 | 1 |
| WUI1 | 1,047,739 | 0.055 | 0.229 | 0 | 0 | 0 | 1 |
| WUI2 | 1,047,739 | 0.289 | 0.454 | 0 | 0 | 1 | 1 |
| Income (ln) | 1,047,739 | 11.059 | 0.493 | 9.304 | 10.711 | 11.420 | 12.287 |
| Retirement (ln) | 1,047,739 | 16.716 | 6.736 | 0.530 | 11.650 | 21.160 | 39.040 |
| Poverty (%) | 1,047,739 | 15.963 | 12.451 | 0.870 | 6.100 | 22.920 | 67.270 |
| Bachelors (%) | 1,047,739 | 18.358 | 10.704 | 0.467 | 9.190 | 26.681 | 45.416 |
| Democrats (%) | 1,047,739 | 28.958 | 35.188 | −100.000 | 1.200 | 51.800 | 100.000 |

Most of the variables in the dataset are relatively independent from each other. However, there is multicollinearity between income-related variables, which is shown in the matrix in Figure 5. Median household income and bachelor's degree attainment are strongly and positively correlated (0.8). Poverty and income are strongly and inversely correlated, as are poverty and bachelor's degree attainment. To reduce multicollinearity in the regression models while still including the most relevant variables, we use a stepwise approach to introduce different variables, as is explained in more detail in Section 3.

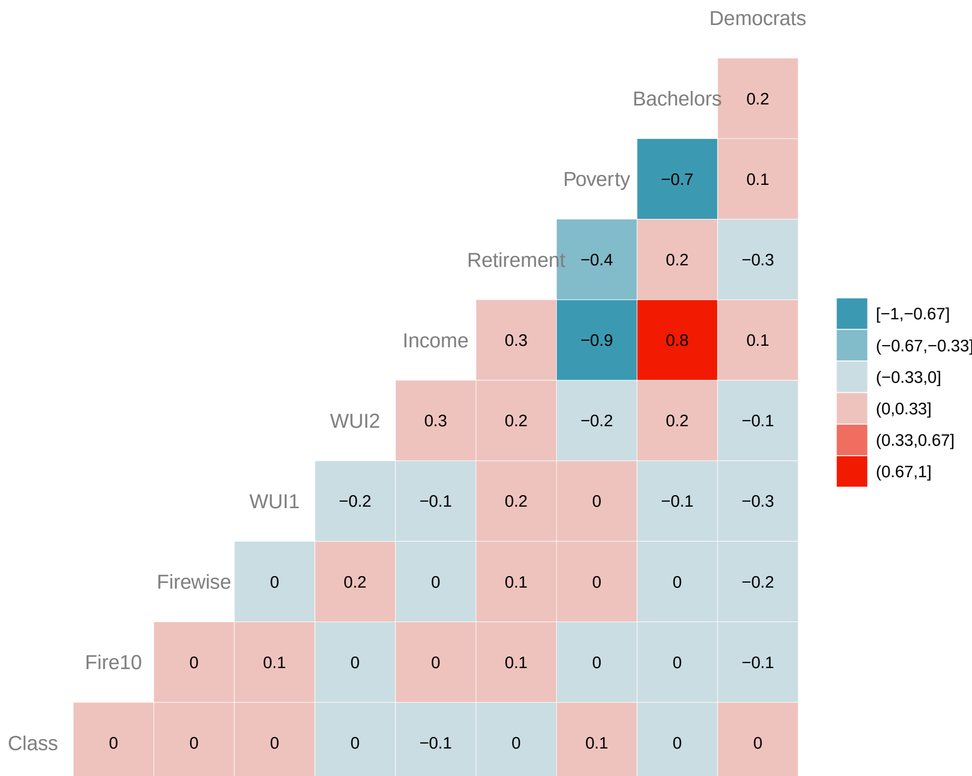


**Figure 5:** Correlation matrix of all variables in the full dataset (Note: Pearson correlation coefficient reported)

# 5 Results

As discussed in detail in Section 3, we rely mainly on binomial regression models and additional measures of probability for the interpretation of results here. We first ran a basic binomial regression with the binary dependent variable of fire-resistant building class and the main independent variable with three factored categories for the pre-1995, 1995-2007, and 2008-2020 time periods corresponding to building code changes. Second, we included socioeconomic covariates in the model. Third, we we included GIS-derived spatial variables in the model, and finally, we included a full combination of spatial and socioeconomic variables in the model. The results are presented in Table 7 below.

The results shown in Table 7 are presented as log-odds, which are simply the logged odds of an outcome of *1* occurring given a one unit increase in each predictor variable while other predictor variables are held constant. The full model on the far right of Table 7 is the preferred model because it has the highest log likelihood and lowest Akaike Information Criterion (AIC). We have also conducted a Wald test on the preferred model, which reports that the model is valid with a p-value of 0.

According to the preferred model, a home built after 2008 has a 0.26 log-odds of being classified as *A*, *B*, or *C* as opposed to being classified as *D* or *S*. This is compared to the reference period of homes built before 1995. In contrast, a home built between 1995 and 2007 has a -1.27 log odds of being classified as a fire-resistant home compared to the reference period of homes built before 1995. The coefficients from each of the binomial regression models are also displayed in the graph in Figure 6.

Each model from the binomial regressions is shown as a different color in Figure 6. The preferred model is displayed in green and is labeled "binom1." The figure shows the relative magnitude of the coefficients and how each predictor performs across models. It is evident from looking at the figure that the dummy variable "Fire10" has a particularly large standard error range. This suggests less precision in this predictor's impact on the outcome variable, which also corresponds the variable's insignificant p-value in the preferred model since it is not significantly different than zero. All other variables in the preferred model are highly significant in helping to predict the outcome.

For binomial logistic regression models, log-odds are generated automatically, but these estimates are not necessarily intuitive for audiences to readily understand. Therefore, we have converted the outcomes from the preferred full model to odds ratios in Table 8. Confidence intervals at the 95% confidence level are also presented to the right of the odds ratios in the table. The odds ratio can simply be interpreted as the odds of an event occurring versus the odds of it not occurring. For example, according to the outcomes from the preferred model, a home built in between 2008-2020 is 1.29 times more likely to be fire-resistant. A home built between 1995-2007 is 0.28 times *less* likely to be fire-resistant (due to the negative sign on the regression coefficient). The interpretation of covariates is similar, but this changes according to units. For example, for each log-level increase in median household income, a home is 0.1 times less likely to be fire-resistant. As bachelor's attainment increases by a percentage point, a home is 1.07 times more likely to be fire-resistant. If a home is located in a Firewise community, it is 1.62 times more likely to be fire-resistant.

Results can also be visualized by graphing the predicted probabilities of an event occurring based on the distribution of one covariate while holding all other variables at their means.

**Table 7:** Binomial regression results

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Fire-resistant building class (binary) | | | |
| | (Base) | (Socioeconomic) | (Spatial) | (Full) |
| Code Year 2008-2020 | $-0.267^{***}$ | $0.274^{***}$ | $-0.346^{***}$ | $0.255^{***}$ |
| | (0.036) | (0.038) | (0.036) | (0.038) |
| Code Year 1995-2007 | $-1.931^{***}$ | $-1.240^{***}$ | $-1.923^{***}$ | $-1.266^{***}$ |
| | (0.046) | (0.047) | (0.046) | (0.047) |
| Median hh income (ln) | | $-2.332^{***}$ | | $-2.265^{***}$ |
| | | (0.024) | | (0.024) |
| Bachelor's attainment (%) | | $0.071^{***}$ | | $0.070^{***}$ |
| | | (0.001) | | (0.001) |
| Democratic lead 2020 (%) | | $-0.001^{***}$ | | $0.001^{***}$ |
| | | (0.0003) | | (0.0003) |
| Firewise | | | $0.547^{***}$ | $0.480^{***}$ |
| | | | (0.062) | (0.067) |
| Fire10 | | | $-0.426^{*}$ | $-0.058$ |
| | | | (0.246) | (0.254) |
| WUI1 | | | $0.680^{***}$ | $0.881^{***}$ |
| | | | (0.027) | (0.034) |
| WUI2 | | | $-0.665^{***}$ | $-0.236^{***}$ |
| | | | (0.023) | (0.026) |
| Constant | $-4.211^{***}$ | $19.983^{***}$ | $-4.128^{***}$ | $19.164^{***}$ |
| | (0.008) | (0.242) | (0.009) | (0.246) |
| Observations | 1,325,148 | 1,048,149 | 1,325,148 | 1,048,149 |
| Log Likelihood | −85,884.020 | −66,783.760 | −84,981.580 | −66,346.420 |
| Akaike Inf. Crit. | 171,774.000 | 133,579.500 | 169,977.200 | 132,712.800 |
| *Note:* | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |


**Figure 6:** Coefficients of the preferred, full model are shown in green and labeled as "binom1." Coefficients of the spatial model are shown in orange and labeled as "binom2." Coefficients of the socioeconomic model are shown in light blue and are labeled as "binom3." Coefficients of the base model are shown in red and are labeled as "binom4."

**Table 8:** Odds ratios of preferred binomial regression model coefficients

| | Coefficients | OR | 2.5 % | 97.5 % |
|---|---|---|---|---|
| Code Year 2008-2020 | 0.255 | 1.290 | 0.180 | 0.328 |
| Code Year 1995-2007 | -1.266 | 0.282 | -1.359 | -1.175 |
| Median hh income (ln) | -2.265 | 0.104 | -2.312 | -2.218 |
| Bachelor's attainment (%) | 0.070 | 1.072 | 0.067 | 0.072 |
| Democratic lead (%) | 0.001 | 1.001 | 0.0004 | 0.002 |
| Firewise | 0.480 | 1.616 | 0.346 | 0.610 |
| Fire10 | -0.058 | 0.943 | -0.598 | 0.404 |
| WUI1 | 0.881 | 2.413 | 0.815 | 0.946 |
| WUI2 | -0.236 | 0.790 | -0.287 | -0.186 |

Two predicted probabilities graphs for median household income and wildland urban intermix are presented below as example, while the remaining graphs of predicted probabilities are presented in Section 8. Each can be interpreted conceptually in a similar way to the odds ratios. For instance, in Figure 7, as the log level of median household income increases, it is predicted that a home is less likely to be classified as fire-resistant. In Figure 8, as the percentage of bachelor's degree attainment increases in a Census tract area, homes in that area are predicted to be more likely to be fire-resistant, though the margin of probability is relatively moderate. If a home is located in a Firewise community, it is predicted that the home is somewhat more likely to be classified as fire-resistant.

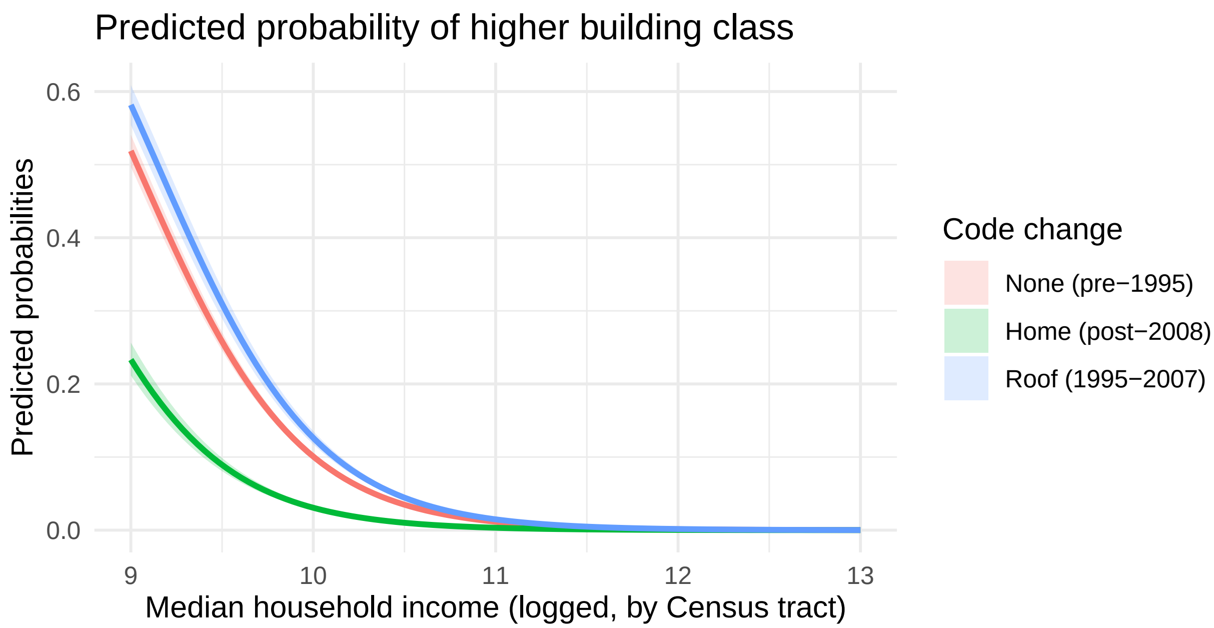


**Figure 7**

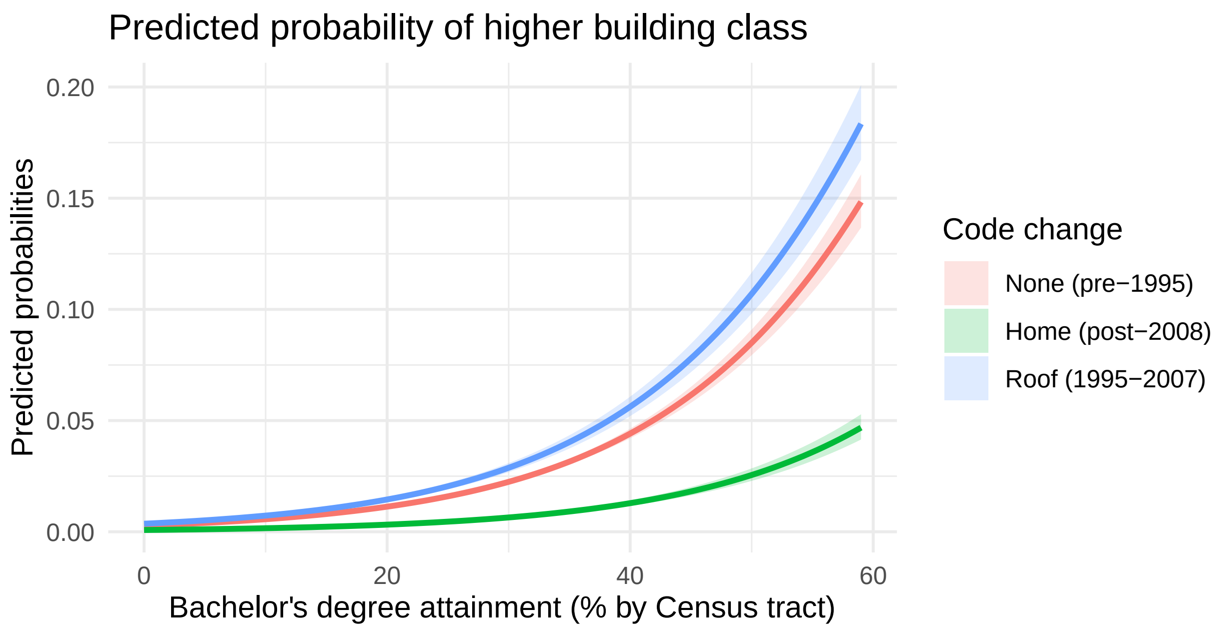


**Figure 8**

# 6 Discussion

We present the results here to lend empirical evidence using multivariate regression analysis methods to establish a better understanding of the relationship between California's building code changes in 1995 and 2008 and general public adoption of higher levels of fire-resistant building materials. Our analysis also focuses on secondary relationships between spatial and socioeconomic characteristics and the outcome of higher levels of fire-resistant building materials across 1,048,149 homes in the five counties included in this study. It appears that, at least for the homes represented in the data used here, the code change in 2008 is positively and significantly associated with higher levels of fire-resistant building classes. The opposite is true of the code change in 1995, but it is also important to note that a home could have a fire-resistant roof (which can have a positive impact on reducing the chances of property destruction during wildfire) and not be included in the higher-level classes of $A$, $B$, or $C$. So perhaps it is unsurprising that roofing-only building code change in 1995 does not appear to have much of an effect on the overall rating of the building class, but this is again descriptive and only representative of the data available within the five California counties of Alameda, Fresno, San Bernardino, Stanislaus, and Sutter.

Some of the covariate results were surprising based on previous findings in the literature. For instance, relatively recent experience with wildfire has been shown to be a major predictor of the adoption of fire-safe practices and adaptive behaviors [Haines et al., 2008, Paveglio et al., 2015]. However, in this study, previous experience with wildfire in the past 10 years does not appear to be significantly associated with the adoption of higher-level building materials. It could be that this experience does have an acute effect on specific households, but this effect may not apply largely to a broad swath of a population. The adaptive capacity or broader local context of different geographic areas can vary widely and affect a community's ability to rebuild effectively in the aftermath of disaster [Kolden and Henson, 2019, Paveglio et al., 2016].

Another surprising and perhaps counterintuitive result is that median household income is inversely related to higher levels fire-resistant building classes. It is possible that this could be due to a higher propensity for risk-taking among wealthier households. Threats from natural hazards and disasters may be perceived differently among households at different income levels [Kolden and Henson, 2019]. It could also be possible that some of these homes are seasonal or secondary homes of wealthier owners who are less interested in preparedness for their additional properties. Other researchers have made conflicting findings regarding income showing, for instance, that households with higher incomes exhibit preferences for fire-safe landscaping around the home more frequently than lower-income households [Wolters et al., 2017]. As Muller and Schulte [2011] points out, wealthier communities have greater tendencies for adaptive behaviors and creating programs at the community level to promote resilience. The direct impact of income on the adaptive behaviors of homeowners is less than straightforward, however, and may be as dependent on local context or even idiosyncratic individual behavior and preferences as other correlates of mitigation actions. Inconsistent findings of the direction of correlation, or any correlation at all, between income and fire-safe mitigation behaviors are cited by Paveglio et al. [2016] and Brenkert-Smith et al. [2012].

Other socioeconomic covariates for political affiliation and educational attainment (measured by bachelor's degree attainment) both have positive and significant associations with higher levels of fire-resistant building classes. Both variables increase the likelihood that a home will be classified as $A$, $B$, or $C$ by slightly more than a factor of one. The positive correlational effect observed here is consistent with several studies' findings [Muller and Schulte, 2011, Ergibi and Hesseln, 2020], but education specifically has been shown to have an enhanced effect when it refers specifically to specialized education or knowledge of mitigation techniques and home resilience to hazards [Brenkert-Smith et al., 2012].

Finally, homes located within key perimeters for Firewise communities, wildland urban intermix, and wildland urban interface areas were all shown to have strong effect sizes. Homes in Firewise communities and intermix areas are strongly and positively associated with higher levels of fire-resistant building classes. Communities that have already adopted adaptive programs and actions, such as the Firewise community program, are likely conducting more outreach and education to promote resilient behaviors and home construction methods [Wolters et al., 2017, Paveglio et al., 2016, Mockrin et al., 2018]. Homes in intermix areas may be more likely to be associated with higher levels of fire-resistant building classes because there may be more enforcement of building codes in these areas since they are highly fire-prone, or people who move to these areas may exhibit other qualities beyond the scope of this study that cause them to be predisposed to taking protective measures. It is uncertain why the associations of intermix and interface areas are opposite from each other. Interface areas are some most heavily wooded areas, and so this level of isolation may select for a certain type of resident with a higher risk-taking preference or higher income.

# 7 Conclusion

In this study, we have constructed a novel dataset by conducting geospatial data processing to create completely new data, collecting socioeconomic indicators, and finally merging these variables with real estate data from the largest real estate database in the US. We have used this dataset to derive empirical findings between major building code changes in California in 1995 (requirement for fire-resistant roofing) and 2008 (requirement for certain fire-resistant building materials in SRAs and certain LRAs). We have also examined the relationships between higher-level fire-resistant building class outcomes and spatial and socioeconomic covariates that are found in much of the literature studying the determinants of adoption of adaptive or mitigating behaviors in fire-prone areas.

The results presented here suggest that the building code change in 2008 may have had a broader impact in encouraging the adoption of higher-level fire-resistant home construction materials than the building code change for roofing in 1995. However, these results are not causal and would benefit from causal examination to infer more precisely the impact and spillover effects of the 2008 building code change. Other factors undoubtedly play a role in home resilience strategies, including local incentives or subsidies, local political framing of wildfire adaptation, the cost and supply of fire-resistant materials and ease of their incorporation into building plans, risk perceptions and awareness, etc. Covariate interactions with these policy changes may also help to explain differences in community resilience and wildfire preparedness.

For researchers, there is a need for future work on this topic to study the behavioral and communal characteristics for greater adoption and perhaps mechanisms to target incentives and subsidies for home design and home retrofits in fire-prone areas. Additional causal work across different geographic areas that demonstrates the direct causal impacts and spillover effects of different types of wildfire resilience policies as well as voluntary resilience and mitigation efforts would be valuable moving forward. For policymakers, these results highlight gaps between public policy and meaningful community resilience measures to protect the public, property, and the local environment from worsening wildfire hazards. Over a quarter of homes in the five counties represented in this dataset are located in one of the most fire-prone areas - wildland urban interface areas - and yet, even for homes built after the building code change in 2008, there is an inverse relationship for homes located in these areas and home construction using fire-resistant materials. A more coordinated policy framework for implementation and enforcement of codes across local and state jurisdictions will be needed to effectively build community resilience to the imminent and growing threat of wildfires in California in the coming decades.

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# 8 Appendix

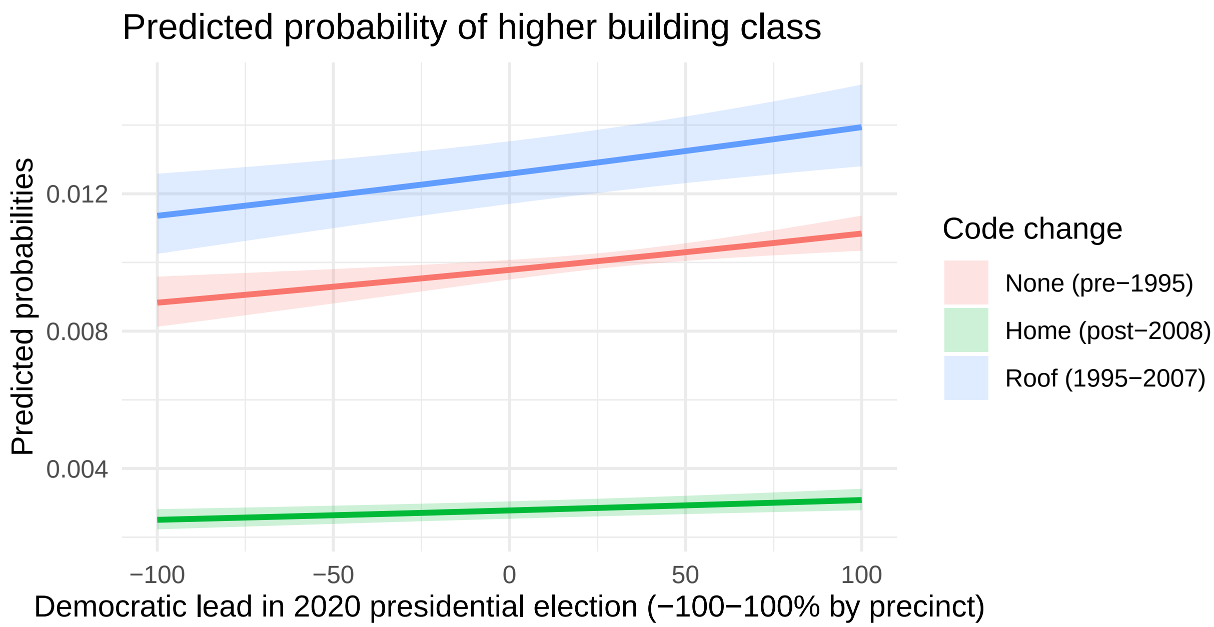


**Figure 9**

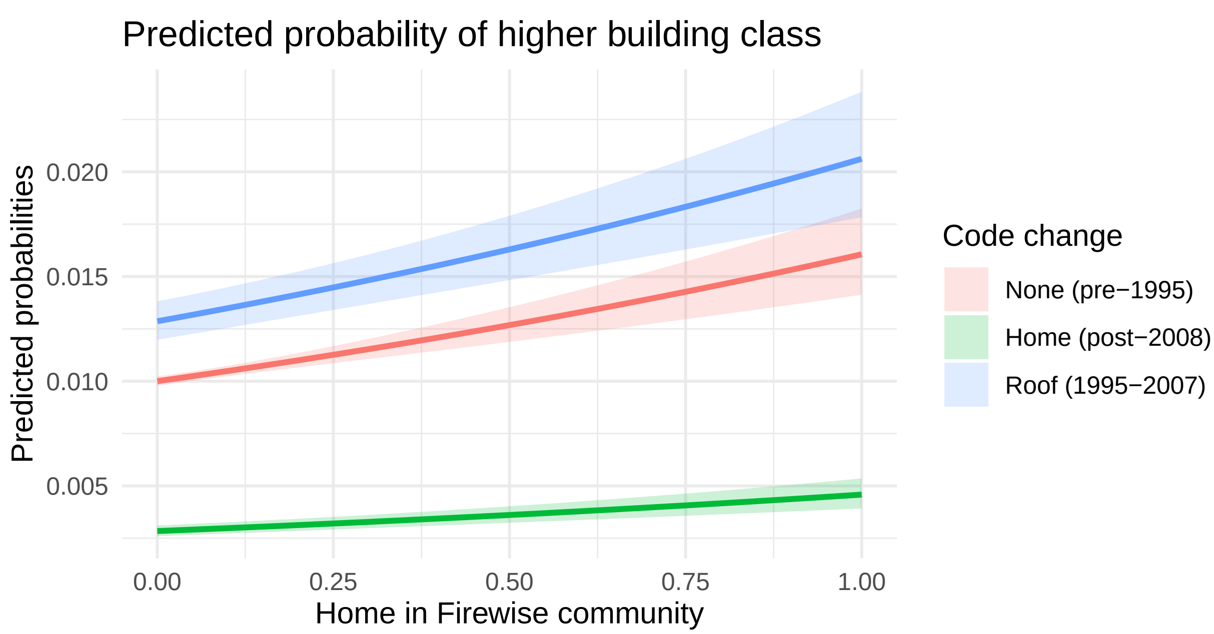


**Figure 10**

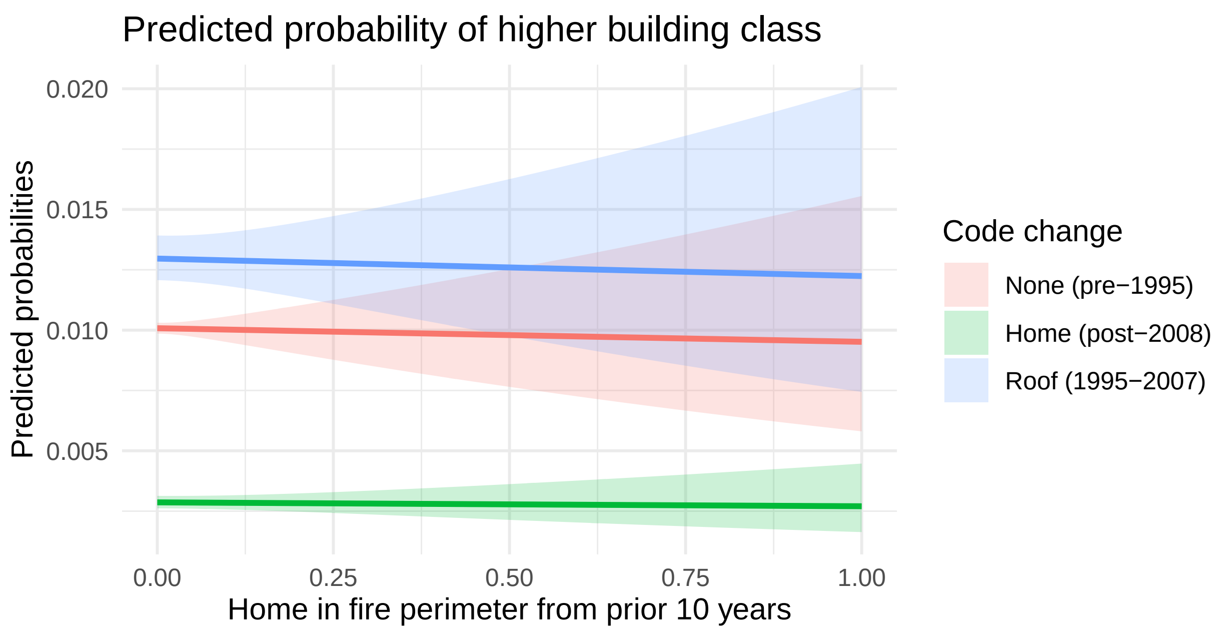


**Figure 11**

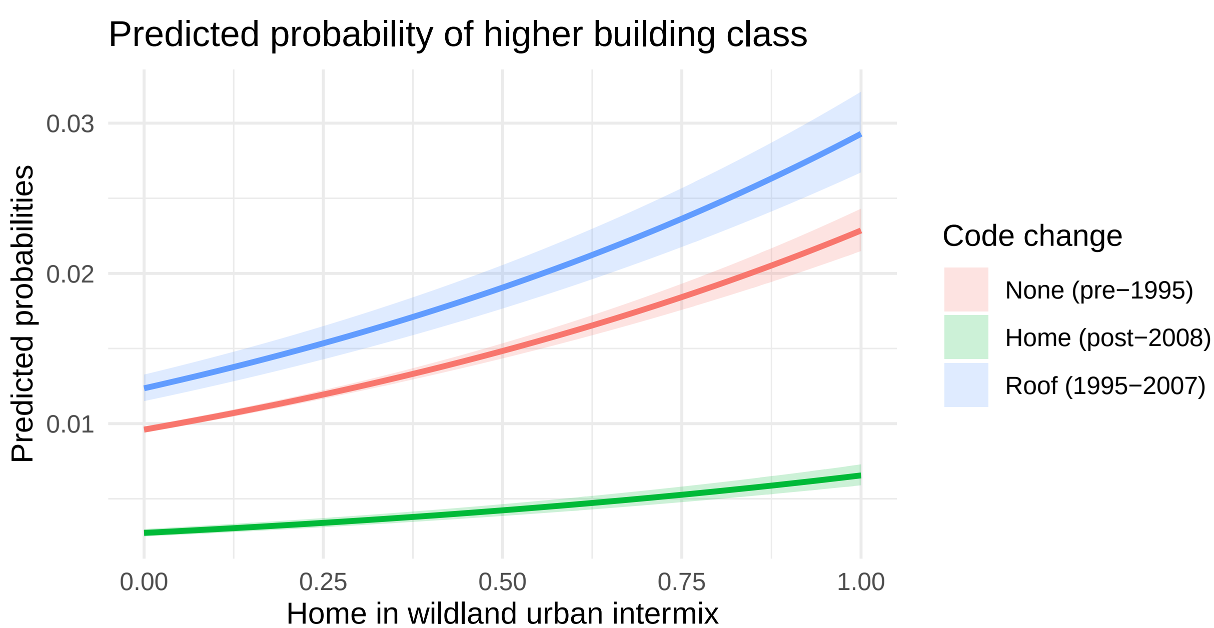


**Figure 12**

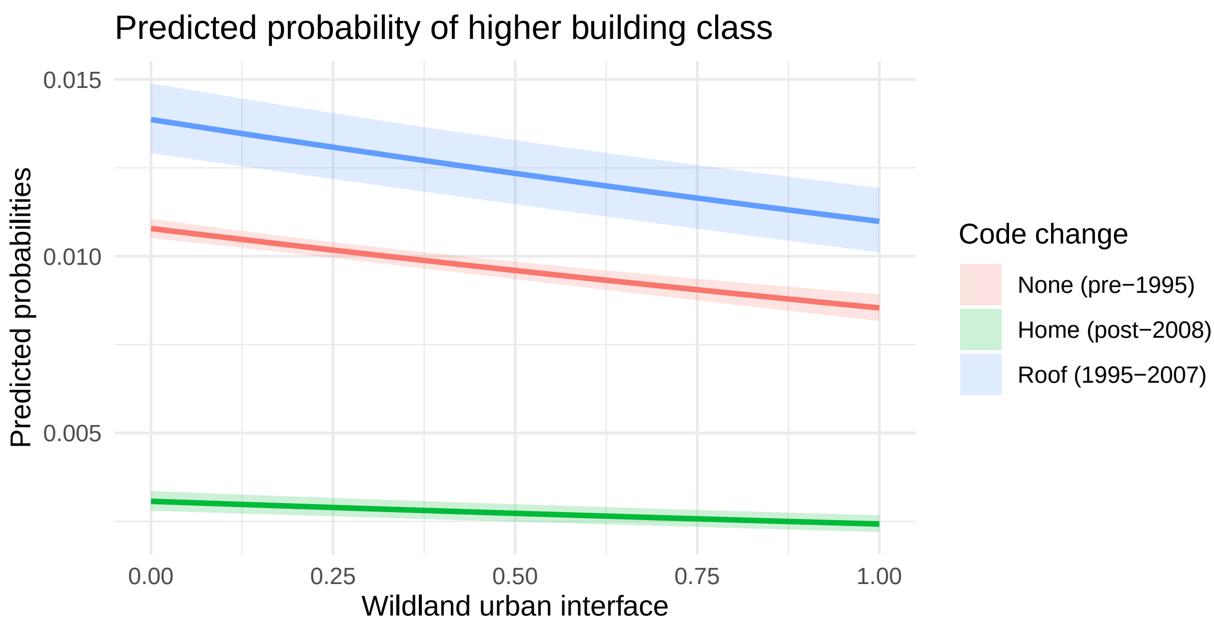
Predicted probability of higher building class
0.015
0.010
0.005
Predicted probabilities
0.00
0.25
0.50
0.75
1.00
Wildland urban interface
Code change
None (pre−1995)
Home (post−2008)
Roof (1995−2007)

**Figure 13**