Mandated vs. Voluntary Adaptation to Natural Disasters: The Case of U.S. Wildfires

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Despite escalating disaster losses and predicted increases in weather-related catastrophes, takeup of protective technologies and behaviors appears limited by myopia, externalities, and other factors. One response to such frictions is to mandate adaptive investment. We measure the effect of California's wildfire building codes on own- and neighboring structure survival using administrative damage and assessment data for most US homes experiencing wildfires since 2000. Differences across jurisdictions and vintages reveal remarkable resilience effects of building codes initially prompted by the deadly 1991 Oakland Firestorm. Codes also benefit neighbors. We use the results to estimate net social benefits of wildfire building standards.

JEL Codes: Q54, Q58, H23, H12, K32

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Worldwide natural disaster losses averaged $218 billion per year during 2016–2020, a 60% increase in real terms over the preceding 30 years.[1] This trend is predicted to accelerate under future climate change. Efficient investment in adaptation is essential in the face of these escalating risks. Yet takeup of protective technologies and behaviors appears to be hindered by a constellation of market frictions. Homeowners misperceive disaster risks and thus the value of protective investments (Hallstrom and Smith 2005; Donovan, Champ, and Butry 2007; Gallagher 2014; McCoy and Walsh 2018; Bakkensen and Barrage, Forthcoming). Monitoring costs and other insurance market imperfections mean that mitigation behaviors may not be accurately reflected in property insurance prices (Kunreuther and Michel-Kerjan 2011; California Department of Insurance 2018; Wagner, Forthcoming). Public disaster spending programs may reduce private incentives for property protection (Kousky, Luttmer, and Zeckhauser 2006; Deryugina 2017; Baylis and Boomhower 2019). And in some settings, spatial externalities across neighboring properties lead to diverging private and social benefits of mitigation (Shafran 2008; Costello, Quérou, and Tomini 2017).

One widely-adopted approach to these market failures is to provide information and subsidies to increase voluntary takeup.[2] A more controversial but increasingly common alternative is to *mandate* investments in resilience.[3] Mandatory standards ensure wider adoption. However, if the regulator misjudges the effectiveness of the required actions, the level of the hazard, or individual risk

1. Loss data are from Munich RE and are in 2020 dollars.

2. Examples in the U.S. include the Ready campaign and Ready.gov website; the Community Rating System under the National Flood Insurance Program; the StormReady, Hurricane Protection Week, and National Tsunami Hazard Mitigation programs; the Firewise USA program; and the Community Wildfire Protection Plan program.

3. Florida has construction standards for hurricane winds, and codes also exist in various regions for winter storms and non-weather disasters such as earthquakes and tsunamis (Federal Emergency Management Agency 2020). In flood-prone areas, U.S. federal rules require homes to be elevated and some localities have imposed even stricter requirements. California, Utah, Nevada, and Pennsylvania have statewide wildfire building standards while in other states, notably Colorado, wildfire codes have been adopted at the local level (Insurance Institute for Business and Home Safety 2019). Australia, New Zealand, France, and Italy also have wildfire building codes (Intini et al. 2020).

preferences, some individuals may be compelled to make costly investments they would have preferred to avoid even if fully informed and fully accountable. Implementing mandatory standards is also more politically challenging.[4] Despite the important differences between these instruments, there is little empirical evidence about outcomes under a mandated resilience regime compared to a counterfactual of purely voluntary takeup.

In this paper, we consider the case of wildfire building codes in California. California has suffered over $40 billion dollars in wildfire property damages in the past 5 years. The state also has among the strictest wildfire building codes in the world. We provide the first comprehensive evaluation of the effect of these codes on own-structure survival as well as neighbor spillovers via structure to structure fire spread. We then embed these empirical estimates in an economic model to calculate net social benefits of wildfire building codes as a function of local wildfire hazard and number of close neighbors.

This analysis takes advantage of a new dataset that includes property-level data for almost all U.S. homes exposed to wildfire between 2000 and 2020. We compiled the data by requesting post-incident damage censuses from numerous emergency management agencies and individual county assessors. We merged these lists of damaged homes to assessor data for the universe of (destroyed and surviving) homes inside wildfire burn areas. The data show that even during catastrophic wildfires, more than 50% of exposed homes survive. One of the key advantages of the new data is the ability to observe and learn from these surviving homes. The property-level loss information also distinguishes the wildfire data from floods and other disasters where loss data are typically available at the zip code or Census tract level. In addition to the new loss data, the empirical work also leverages emerging tools in spatial analysis, including high-resolution aerial imagery and precise "rooftop" geocoding of structure locations.

The empirical design leverages rich variation in building code requirements

4. For example, efforts to adopt statewide wildfire building standards in Oregon and Colorado have failed politically (Sommer 2020).

across space and over time. The complex nature of building regulation in California creates a patchwork of wildfire standards across localities. We also observe fires in other states that do not have wildfire building codes. In all of these places, we observe homes built before and after changes in California's codes. This identifying variation yields credible counterfactual predictions for how homes would have performed in the absence of California's standards. Our preferred statistical model is a fixed effects regression that compares the likelihood of survival for homes of different vintages on the same residential street during the same wildfire event. These street fixed effects allow us to compare groups of homes that experience essentially identical wildfire exposures.

We find remarkable vintage effects for California homes subject to the state's wildfire standards. A 2008 or newer home is about 16 percentage points (40%) less likely to be destroyed than a 1990 home experiencing an identical wildfire exposure. There is strong evidence that these effects are due to state and local building code changes - first after the deadly 1991 Oakland Firestorm, and again with the strengthening of wildfire codes in 2008. The observed vintage effects are highly nonlinear, appearing immediately for homes built after building code changes. There are no similar effects in areas of California not subject to these codes or in other states that lack wildfire codes.

We also find that code-induced mitigation benefits neighboring homes, consistent with reduced structure-to-structure spread. These neighbor effects are in keeping with anecdotal reports of home-to-home spread as a factor in urban conflagrations (Cohen 2000; Cohen and Stratton 2008; Cohen 2010).[5] Our results imply that, all else equal, code-induced mitigation by a neighbor located less than 10 meters away (within the distance fire experts refer to as the home ignition zone) reduces a home's likelihood of destruction during a wildfire by about 2.5 percentage points (6%). This benefit is even larger when homes have multiple close neighbors.

5. We are also aware of at least one insurance company which will not sell homeowners insurance to homes located next to a home with a wood roof in high-risk areas (Allstate Indemnity Company 2018).

Finally, we embed our estimates of building code benefits in an economic model and calculate the approximate net social benefits of such a policy for a random sample of California homes in wildfire hazard areas. Like other disaster risks, many homeowners are only partially insured (or in the extreme, wholly uninsured) against the full cost of replacing a structure destroyed by wildfire (Klein 2018; California Department of Insurance 2018). This means that the benefits of building codes include not only reductions in expected losses but also additional insurance value due to reduced household exposure to uninsured risk. Our calculations find that wildfire building codes deliver unambiguously positive benefits in the most fire-prone areas of the state, especially where homes are clustered closely together and thus create large risk spillovers. In areas with more moderate wildfire risk, building standards for new homes can also be justified given reasonable assumptions about household risk aversion, future increases in wildfire hazard, and/or co-benefits of building codes (such as reductions in public expenditures on wildland firefighting). On the other hand, the costs of retrofitting existing homes to meet current wildfire building standards are substantial and our analysis suggest full retrofits are only economic in areas with extreme wildfire hazard.

These results are broadly relevant to natural disaster management. In this important setting, a standards-based approach achieved substantially greater compliance with risk mitigation practices. The policy nearly halves loss risk when structures are exposed to the hazard. Moreover, a cost-benefit calculation implies that low takeup in the absence of standards is likely driven by market failures as opposed to a lack of cost-effectiveness. These facts can inform policies to mitigate other risks like floods, hurricanes, tornadoes, and heat waves, where voluntary takeup of adaptation investments also appears to be limited.

This work also has immediate implications for wildfire policy. Our results imply there are gains to be realized from strengthening building codes in other states and countries to match California's. This evidence is relevant to current proposals in Oregon, Washington, and other states.[6] Meanwhile, California is moving to expand the geographic coverage of designated wildfire hazard zones and reduce the ability of local jurisdictions to opt out of recommended standards.[7] Separately, new California legislation from 2020 provides financial incentives for retrofits of existing homes in wildfire-prone areas.[8] The law specifically calls for support of "cost effective" retrofits, a concept for which the evidence in this study is essential. Additionally, policymakers are confronting pressing issues of insurance rate reform in response to mounting wildfire losses. One key debate is the degree to which individual investments improve structure survival and should thus be rewarded through regulated insurance discounts (California Department of Insurance 2018). This paper's evidence on the effectiveness of such investments during real wildfires bears directly on this question.

Our work builds on previous studies of natural hazard mitigation. For wildfires, a number of engineering and forestry studies describe the effects of construction materials and vegetation management on structure resilience (Gibbons et al. 2012; Syphard et al. 2012; Syphard, Brennan, and Keeley 2014; Alexandre et al. 2016; Syphard, Brennan, and Keeley 2017; Kramer et al. 2018; Syphard and Keeley 2019). Our paper focuses on the effects of a mandatory mitigation policy, while these previous studies measure technology effectiveness (i.e., survival of homes whose owners did vs. did not choose to take mitigation measures). Two studies on the related topic of hurricanes do consider building codes, with conflicting results. Dehring and Halek (2013) is a small case study of several hundred homes during Hurricane Charley in 2004. Simmons, Czajkowski, and Done (2018) study aggregate zip-code level data on annual insurance claims by homes built in different decades to infer benefits of hurricane building codes in Florida. In contrast, our study uses highly

6. See, e.g., Profita, Cassandra. "The Labor Day Fires Burned Towns and Homes. Oregon Has a Plan to Avoid a Repeat." Oregon Public Broadcasting, September 7, 2021.

7. S.B. 63, 2021–2022, California. https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=202120220SB63.

8. A.B. 38, 2019–2020, California. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201920200AB38.

granular property- and event-level loss data for a large sample of wildfires covering several states. Across a range of natural hazards, a parallel engineering literature attempts to calculate the value of building codes through modeling and simulation (e.g. Federal Emergency Management Agency 2020). Finally, our work is methodologically related to a separate literature in economics on building codes and household energy consumption (Jacobsen and Kotchen 2013; Levinson 2016).

This study makes five contributions. First, we provide the first comprehensive evaluation of the effects of wildfire building codes on structure survival. Beyond the wildfire context, this result improves our understanding of disaster resilience under standards-based vs. voluntary policies. Second, we provide the first empirical estimates of the spillover benefits of wildfire mitigation investments to neighboring properties. Third, we compile a comprehensive dataset of structure-level outcomes in wildfires across several states that, to our knowledge, is the most complete accounting in existence. This new dataset will enable future work on the economics of catastrophic wildfire risk. Fourth, we approach the topic in a causal framework with an explicit empirical design, where previous work is primarily descriptive or relies on regression adjustment. Finally, we embed the empirical estimates in an economic model to calculate net social benefits that account for local hazard, neighbor externalities, and household risk aversion.

The rest of the paper proceeds as follows. Section 1 discusses structure survival in wildfires and California's history of building code updates. Section 2 describes the data and spatial analysis. Section 3 outlines the empirical strategy, and Section 4 presents the results. Section 5 develops the model of net social benefits and Section 6 concludes.

1 Wildfire Building Codes in California and Other States

> *"Unlike a flash flood or an avalanche, in which a mass engulfs objects in its path, fire spreads because the requirements for com-*

> *bustion are satisfied at locations along the path... A wildland fire cannot spread to homes unless the homes and their adjacent surroundings meet those combustion requirements."* Jack D. Cohen, *Journal of Forestry*, 2000.

Established forestry and engineering evidence supports the importance of the so-called home ignition zone in determining structure resilience to wildfires. The home ignition zone includes the design of the home itself as well as an imagined area extending 30 meters away from the structure. Fire scientists emphasize the elimination of flammable materials inside this zone (e.g., Cohen 2000, 2010; Calkin et al. 2014). This guidance applies to both vegetation around the home ("defensible space") and the construction of the home itself, especially the roof.

Among U.S. states, California has gone the furthest in mandating takeup of wildfire resilience investments by property owners. However, the application of these codes varies throughout the state. In areas where CAL FIRE provides firefighting services (State Responsibility Area or SRA), the state directly determines building standards. Within incorporated cities and other areas with their own fire departments (Local Responsibility Area or LRA), local governments have historically had greater control over code requirements.

The development of the modern standards began with the Oakland Hills Firestorm of 1991, which killed 25 people and caused $1.5 billion in property damage. The tragedy led to a series of legislative actions during the mid-1990s that required more fire-resistant roofing and maintenance of vegetation immediately adjacent to the home. The first of these was the so-called Bates Bill of 1992 (Assembly Bill 337). Among other changes, the Bates Bill encouraged stronger building standards in LRA areas by requiring CAL FIRE to produce maps of recommended Very High Fire Hazard Severity Zones (VHFHSZ). In LRA areas, local governments could then choose whether or not to adopt these recommended hazard maps (and thus the accompanying building standards). This designation process unfolded over several years, with hundreds of local governments adopting or rejecting CAL FIRE's proposed VHFHSZ maps at different times. According to Troy 2007, 151 of 208 local governments (73%) either adopted the VHFHSZ regulations or claimed to have promulgated equally strong existing rules.[9]

On the heels of the Bates Bill, Assembly Bill 3819 of 1994 increased requirements for ignition-resistant roofs. These requirements applied in all SRA areas and in the subset of LRA areas where local governments had adopted recommended VHFHSZs. Roofing materials are rated Class A, B, C, or unrated.[10] Starting in 1995, the law required Class B roofs on newly-constructed or reroofed homes in regulated areas. In 1997, the requirement increased to Class A roofs in high-hazard areas (a substantial improvement in fire resistance). Finally, Assembly Bill 423 in 1999 simplified enforcement of the new roofing codes by outlawing the use of unrated roofing materials throughout the state.

The collective effect of these mid-1990s building code reforms was to substantially increase the fire resistance of roofs on newly-constructed homes in regulated areas after about 1997. The roofing requirements also applied to existing homes, but only at the time of roof replacement. Any homeowner in a regulated area who replaced more than 50% of the roof surface in a single year was in principle obligated to comply. The defensible space provisions also applied to existing and new homes. However, in practice, the primary point of enforcement for these codes was at the time of new construction; enforcement effort for existing homes was limited (see e.g., Maclay 1997).

California strengthened its wildfire codes again in 2008 with the so-called Chapter 7A standards of the California Building Code. These requirements apply to all homes built in 2008 or later in SRA areas and in LRA areas where proposed VHFHSZ designations have been accepted. The codes apply to many dimensions of new homes. Roofs must be rated class A or B, eaves

9. For a detailed qualitative study of the determinants of local VHFHSZ adoption decisions, see Miller, Field, and Mach (2020).

10. These ratings are earned through laboratory testing; for example, the Class A test involves placing a 12-inch by 12-inch burning brand on the roof material under high wind conditions. The material must not ignite for 90 minutes.

and exterior siding must be fire resistant, vents must covered by a fine wire mesh to resist ember intrusion, windows and doors must resist fire for at least 20 minutes, and decks and other building appendages must be built of non-combustible materials. Chapter 7A also includes additional requirements for defensible space.

The damage data collected for this study also include wildfires in Arizona, Colorado, Oregon, and Washington. None of these had statewide wildfire building standards at the time of the included fires (Insurance Institute for Business and Home Safety 2019). Some local governments – particularly in Colorado – have adopted local standards that include a diverse mix of rules about roofs, other construction materials, and/or defensible space. Our empirical analysis excludes a small number of fires in the comparison states that overlap areas known to have local wildfire building standards.[11]

While the non-California homes in this study are not subject to mandatory standards, they are targeted by a range of information and incentive programs that seek to increase voluntary home hardening. Programs active in these states include FireWise USA (National Fire Protection Association), the Community Wildfire Protection Plan program (United States Forest Service and Department of Interior), the Fire Adapted Communities Coalition (numerous public agencies and NGOs), the Ready, Set, Go! program (International Association of Fire Chiefs), and numerous other initiatives.

2 Data and Spatial Analysis

This section describes the construction of the database of wildfire damages, property tax assessment information, and structure locations.

11. These are the 2012 Waldo Canyon Fire, 2013 Black Forest Fire, and 2018 Mile Marker 117 Fire in El Paso County, Colorado (Quarles et al. 2013) and the 2012 High Park Fire and 2020 Cameron Peak Fire in Larimer County, Colorado (Larimer County 2020).

2.1 Homes and Damage Data

Damage Inspection Data

We sought to assemble as comprehensive a database as possible of administrative records for homes destroyed or damaged by wildfire in the United States. For recent wildfires in California, this information is managed by CAL FIRE. For earlier California fires and for fires in other states, we contacted individual county assessors (who track these damages in order to update property tax assessments) and other agencies to request historical records of structure damages. To our knowledge, the resulting database is the most complete accounting that exists of U.S. homes lost to wildfire.

California 2013–2020: In California, the CAL FIRE Damage Inspection (DINS) database is a census of destroyed and damaged homes following significant wildfire incidents during 2013–2020. The data include street address and assessor parcel number (APN); limited structure characteristics; and for some fires, an additional sample of undamaged homes. The damage variable has four levels: destroyed ($>$ 50% damage), major (26–50%), minor (10–25%), and affected (1%–9%). Of these, "destroyed" is the most commonly reported damage category and the only category that appears consistently across all fires. The lack of partially-destroyed structures is consistent with case study observations in Cohen (2000) and subsequent research. We thus follow the literature and focus on "destroyed" as our primary outcome.

California 2003–2013: Data for pre-2013 wildfires in California come from two sources. For the 2003 and 2007 San Diego fire storms, we received damage assessment data from San Diego County. For other counties, CAL FIRE staff provided us with a large collection of unformatted historical damage assessment reports that we compiled and standardized to be usable for research.

Other States: Using ICS-209 incident reports, we identified the 15 counties in states other than California with the greatest number of structures lost to wildfire since 2010. We then contacted county assessors in each of these counties to request damage data. We have successfully received structure-level damage data from 11 of these 15 counties.

Appendix Table 6 includes the full list of wildfires in the dataset.

Property Tax Assessment Data

We merge the damage records to comprehensive assessment data for all U.S. homes from the Zillow ZTRAX database. The ZTRAX data include information on year built, effective year built (in the case of remodels), building square footage, and other property characteristics. The merge from damage data to ZTRAX uses assessor parcel numbers, and we validate the accuracy of this merge by comparing street addresses across the two datasets. We restrict the data to include only single family homes, which account for most properties inside the wildfire perimeters in our sample. For each incident, we merge the damage data to the most recent historical assessment data from the pre-fire period. In other words, we merge to the population of single family homes that existed immediately prior to the start of the fire. Appendix Table 6 shows the number of single family homes inside of each wildfire perimeter and the share destroyed.

2.2 Spatial Analysis and Dataset Construction

Identifying Structure Rooftop Locations

This study uses the physical locations of the homes in the data in two ways. First, homes must be spatially assigned to building code jurisdictions and to wildfire burned areas. Second, the measurement of spillovers across properties requires precise distances between neighboring structures. The street address-based geocoding methods typically used in academic research are not sufficiently detailed for this second purpose, which requires accurate structure locations at a meter scale. We solved this challenge by combining several spatial datasets to identify precise rooftop locations. First, we limit the population of ZTRAX homes to all homes in zip codes where at least one home was destroyed. We then merge these ZTRAX records to parcel boundary maps from county assessors using assessor parcel numbers. This yields a parcel polygon for each home. We then use comprehensive building footprint maps from Microsoft to identify the largest structure overlaying each parcel.[12] We call this location the "footprint location." Figure 1 shows an example for Redding, California in the area of the 2018 Carr Fire. Gray lines are parcel boundaries from the Shasta County Assessor. Blue polygons are building footprints. The purple and yellow markers show the assigned rooftop locations for each structure. Yellow markers show homes that are reported as destroyed in the damage data.

This rooftop geocoding method generates highly accurate locations, but it is dependent on the availability of high-quality parcel boundary GIS data. In areas where such data are not available (representing 13% of homes in the final analysis dataset), we instead geocode home locations using the ESRI StreetMap Premium geolocator, a commercially-available address-based product. Our quality checking shows that these locations (henceforth "address-based locations") are generally reliable to the parcel level but not always to the structure rooftop level. Appendix Section C describes the geocoding in more detail.

Validating Locations and Damage Reports

We quality check the calculated property locations and the damage report data using high-resolution aerial imagery from NearMap. The base image in Figure 1 shows an example. The detailed imagery allows us to manually confirm the accuracy of structure locations, which closely coincide with the blue building footprints in the figure. In addition, the NearMap imagery includes post-fire surveys for many of the incidents in our database. Figure 1 illustrates how destroyed properties are readily visible in these surveys, which allows us to confirm the accuracy and completeness of the damage data. Appendix Table 4 reports accuracy rates in a random sample of homes. For damage reports, 99%

12. The Microsoft U.S. Building Footprints Database is publicly available at https://github.com/microsoft/USBuildingFootprints.

of reported outcomes match the ground truth imagery. For rooftop locations, 98% of the assigned structure locations are on top of the structure rooftop in the ground truth imagery (with 99%+ accuracy in densely developed areas). Locations that rely on street address based geocoding tended to be accurate to the parcel but not always to the actual structure rooftop – about 75% of these assigned locations are on top of the structure rooftop in the ground truth imagery.

Spatial Merge to Wildfire Perimeters and Code Jurisdictions

We restrict the dataset to homes located within final wildfire perimeters (plus a 20-meter buffer). Depending on the state and time period, these digital perimeter maps come from the California Forest and Range Assessment Program (FRAP), the Monitoring Trends in Burn Severity (MTBS) dataset, or the National Interagency Fire Center (NIFC). We merge the homes data to spatial data on fire protection responsibility (SRA vs. LRA) and designated fire hazard (FHSZ) that together determine building codes in a given location in California. We use historical GIS maps provided by CAL FIRE to assign homes to code regimes according to the codes in effect when the home was built.[13]

Calculating Distances Between Neighboring Homes

We construct two measures of distance between homes. The first is the minimum distance between the building footprint polygons associated with the two structures (henceforth the "wall-to-wall" distance). This measure is only available for homes where we assign locations based on building footprints. The second metric uses the distance between assigned point locations, which are available for all homes in the dataset. We call this metric the "centroid to centroid" distance because these points are meant to correspond to the center of the roof. The wall to wall distance is our preferred measure because it more

13. For SRA/LRA boundaries, the historical map data include updates in 1990, 1996, 2003, 2005, and annually from 2010–2020. For FHSZ, the historical map data include updates in 1985, 1998, 2007, and 2008.

accurately captures space between homes and because the footprint-geocoded locations are more accurate than the address-based location points (Appendix Table 4). Our main estimates of neighbor spillovers use the restricted sample of homes for which wall to wall distances are available. For robustness, we also show specifications that use centroid to centroid distances and the full sample of homes.

We identify up to 15 nearest neighbors within one kilometer for each home in the final dataset. Panel (b) of Figure 1 shows two examples. Each image shows wall-to-wall distances (in meters) from the structure marked "0". Appendix Table 2 summarizes the distribution of number of neighbors at various distances.

Data Summary

The final dataset includes 55,408 single family homes exposed to 112 wildfires in California, Arizona, Colorado, Oregon, and Washington between 2003 and 2020. Thirty-nine percent of these were destroyed. Appendix Figure 1 shows the distribution of year built and fraction destroyed by year built for the full dataset. Appendix Table 6 reports the number of exposed and destroyed homes for each fire.

3 Empirical Strategy

This section describes the empirical design used to measure the effect of wildfire building codes on structure survival. To fix ideas, Figure 2 provides an example of the merged dataset for the 2018 Woolsey Fire in Los Angeles County. The green and purple markers indicate locations of surviving and destroyed single family homes inside the final fire perimeter. The street map data give a sense of development density. The intensity of losses varies significantly within the burned area. Near Malibu, a large share of affected homes were lost. Further north, however, there are several areas where most homes inside the fire perimeter escaped destruction. These differences reflect varying fire conditions, firefighter response times, landscape vulnerability, structure characteristics, and potentially numerous other factors. This heterogeneity adds noise to empirical analysis of structure survival. It may also introduce bias if year built or other structure traits vary similarly within burned areas. We address these challenges using an empirical design that compares the likelihood of survival for homes of different vintages on the same residential street during the same wildfire. We attribute these vintage effects to building codes by comparing vintage effects across jurisdictions with and without wildfire building codes.

3.1 Treatment Groups

Throughout the rest of the paper, we consider three types of jurisdiction. The first is SRA, where compliance with California building codes was mandatory. The second is LRA areas that were ever recommended by CAL FIRE as VHFHSZ areas (henceforth, "LRA-VHFHSZ"). To be clear, this group includes all proposed VHFHSZ regardless of whether local governments accepted the designation. There is no centralized database that records local VHFHSZ adoption decisions, but Troy (2007) reports high rates of adoption.[14] The final treatment group is areas without wildfire building codes (henceforth, "no-codes"). This includes LRA areas in California that were never recommended for consideration as VHFHSZ, as well as fires in areas of Arizona, Colorado, Oregon, and Washington without any state or local wildfire building codes. Appendix Table 1 reports the number of homes in each treatment group.

14. In addition, historical news accounts show that cities that rejected the official VHFHSZ designation often still adopted the underlying code requirements in the recommended areas. This seems to have been an attempt to achieve the state-recommended resilience requirements while avoiding the VHFHSZ label due to fears about property values (Sullivan 1995; Snyder 1995; Stewart 1995; Yost 1996; Grad 1996). One state fire official's response: "We didn't care if they called it a nuclear-free zone, as long as they adopted the regulations" (Maclay 1997).

3.2 Own-structure survival

Event study figures

We begin the regression analysis with the following event study-style model for home i on street s exposed to wildfire incident f. We estimate this model separately for the SRA, LRA-VHFHSZ, and no-codes groups.

$$1[Destroyed]_{isf} = \sum_{v=v_0}^{v=V} \beta_v D_i^v + \gamma_{sf} + X_i \alpha + \epsilon_{isf} \tag{1}$$

The outcome variable is equal to one for destroyed homes and zero otherwise. The V variables $D_i^{v_0}, ..., D_i^V$ are indicator variables equal to one if house i's year built falls into bin v. The main parameters of interest are the coefficients β that correspond to these vintage bins. These give the effect of each vintage on probability of survival when exposed to wildfire. The street fixed effects γ_{sf} include separate indicator variables for each street name-zip code combination within fire perimeter f. These fixed effects sweep away arbitrary patterns of damage across streets within the fire perimeter, so that the model is identified by average differences in survival between homes of different vintages on the same street. We also estimate models with finer and coarser fixed effects, including models with incident instead of street fixed effects.

The additional control variables X_i include controls for wildfire vulnerability at the home site. These include ground slope, aspect, and vegetation type from LANDFIRE (Rollins 2009). Some specifications also include property characteristics (lot size, building square footage, number of bedrooms).

Difference in differences

We summarize the overall effects of the wildfire building standards using a difference-in-differences (DiD) model that pools jurisdictions and time periods. We divide the sample into 3 time periods: before 1998; 1998–2007; and 2008 onwards. The latter two periods correspond to the end of the mid-1990s roofing reforms and the introduction of the Chapter 7A requirements.

3.3 Structure to structure spread

To measure the effect of code-driven mitigation on likelihood of structure-to-structure spread, we estimate the effect of building vintage on likelihood of survival for neighboring homes. Our regression models are of the form,

$$1[Destroyed]_{isf} = \sum_{j=1}^{J} \rho_j NoCode_j + \sum_{j=1}^{J} \phi_j Code_j + \sum_{v=v_0}^{V} \beta_v D_i^v + \gamma_{sf} + X_i\alpha + \epsilon_{isf} \tag{2}$$

Like Equation (1), this specification controls for own year of construction and street-by-incident fixed effects. The additional regressors $NoCode_j$ and $Code_j$ are the number of neighbors within various distance bins j that were built before and after wildfire building codes. Homes are considered post-code in 1998 in SRA areas and in the year the area was first recommended as a VHFHSZ in LRA VHFHSZ areas. The coefficients ρ_j and ϕ_j for $j = 1, ..., J$ give the effect of these neighbors on own-structure survival. Our preferred specification uses 10-meter bins of wall-to-wall distance. For robustness, we also estimate a specification using centroid to centroid distances. With this latter measure, we define the closest bin as 0-30 meters because 30 meters roughly corresponds to 10 meters of wall-to-wall distance.[15] We apply some additional sample exclusions when estimating Equation 2: The sample is restricted to California since we can only reliably calculate footprint locations for California homes. We further drop condominiums and townhomes to focus on detached single family homes.

This regression identifies the causal effect of code-induced mitigation by neighboring homes if the code regime for neighboring homes is uncorrelated with other determinants of structure- and neighborhood-level risk. This assumption is bolstered by the street fixed effects, which focus on highly local variation.

15. The median building footprint area in the sample is 260 m^2. A hypothetical circular roof would thus have a radius of 9.1 meters and the centroid-to-centroid distance between two such homes would be 18.2 + wall-to-wall distance.

Intuitively, this specification compares homes on the same street during the same wildfire whose nearest neighbors were built in different years. One might still worry, however, that even within these narrow comparisons and even after controlling for own age, the age of a home's neighbors may still be correlated with other wildfire risk factors. We address this concern by exploring estimates for homes located slightly further away as a placebo check. Properties located 50 to 100 meters away are outside of the 30-meter home ignition zone and so present more limited direct ignition threat, but should otherwise be subject to the same potential omitted variables as directly adjacent homes.

4 Results and Discussion

4.1 Own-structure survival

4.1.1 Graphical Evidence

Figure 3 shows the raw mean of *Destroyed* for State Responsibility Area homes according to year of construction. About 35% of exposed homes built prior to the mid-1990s were destroyed. These destruction probabilities begin to fall for homes built after the mid-1990s, decreasing quickly to about 20%. This sharp improvement in resilience corresponds in time to the post-Oakland Firestorm building reforms.

There is also some evidence in Figure 3 that homes built before about 1980 may be less likely to be destroyed than homes built just prior to the roof requirements. This may reflect the fact these older homes are more likely to have been re-roofed at least once after the mid-1990s and complied with the requirement for ignition-resistant materials at roof replacement. This pattern would imply a replacement cycle of about 30-40 years. Actual data on roof service lifetimes is scarce, but this period is within the range proposed by the National Association of Home Builders and other sources (National Association of Home Builders 2007). To the extent that some pre-building code homes may be re-roofed with code-compliant materials, our estimates of building code effects are conservative.

Appendix Figure 2 shows that homes built before and after the building code changes are otherwise comparable. There are no meaningful changes in site-level predictors of fire risk, like ground slope, or in structure characteristics such as building square footage.

Figure 4 presents the event study estimates from Equation (1). The top panel shows homes in SRA, where WUI building codes are mandatory. The markers show estimates and 95% confidence intervals for two-year vintage bins. The omitted bin is 1987-1988, so that these estimates can be interpreted as percentage-point differences in likelihood of destruction relative to a 1987 home. The vintage effects are flat prior to about 1993, and then begin to decrease clearly during the 1995–1999 period. The point estimates suggest additional reductions in loss probability following the adoption of the Chapter 7A codes in 2008, although the small number of homes in those bins leads to somewhat noisy vintage estimates. The overall difference in loss probability between a 1987 home and a 2008+ home is about 15 percentage points.

The middle panel shows homes in LRA areas that CAL FIRE recommended for Very High Fire Hazard Severity Zone designation. These areas again show flat trends in resilience prior to the 1991 Oakland Firestorm and subsequent Bates Bill. After the Bates Bill takes effect, the figure shows steady improvements that persist for about 12 years. The slope of these improvements appears more gradual than in SRA areas, which would be consistent with varied timing of adoption of the recommended codes across hundreds of individual municipalities. The post-2008 estimates are again noisy but imply further improvements in resilience following adoption of the Chapter 7A bulding codes.

Finally, the bottom panel of Figure 4 shows vintage effects for homes in areas not subject to California's codes. This includes fires in areas of Arizona, Colorado, Oregon, and Washington with no state or local wildfire building codes. It also includes LRA areas in California that were never recommended as Very High Fire Hazard Severity Zones. There are relatively few homes in these groups (Appendix Table 1), so we pool them together and use wider ten-year vintage bins to increase precision. Unlike the top two panels, there is little evidence of improved resilience for homes built since the mid 1990s in areas without wildfire building codes.

4.1.2 Difference-in-Differences Estimates and Robustness Checks

The regression estimates in Table 1 summarize the effects of building code regimes on structure resilience. We show estimates for SRA, LRA-VHFHSZ, and no-codes areas. The various group by time period estimates can be interpreted as percentage point differences in likelihood of destruction relative to the reference category, which is pre-1998 homes in no-code areas. Column (1) shows the results with street by fire fixed effects. The near-zero coefficient on SRA $*$ Before 1998 implies that SRA homes built before the end of the mid-1990s building codes reforms perform similarly to homes of the same vintage in no-code areas. In contrast, SRA homes built during 1998–2007 or 2008–2016 perform 11.2 percentage points and 15.9 percentage points better, respectively. Differencing the pre-post differences across code areas yields a DiD estimate of 13.1 percentage points. The same pattern exists for LRA VHFHSZ areas, with no difference before 1998 and substantial improvements in the post-code periods. The DiD estimate for LRA VHFHSZ areas is 12.2 percentage points. Lastly, these improvements are smaller or absent in the no-codes comparison group, where homes built in the latter two time periods show only minor improvements that are not statistically distinguishable from zero. This is further evidence that the improvements in the code areas are due to building codes as opposed to other time-varying factors. The regression also includes controls for topography and vegetation. As expected, slope steepness at the home site increases vulnerability. A home on a 10 degree slope would be six percentage points less likely to survive than an otherwise-identical home on flat ground. This specification also includes fixed effects for the dominant vegetation type in the area of the home.[16]

The remaining columns of Table 1 explore alternative specifications. Col-

16. We assign vegetation types as the most common fuel model in a 25-meter radius around the home.

umn (2) adds building characteristics from the assessor data. Building square footage, number of bedrooms, and lot size do not appear to have meaningful effects on survival after controlling for year built and street. Home characteristics data are missing for about 20% of homes, which shrinks the sample in this third column. The final three columns show different sets of fixed effects. Column (3) includes separate fixed effects for each group of 100 adjacent homes on each street (ordered by house number). This specification addresses a potential concern that some streets in the sample include many hundreds of homes. The more granular fixed effects do not materially change the estimates. Column (4) groups homes on the same street and side of the street, assuming that house numbers follow the convention of odd and even numbers on opposite sides. This specification also does not change the results. Finally, Column (5) omits the street fixed effects and instead uses incident fixed effects. These incident dummies absorb fire-specific severity and arbitrary time trends in preparedness, but unlike the street fixed effects they do not adjust for differences between exposed homes within the same wildfire incident. The point estimates are slightly larger in SRA areas and slightly smaller in LRA VHFHSZ areas. Notably, the R^2 with incident fixed effects is smaller than with street fixed effects (0.39 vs 0.63). This difference implies that the street fixed effects remove variation in fire severity and other factors within incidents that might otherwise threaten identification. Nevertheless, the estimates are broadly stable across specifications. None of the estimated effects in Columns (2) through (5) are statistically different from those in Column (1).

In principle, the street fixed effects design could underestimate the effect of building codes due to the spillover benefits that we document in the next section. If code-induced investments also benefit nearby pre-code homes, the difference in outcomes between post-code and pre-code homes will understate the true effect of codes on survival.[17] This attenuation could be exacerbated by street fixed effects, which by construction are focused on homes located relatively close to each other. Such reasoning might lead one to prefer incident

17. This is a violation of the Stable Unit Treatment Value Assumption, or SUTVA (Rubin 1980).

fixed effects. In practice, as we show in the next section, spillovers are highly localized and are small compared to the own-resilience effects. In the spirit of exhaustiveness, Appendix Table 3 investigates the quantitative significance of SUTVA concerns by controlling directly for the number of pre- and post-code near neighbors in the street fixed effects regression. Ultimately, the differences in the estimated building code effects across these approaches – street fixed effects, incident fixed effects, and street fixed effects directly controlling for spillovers – are small enough that the various results are not statistically different.

4.2 Spillovers to neighboring properties

This section discusses the spillover benefits of code-induced mitigation to neighboring homes. Figure 5 shows regression results for Equation (2). The top panel shows effects of the presence of pre-code neighbors at various wall-to-wall distances. One or more pre-code neighbors within 0-10 meters increases own-structure loss probability during a wildfire by about 3 percentage points. These effects attenuate with distance, going to zero at 30-40 meters. Notably, this is the distance that wildfire managers consider to be the home ignition zone - the distance within which flammable material presents a risk of structure ignition (Cohen 2000, 2010; Calkin et al. 2014). The near-zero estimates beyond 40 meters bolster the validity of our research design. If our estimates for the nearest neighbors were biased by omitted predictors of resilience that co-vary within neighborhoods, one would expect that bias to also appear in estimates for homes another few dozen meters away (Figure 1b provides a useful illustration of these small distances).

The bottom panel shows the estimates for post-code neighbors. The confidence intervals for these estimates are wider since we observe fewer post-code homes. However, the point estimates suggest that the presence of close neighbors built under WUI building codes does not increase own-structure loss probability. There is also no implied effect of further-away post-code neighbors on own survival, offering additional placebo evidence to support the identifying assumptions behind this regression.

Table 2 reports regression estimates for near neighbors that allow effects to vary with the number of neighbors. Column (1) considers neighbors at a wall-to-wall distance of less than 10 meters. A single pre-code neighbor increases own-structure loss risk by 2 percentage points. Two or more pre-code near neighbors increases the effect to 3.1 percentage points. This latter category mostly represents the effect of homes with two neighbors, given that very few homes have more than two neighbors within 10 meters (Appendix Table 2). The estimated effects of nearby post-code neighbors are close to zero. Column (2) shows the same regression using a restricted sample of areas where our measured distances between homes are likely to be particularly accurate. This sample includes denser areas (homes with at least 10 neighbors within a 200 meter radius; see Appendix Table 4) and fires since 2013 (for older incidents, it is more likely that parcel boundaries have changed since the fire). The estimated risk posed by pre-code neighbors is slightly larger in this specification, perhaps due to measurement error in wall-to-wall distances in the full sample. The estimates for post-code neighbors are again zero. As another robustness check, Columns (3) and (4) present similar results based on the centroid-to-centroid distance measure. One pre-code neighbor within 30 meters of centroid distance – roughly equivalent to 10 meters of wall distance – increases own loss risk by 2.6 percentage points, and two or more increases risk by 5 percentage points. Again, the point estimates for post-code neighbors are much smaller and close to zero.

5 Net Social Benefits of Building Standards

The empirical results show that compared to reliance on voluntary action alone, California's wildfire building codes substantially reduced average structure loss risk during a wildfire. They also reduced the risk to a close neighbor's home. Having documented these large resilience benefits, we now embed the results in a simple economic model in order to benchmark the approximate net social benefits of wildfire building codes. We use our estimates to explore the minimum annual disaster probability at which universal mitigation investment is welfare-improving, given various values of neighborhood density and household risk aversion. This exercise is intentionally simple and abstracts from many theoretical and practical details that warrant investigation in future work.[18]

5.1 An Empirical Model of Hazard Mitigation

N identical individuals own homes in a neighborhood with an annual probability p^F of a disaster. In the event of a disaster, each home i's baseline probability of destruction is p_0^D. Up-front investment in a binary mitigation measure with cost m by homeowner i reduces own loss risk during a disaster by τ_{ii} and also reduces loss risk by τ_{ji} for a subset of neighbors $j \neq i$ (for example, in our application τ_{ji} is non-zero for neighbors within some distance of home i and zero for the remaining homes). Mitigation benefits are additive so that a home's destruction probability during a disaster is $p_i^D = p_0^D - M_i\tau_{ii} - \sum_{j\neq i} M_j\tau_{ij}$, where $M_i \in \{0, 1\}$ is the homeowner's binary mitigation decision. We capture myopia with perceived disaster probabilities $\hat{p}_i^F \leq p^F$. These perceived probabilities vary across households.

Consistent with stylized facts (e.g., Klein (2018)), disaster losses are partially insured: destruction of the home imposes insured losses L^I for the insurer and uninsured losses L^U for the homeowner. We initially assume frictionless property insurance markets that offer coverage at actuarially fair annual premia $k_i = p^F p_i^D L^I$. The coexistence of uninsured risk exposure and actuarially fair premiums reflects uninsurable losses (for example, mental and emotional distress) and/or household myopia. The exposition in this section uses a static model with no discounting. Our actual calculations assume that households discount future costs and benefits at a 5% annual rate.

We define two potential measures of net benefit, *risk-neutral cost effectiveness* and *expected utility benefit*. Risk-neutral cost effectiveness is simply the

18. A more detailed theoretical treatment of private risk mitigation can be found in Costello, Quérou, and Tomini (2017).

difference in expected cost with and without mitigation. Expected utility benefit accounts for additional benefits from reduced exposure to uninsured risk. Appendix Section D presents a sketch of the expected utility model. Actually calculating expected utility requires strong assumptions about households' risk aversion, permanent income, ability to smooth across time periods, and other factors. We focus the derivation in this section on risk-neutral cost effectiveness (hereafter, "cost effectiveness"). We note that cost effectiveness is a lower bound on net benefits as long as homeowners are not risk-loving.

Total expected cost across households is,

$$\sum_{i=1}^{N}[p^F(p_0^D - \sum_{j=1}^{N} M_j\tau_{ij})(L^I + L^U) + M_i m] \tag{3}$$

The social benefit of mitigation by a homeowner is the sum of private and external benefits (reduced loss probability) minus mitigation costs,

$$p^F(\tau_{ii} + \sum_{j\neq i}\tau_{ji})(L^I + L^U) - m \tag{4}$$

In contrast, a homeowner's perceived change in private expected losses with mitigation is,

$$\hat{p}_i^F\tau_{ii}(L^I + L^U) - m \tag{5}$$

The presence of internalities ($\hat{p}_i^F$) and externalities (τ_{ji}) means that Expression (5) is weakly less than Expression (4). If households minimize perceived private expected cost, the voluntary takeup rate will be,

$$\mu = \frac{1}{N}\sum_{i=1}^{N}\mathbb{1}[\hat{p}_i^F\tau_{ii}(L^I + L^U) \geq m] \tag{6}$$

which depends on the distribution of perceived probabilities. Assuming $\hat{p}_i^F$ is independently distributed, total actual expected costs under voluntary takeup are $\sum_{i=1}^{N}[p^F(p_0^D - \sum_{j=1}^{N}\mu\tau_{ij})(L^I + L^U) + \mu m]$.

Now consider a policy requiring mitigation by all households. Total expected cost is given by setting $M_i = 1$ for all households in Expression (3). The difference in expected cost under the mandate vs. the voluntary regime is,

$$(1-\mu)\Big[p^F[\sum_{i=1}^{N}\sum_{j=1}^{N}\tau_{ij}(L^I+L^U)] - Nm\Big] \tag{7}$$

The Samuelson (1954)-style expression inside the outer brackets is the sum of private and external mitigation benefits minus total mitigation costs. The factor of $(1-\mu)$ reflects takeup by a fraction μ of the population without the mandate. A mandate weakly reduces total expected cost if the social value of mitigation (Expression 4) is positive and strictly increases expected cost if the social value of mitigation is negative.

Before proceeding, it is worth noting some restrictions in this model. We assume additive mitigation benefits. There is some support for this in the data - for example, the approximate linearity of risk spillovers for one vs. two near neighbors in Table 2. A more complex model could instead allow the benefits of mitigation to vary with mitigation effort by others, so that mitigation becomes a strategic game between homeowners.[19] We also assume identical homes and homeowners within the neighborhood and independently distributed perceived disaster probabilities. We explore heterogeneity in fire risk and neighborhood density across neighborhoods (zip codes) in the empirical implementation. Expanding the model to allow for greater heterogeneity within neighborhoods would allow a more nuanced exploration of the distribution of net benefits. We see these extensions as useful areas for future work, but prefer this simple and transparent model for the purposes of benchmarking approximate net benefits.

5.2 Implementation

We implement the model for a random sample of 100,000 homes in 424 California zip codes in wildfire hazard areas. Each zip code is modeled as a separate

19. Shafran (2008) develops such a model for vegetation maintenance in wildfire areas.

neighborhood with its own fire probability and number of close neighbors affected by risk spillovers.

Mitigation Benefits

The empirical results in Section 4 allow us to estimate τ_{ii} and τ_{ij}. The reduced form estimates of the effect of building codes on structure survival can be seen as intent-to-treat estimates of the effect of mitigation investment. Given a rate of voluntary takeup for the bundle of mitigation measures in the building code, the standard Wald estimator gives τ_{ii} and τ_{ij} as the ratio of the reduced form estimates and the difference in takeup rates in the codes and no-codes areas.[20] In the theoretical model, voluntary takeup μ depends on beliefs about fire risk and might thus be expected to vary between neighborhoods. In practice, survey data on voluntary mitigation is scarce and the available data do not allow us to calculate neighborhood-specific voluntary takeup rates. Our base calculation uses a voluntary takeup rate of one-third. Appendix Section E describes how we calculate this takeup rate based on CAL FIRE inspections of destroyed and surviving homes for a sample of recent California wildfires, including caveats about limitations of the data (which is nevertheless the best existing survey evidence for our purposes).

Our reduced form estimate for own survival benefit for SRA homes implies a value of τ_{ii} of 0.195 ($\frac{.13.1}{1-0.33} = 0.195$). For τ_{ij}, our reduced form estimate of neighbor benefits in Table 2 is 2.3 percentage points for neighbors up to 10 meters away in wall-to-wall distance (and close to zero beyond 10 meters). The effect also appears approximately linear in number of neighbors that mitigate, at least over the limited range of number of neighbors that we can observe in the data. Thus, our estimate of τ_{ij} is 0.034 for each neighbor within 10 meters ($\frac{-.0.023}{1-0.33} = -0.034$) and zero for all further-away neighbors.[21]

20. See e.g., Angrist and Pischke (2009) p. 127-133. This calculation assumes perfect compliance by homes subject to codes and a homogeneous effect of mitigation on structure survival.

21. In principle, mitigation at further-away homes also benefits home i through potential "domino effects": a near neighbor becomes less likely to ignite due to action by that neighbor's neighbor. Our estimates imply that these effects are small on average (on the order of

Sampling at-risk homes

Unlike the empirical analysis of building code effects, which uses homes located inside historical wildfire perimeters, the net benefits calculation considers a group of homes sampled randomly from *all* California homes in fire hazard areas. To construct this sample, we start from all California homes in designated wildfire severity zones (SRA or LRA) and filter out zip codes containing fewer than 100 homes. We then randomly draw $min(n, 250)$ homes from each remaining zip code where n is the number of homes in the zip code. This yields a sample of 100,230 homes subject to wildfire building codes in 424 zip codes.

We identify each home's annual wildfire exposure probability p^F using data from the United States Forest Service (USFS) Wildfire Risk to Communities project. This measure captures the annual probability of moderate to severe wildfire exposure (Scott et al. 2020).[22] We also identify each home's number of neighbors within 30 meters of centroid to centroid distance. This roughly corresponds to the number of neighbors within 10 meters of wall-to-wall distance (see footnote 15) and is less demanding to calculate in this new random sample of homes.

Costs and Losses

Our main estimates of mitigation costs come from Headwaters Economics (2018). That study uses construction estimating tools from R.S. Means to calculate the additional cost to build a home that complies with California's Chapter 7A wildfire code. Overall, that study reports zero cost difference between code-compliant and standard designs. This counter-intuitive result arises because one aspect of code-compliant construction (exterior siding) is substantially *less* expensive than standard designs. These savings offset increased costs for roofing, landscaping, and other areas. Our main estimate of

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0.034^2).

22. We use the product of Burn Probability (the total annual wildfire probability) and Flame Length Exceedance Probability 4 (conditional on any fire, the probability that the fire will reach moderate or greater threat status).

code compliance costs ignores savings from code-compliant siding on the theory that owners would make this choice even without standards. This gives a cost estimate of $15,660. We also report results using alternative cost estimates from the National Association of Home Builders. Their estimated wildfire code compliance costs for newly-built California homes include a low scenario of $7,868 and a high scenario of $29,429 (Home Innovation Research Labs 2020).[23] Finally, we show a "retrofit" scenario based on Headwaters Economics' estimate of $62,760 to fully replace roofing and exterior walls on an existing home.

Our assumed losses for a home destroyed by wildfire include rebuilding costs, belongings and contents of the home, alternative living costs while the home is rebuilt, and costs for debris removal and hazardous waste cleanup. Rebuilding, contents, and alternative living arrangements costs come from the FEMA Hazus model (Federal Emergency Management Agency 2021). We match as closely as possible the characteristics of the model home used to estimate code compliance costs in Headwaters Economics (2018).[24] We regionally adjust these costs to California using geographic adjustment factors from R.S. Means provided in the Hazus model. The resulting cost of reconstruction and contents losses is $766,725. The Hazus cost for alternative living arrangements and disruption (e.g., moving costs) for 24 months is $61,696. For debris removal (which is borne by homeowners) and hazardous waste cleanup (borne by governments), we add a total of $150,000.[25]

We assume that mitigation investments have a protective lifetime of 40 years.

23. These are costs to meet the International Wildland Urban Interface Code, which is similar to the Chapter 7A code. In the low scenario, we ignore $3,839 of gross savings from code-compliant siding as we do for Headwaters Economics (2018).

24. The model home in Headwaters Economics (2018) is a 2,500 square-foot single-story home with 2-car garage constructed in Montana for $140 per square foot. We use Hazus cost estimates for the same size, number of stories, and garage in the "custom" construction class, the closest corresponding cost category.

25. For cleanup and debris removal costs, see Klein (2018); Lewis, Sukey, "Cleaning Up: Inside the Wildfire Debris Removal Job That Cost Taxpayers $1.3 Billion." *The California Report*, July 19, 2018; and Bizjak, Tony, "State's Effort to Clean Up After the Camp Fire is Off to a Rocky Start", *Sacramento Bee*, January 13, 2019.

In the absence of mitigation investment, the probability of loss when exposed to wildfire for a home with no close neighbors is 44%.[26] Households discount future costs and benefits at 5% per year.

5.3 Results of Net Benefit Calculation

Figure 6 illustrates the results of this calculation. The scatter plot shows zip code-level averages of annual wildfire hazard and number of near neighbors. The wildfire hazard reaches strikingly high levels: several zip codes face annual event probabilities above 2% per year, implying a significant wildfire exposure every 50 years on average. The color scale shows the social benefit of mitigation investment in each zip code following Expression (4). The dashed black line shows a threshold for positive net benefits of building standards. Homes to the right of this line have lower expected costs with mitigation investments than without. The threshold bends to the left as the average number of neighbors increases due to the spillover benefits of mitigation across properties. For a home with zero near neighbors, the break-even annual wildfire hazard is about 0.45%. The break-even annual hazard for a home with 1 near neighbor is 0.39% and for a home with 4 near neighbors it is 0.27%.

These cost effectiveness estimates are a lower bound on the net benefits of universal mitigation. One important reason for this is that many homeowners are substantially underinsured for natural disaster losses. Mitigation investments yield additional welfare benefits by reducing exposure to uninsured risk. Even for properties covered by homeowners insurance, Klein (2018) reports that coverage limits for wildfire-destroyed properties are often up to 50% below actual losses. Table 3 reports break-even annual wildfire probabilities for a home with 1.2 near neighbors (the sample mean) based on the expected utility model in Appendix Section D. Although this model requires additional strong assumptions, these back-of-the-envelope numbers depict how risk aversion might affect program benefits. For example, if code compliance costs $15,660, a homeowner

26. The approximate destruction probability for SRA homes under current codes is $0.4 - .156 = .244$ (Table 1). Combined with the own-structure mitigation effect, this gives the implied loss probability in the absence of mitigation: $.244 + .195 = 0.44$.

with a coefficient of relative risk aversion of 5 and an insurance policy covering two thirds of total losses would be better off investing in mitigation wherever the annual probability of a damaging wildfire exceeds 0.33%.[27]

Table 3 also reports results using other estimates of mitigation cost. The zero net cost estimate from Headwaters Economics (2018) leads to positive benefits for any level of hazard. The two additional estimates from Home Innovation Research Labs (2020) bracket the main cost estimate. Finally, the estimated retrofit cost of $62,760 results in much higher break-even hazard levels for existing homes. This kind of full retrofit to existing homes appears to generate positive benefits only for a handful of areas with extreme fire hazard.

Beyond risk aversion, WUI building codes likely have additional benefits that are not included in our calculations. These include reductions in public expenditures on firefighting during large wildfires (Baylis and Boomhower 2019), reduced demand for public assistance among fire victims (Deryugina 2017), avoided emotional and mental distress, and less need for public safety power shutoffs that interrupt electricity service during high fire-risk periods.[28] Moreover, if imperfections in property insurance markets cause premiums to systematically exceed expected damages, then mitigation becomes more attractive because it reduces the risk which must be insured in the imperfect insurance market. Scientists also agree that annual wildfire probabilities are increasing throughout North America such that net benefits of WUI building codes will grow in the future. On the other hand, a more detailed analysis would need to consider possible heterogeneity in household net benefits. If some individuals have very high perceived private costs of choosing fire resistant materials and landscaping (perhaps due to strong aesthetic preferences), building standards could be costly for these households.

27. Studies of the property insurance market generally report high implied levels of relative risk aversion. Cohen and Einav (2007) and Sydnor (2010) examine deductible choices in auto and homeowners insurance respectively and find double-digit values for the mean household across a variety of specifications. Evidence from other markets suggests values closer to the low single digits (e.g., Gertner 1993; Chetty 2006).

28. For a systematic review of catastrophic wildfire costs, see Feo et al. (2020).

In summary, our empirical estimates and model calculations suggest that wildfire building codes yield unambiguous benefits in the most fire-prone areas of California, especially when homes are clustered closely together such that there are large risk spillovers. For areas with lower fire risk, the sign of net benefits is more sensitive to modeling choices and the assumed co-benefits of building codes. Further work on the cost-effectiveness of wildfire mitigation measures in low- and moderate-risk areas is an important area for additional research.

6 Conclusion

Efficient investment in adaptation is essential in the face of rapidly accelerating disaster losses. Yet takeup of protective technologies and behaviors is thought to be constrained by misperception of risk, insurance market failures, spatial externalities, and other frictions. The pressing question facing researchers and policymakers is how to best respond to these market barriers. One suite of policies focuses on increasing voluntary takeup through information or subsidies. Another option is to override individual decisions and mandate certain investments in hazard areas. These policies may differ substantially in their effects and their political acceptability.

This study contributes evidence on the effects and net economic benefits of a mandatory adaptation policy. We provide the first comprehensive empirical evaluation of California's strict wildfire building codes. The analysis uses a new dataset of property-level data on U.S. homes destroyed by wildfire that was created for this study. The new data combine nationwide property characteristics information with post-fire damage assessment records collected from numerous local and state agencies. This resource has three important advantages: it collects and harmonizes previously disparate damage data; it contains a complete record of homes that survive as well as homes that are destroyed; and unlike data for floods and other losses, it is reported at the individual property level. Beyond this study, the new data will enable additional important research on disaster losses.

The empirical analysis in this study is bolstered by our ability to observe differences in building code regimes over time, across jurisdictions within California, and between California and other states. The empirical strategy isolates the effect of building code changes using a fixed effects design that compares outcomes for pre- and post-code homes on the same residential street. This approach narrows the comparison to homes experiencing essentially identical wildfire exposures.

The results show that compared to reliance on voluntary action alone, California's wildfire building codes reduced average structure loss risk during a wildfire by 16 percentage points, or about a 40% reduction. They also reduced the risk to a close neighbor's home by about 2 percentage points or 6%. These striking results imply materially different levels of resilience in communities with and without such codes. Moreover, the spatial externalities provide a classic rationale for public policy intervention even if homeowners were fully informed and rational about wildfire risk.

Having documented these large resilience benefits, we then show how the empirical results can be embedded in an economic model that accounts for mitigation costs, spatial spillovers, and risk preferences. We use our results and other values from the literature to provide a back-of-the-envelope approximation of the minimum annual wildfire risk at which universal mitigation generates positive net benefits. In the most fire-prone areas of California, the calculation shows large net benefits of building codes for new homes. Given the high cost of fully retrofitting existing homes to modern standards, full retrofits do not pass a benefit-cost test in most areas. An important task for future research is to identify individual low-cost investments that can cost-effectively improve the resilience of existing homes in high hazard areas.

In summary, the data show that an adaptation mandate substantially improved resilience to wildfires and a cost-benefit approximation suggests that low takeup without standards is more likely driven by market failures than by fully-informed individual decisionmaking. These results are immediately applicable to policy debates in the U.S., Canada, Australia, the European

Union, and other jurisdictions that are seeking to respond to escalating wildfire risk. More broadly, these facts should be of interest to policymakers and researchers confronting other hazards like floods, hurricanes, and heat waves where voluntary takeup of self-protective investments seems to be constrained by similar barriers. As climate change continues to increase disaster losses, this type of research on the role of public policy and market incentives in shaping adaptation is increasingly urgent.

References

Alexandre, Patricia M, Susan I Stewart, Nicholas S Keuler, Murray K Clayton, Miranda H Mockrin, Avi Bar-Massada, Alexandra D Syphard, and Volker C Radeloff. 2016. "Factors Related To Building Loss Due To Wildfires In The Conterminous United States." *Ecological Applications* 26 (7): 2323–2338.

Allstate Indemnity Company. 2018. *California Homeowner's Insurance Rate Filing 18-2993.* California Department of Insurance.

Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton University Press.

Bakkensen, Laura, and Lint Barrage. Forthcoming. "Going Under Water? Flood Risk Belief Heterogeneity And Coastal Home Price Dynamics." *The Review Of Financial Studies.*

Baylis, Patrick, and Judson Boomhower. 2019. *Moral Hazard, Wildfires, And The Economic Incidence Of Natural Disasters.* NBER Working Paper No. 26550.

California Department of Insurance. 2018. *The Availability And Affordability Of Coverage For Wildfire Loss In Residential Property Insurance In The Wildland-Urban Interface And Other High Risk Areas Of California.* Technical report.

Calkin, David E., Jack D. Cohen, Mark A. Finney, and Matthew P. Thompson. 2014. "How Risk Management Can Prevent Future Wildfire Disasters In The Wildland-Urban Interface." *Proceedings Of The National Academy Of Sciences* 111 (2): 746–751.

Chetty, Raj. 2006. "A New Method of Estimating Risk Aversion." *American Economic Review* 96, no. 5 (December): 1821–1834.

Cohen, Alma, and Liran Einav. 2007. "Estimating Risk Preferences from Deductible Choice." *American Economic Review* 97, no. 3 (June): 745–788.

Cohen, J.D., and R. Stratton. 2008. *Home Destruction Examination: Grass Valley Fire.* US Department of Agriculture, Forest Service, Report R5-TP-026b.

Cohen, Jack D. 2000. "Preventing Disaster: Home Ignitability In The Wildland-Urban Interface." *Journal Of Forestry* 98 (3): 15–21.

———. 2010. "The Wildland-Urban Interface Fire Problem." *Fremontia* 38 (2-3): 16–22.

Costello, Christopher, Nicolas Quérou, and Agnes Tomini. 2017. "Private Eradication Of Mobile Public Bads." *European Economic Review* 94:23–44.

Dehring, Carolyn A, and Martin Halek. 2013. "Coastal Building Codes And Hurricane Damage." *Land Economics* 89 (4): 597–613.

Deryugina, Tatyana. 2017. "The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance." *American Economic Journal: Economic Policy* 9, no. 3 (August): 168–98.

Donovan, Geoffrey, Patricia Champ, and David Butry. 2007. "Wildfire Risk And Housing Prices: A Case Study From Colorado Springs." *Land Economics* 83 (2): 217–233.

Federal Emergency Management Agency. 2020. *Building Codes Save: A Nationwide Study,* November.

———. 2021. *Hazus Inventory Technical Manual,* February.

Feo, Teresa J., Samuel Evans, Amber J. Mace, Sarah E. Brady, and Brie Lindsey. 2020. *The Costs Of Wildfire In California: An Independent Review Of Scientific And Technical Information.* California Council on Science and Technology.

Gallagher, Justin. 2014. "Learning about an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States." *American Economic Journal: Applied Economics* 6, no. 3 (July): 206–33.

Gertner, Robert. 1993. "Game Shows And Economic Behavior: Risk-Taking On "Card Sharks"." *The Quarterly Journal Of Economics* 108 (2): 507–521.

Gibbons, Philip, Linda Van Bommel, A Malcolm Gill, Geoffrey J Cary, Don A Driscoll, Ross A Bradstock, Emma Knight, Max A Moritz, Scott L Stephens, and David B Lindenmayer. 2012. "Land Management Practices Associated With House Loss In Wildfires." *Plos One* 7 (1): e29212.

Grad, Shelby. 1996. "O.C. Stopped Warning Of 'High-Hazard' For Fire Area." *Los Angeles Times* (October).

Hallstrom, Daniel G., and V. Kerry Smith. 2005. "Market Responses To Hurricanes." *Journal Of Environmental Economics And Management* 50 (3): 541–561.

Headwaters Economics. 2018. *Building A Wildfire-Resistant Home: Codes And Costs,* November.

Home Innovation Research Labs. 2020. *Cost Impact Of Building A House In Compliance With IWUIC.* Report No. CR1328-2 12302020, December.

Insurance Institute for Business and Home Safety. 2019. *Wildfire Codes & Standards: State-By-State Reference Guide.*

Intini, Paolo, Enrico Ronchi, Steven Gwynne, and Noureddine Bénichou. 2020. "Guidance On Design And Construction Of The Built Environment Against Wildland Urban Interface Fire Hazard: A Review." *Fire Technology* 56:1853–1883.

Jacobsen, Grant, and Matthew Kotchen. 2013. "Are Building Codes Effective At Saving Energy? Evidence From Residential Billing Data In Florida." *The Review Of Economics And Statistics* 95 (1): 34–49.

Klein, Kenneth S. 2018. "Minding The Protection Gap: Resolving Unintended, Pervasive, Profound Homeowner Underinsurance." *Connecticut Insurance Law Journal* 15.

Kousky, Carolyn, Erzo F. P. Luttmer, and Richard J. Zeckhauser. 2006. "Private Investment And Government Protection." *Journal Of Risk And Uncertainty* 33 (1): 73–100.

Kramer, H Anu, Miranda H Mockrin, Patricia M Alexandre, Susan I Stewart, and Volker C Radeloff. 2018. "Where Wildfires Destroy Buildings In The US Relative To The Wildland–Urban Interface And National Fire Outreach Programs." *International Journal Of Wildland Fire* 27 (5): 329–341.

Kunreuther, Howard C., and Erwann O. Michel-Kerjan. 2011. *At War With The Weather: Managing Large-Scale Risks in a New Era of Catastrophes.* MIT Press.

Larimer County. 2020. *Residential Requirements: A Guide For The General Contractor Or Home Builder.* Larimer County Community Development Division, June.

Levinson, Arik. 2016. "How Much Energy Do Building Energy Codes Save? Evidence from California Houses." *American Economic Review* 106, no. 10 (October): 2867–94.

Maclay, C.K. 1997. "State Fire Prevention Law Fizzles." *Contra Costa Times* (August).

McCoy, Shawn J., and Randall P. Walsh. 2018. "Wildfire Risk, Salience And Housing Demand." *Journal Of Environmental Economics And Management* 91:203–228.

Miller, Rebecca K, Christopher B Field, and Katharine J Mach. 2020. "Factors Influencing Adoption And Rejection Of Fire Hazard Severity Zone Maps In California." *International Journal Of Disaster Risk Reduction,* 101686.

National Association of Home Builders. 2007. *Study Of Life Expectancy Of Home Components,* February.

Quarles, Stephen, Pam Leschak, Rich Cowger, Keith Worley, Remington Brown, and Candace Iskowitz. 2013. *Lessons Learned From Waldo Canyon.* Insurance Institute for Business & Home Safety.

Rollins, Matthew G. 2009. "LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment." *International Journal of Wildland Fire* 18 (3): 235–249.

Rubin, Donald B. 1980. "Randomization Analysis Of Experimental Data: The Fisher Randomization Test Comment." *Journal Of The American Statistical Association* 75 (371): 591–593.

Samuelson, Paul A. 1954. "The Pure Theory Of Public Expenditure." *The Review Of Economics And Statistics* 36 (4): 387–389.

Scott, Joe H, Julie W Gilbertson-Day, Christopher Moran, Gregory K Dillon, Karen C Short, and Kevin C Vogler. 2020. *Wildfire Risk To Communities: Spatial Datasets Of Landscape-Wide Wildfire Risk Components For The United States.* Forest Service Research Data Archive.

Shafran, Aric P. 2008. "Risk Externalities And The Problem Of Wildfire Risk." *Journal Of Urban Economics* 64 (2): 488–495.

Simmons, Kevin M, Jeffrey Czajkowski, and James M Done. 2018. "Economic Effectiveness Of Implementing A Statewide Building Code: The Case Of Florida." *Land Economics* 94 (2): 155–174.

Snyder, Tom. 1995. "New Fire Safety , Roof Regulations Considered - City To Discuss Guidelines Oct. 3." *The Orange County Register* (September).

Sommer, Lauren. 2020. "Rebuilding After A Wildfire? Most States Don't Require Fire-Resistant Materials." *National Public Radio* (November).

Stewart, George. 1995. "North Tustin Spared From Fire Map." *The Orange County Register* (December).

Sullivan, Julie Fate. 1995. "City Spares Area From Fire Hazard Designation." *Los Angeles Times* (October).

Sydnor, Justin. 2010. "(Over)Insuring Modest Risks." *American Economic Journal: Applied Economics* 2 (4): 177–199.

Syphard, Alexandra D, Teresa J Brennan, and Jon E Keeley. 2014. "The Role Of Defensible Space For Residential Structure Protection During Wildfires." *International Journal Of Wildland Fire* 23 (8): 1165–1175.

———. 2017. "The Importance Of Building Construction Materials Relative To Other Factors Affecting Structure Survival During Wildfire." *International Journal Of Disaster Risk Reduction* 21:140–147.

Syphard, Alexandra D, and Jon E Keeley. 2019. "Factors Associated With Structure Loss In The 2013–2018 California Wildfires." *Fire* 2 (3): 49.

Syphard, Alexandra D, Jon E Keeley, Avi Bar Massada, Teresa J Brennan, and Volker C Radeloff. 2012. "Housing Arrangement And Location Determine The Likelihood Of Housing Loss Due To Wildfire." *Plos One* 7 (3): e33954.

Troy, Austin. 2007. "A Tale Of Two Policies: California Programs That Unintentionally Promote Development In Wildland Fire Hazard Zones." *Living On The Edge (Advances In The Economics Of Environmental Resources, Volume 6). Emerald Group Publishing Limited,* 127–140.

Wagner, Katherine R. H. Forthcoming. "Adaptation And Adverse Selection In Markets For Natural Disaster Insurance." *American Economic Journal: Economic Policy.*

Yost, Walt. 1996. "Accord Douses Controversy On Fire Protection." *Sacramento Bee* (October).

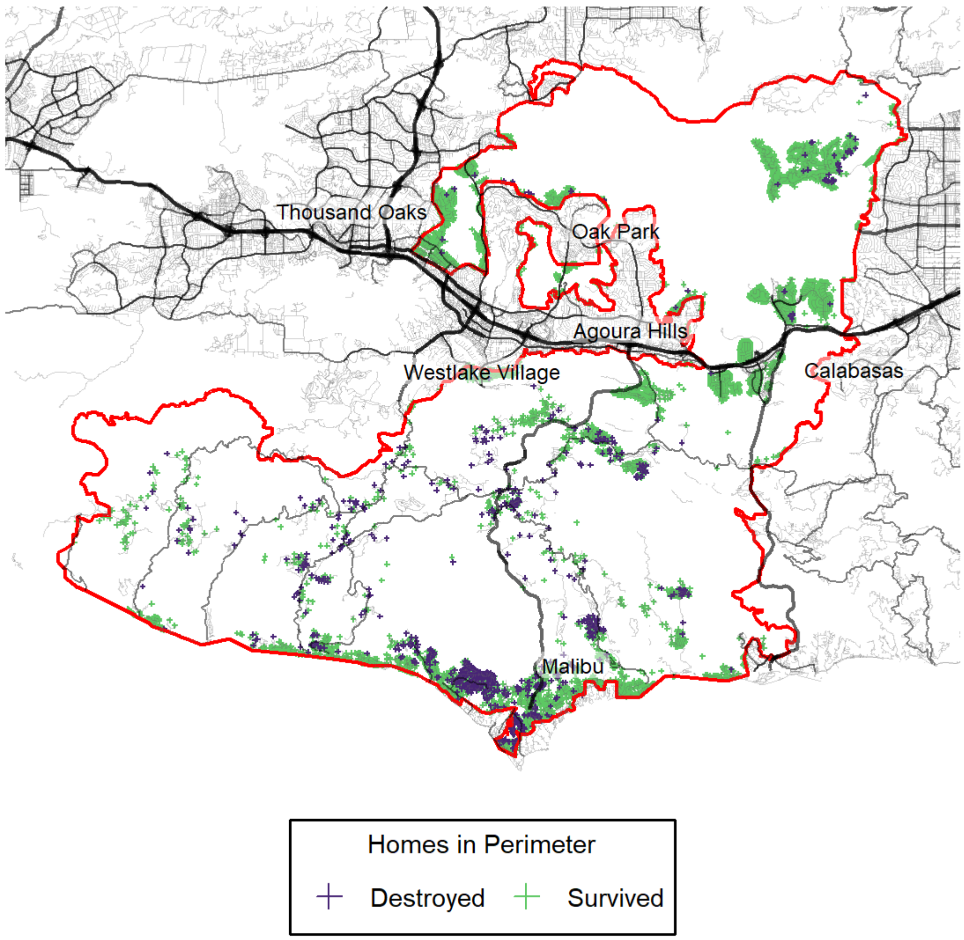
Figure 1: Building and Validating the Dataset

(a) Roof Locations and Damage Reports

(b) Distance Between Structures

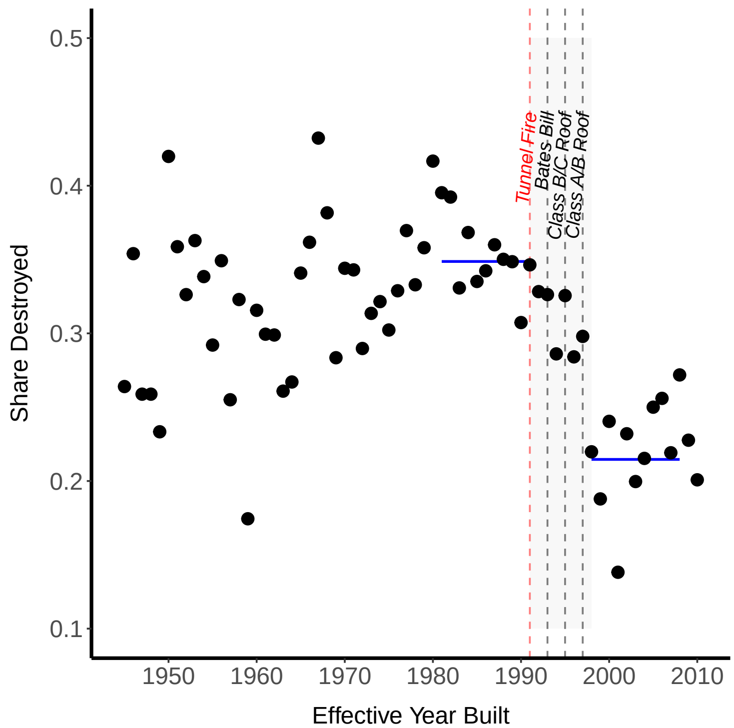
Notes: Best viewed in color. **(Panel a)** Homes affected by the Carr Fire (2018). Markers are geocoded structure locations. Green square markers are structures reported as destroyed in the damage inspection data; yellow circular markers are all other homes in the data. The background image is aerial imagery before and after the Carr Fire from NearMap. Blue building shapes and gray parcel outlines are the building footprint data and assessor parcel boundary data used to identify structure locations (see text for details). **(Panel b)** Examples of calculated distances between structure walls. Images are pre-fire aerial imagery of homes affected by the Thomas Fire (2017) and Tubbs Fire (2017). Figure shows the wall-to-wall distance from the structure marked '0' to the other homes.

Figure 2: Merged data example: Structure-level outcomes in the Woolsey Fire



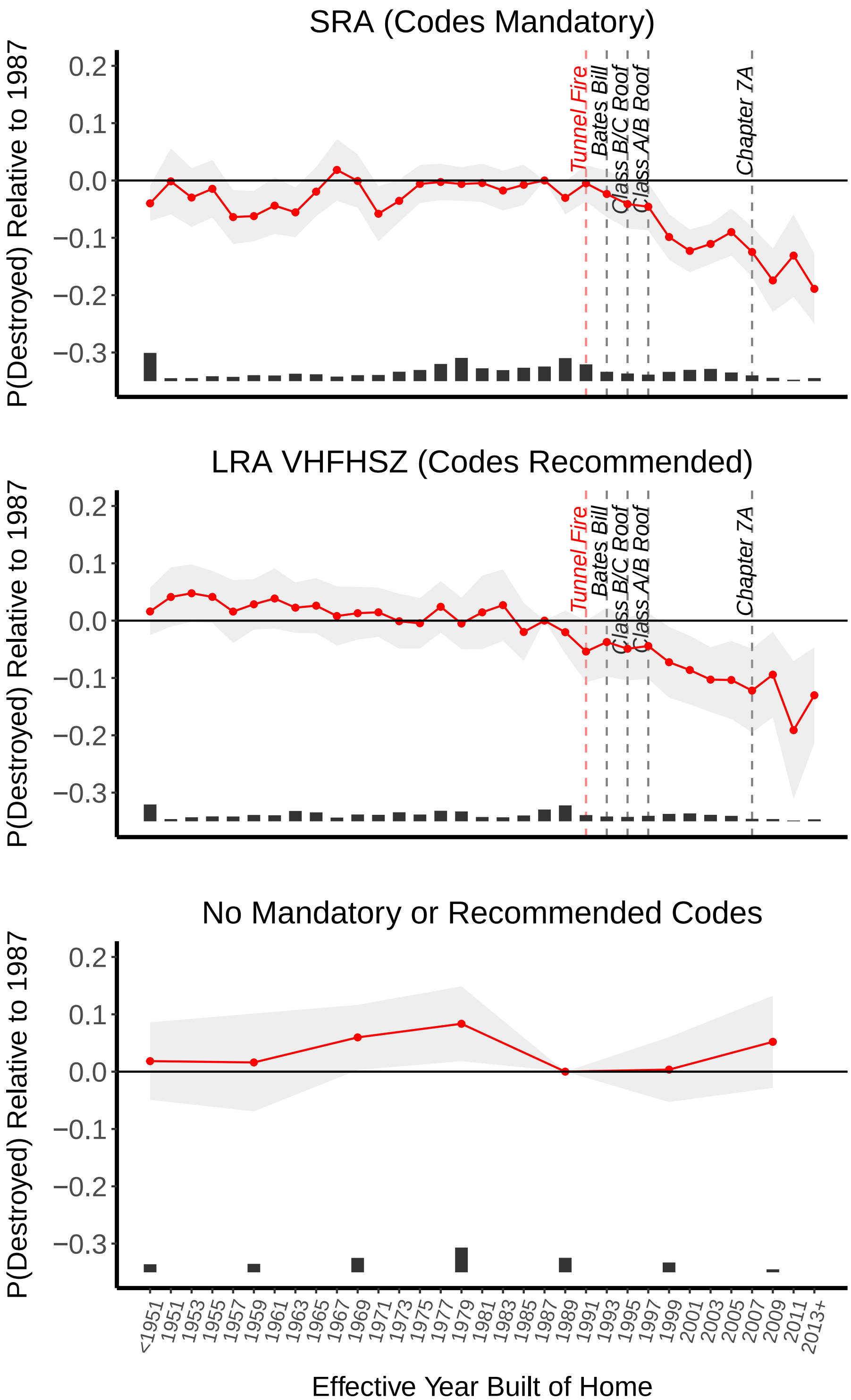
Notes: Best viewed in color. Example of merged inspection, assessor, and fire perimeter data for one fire in our dataset. Markers indicate the locations of single family homes inside the final Woolsey Fire perimeter (shown in red). Purple homes are reported destroyed in damage inspection data; green homes are all remaining homes in the ZTRAX assessment data. Street map data are from Open Street Map.

Figure 3: Share Destroyed by Year Built in Mandatory Code Areas



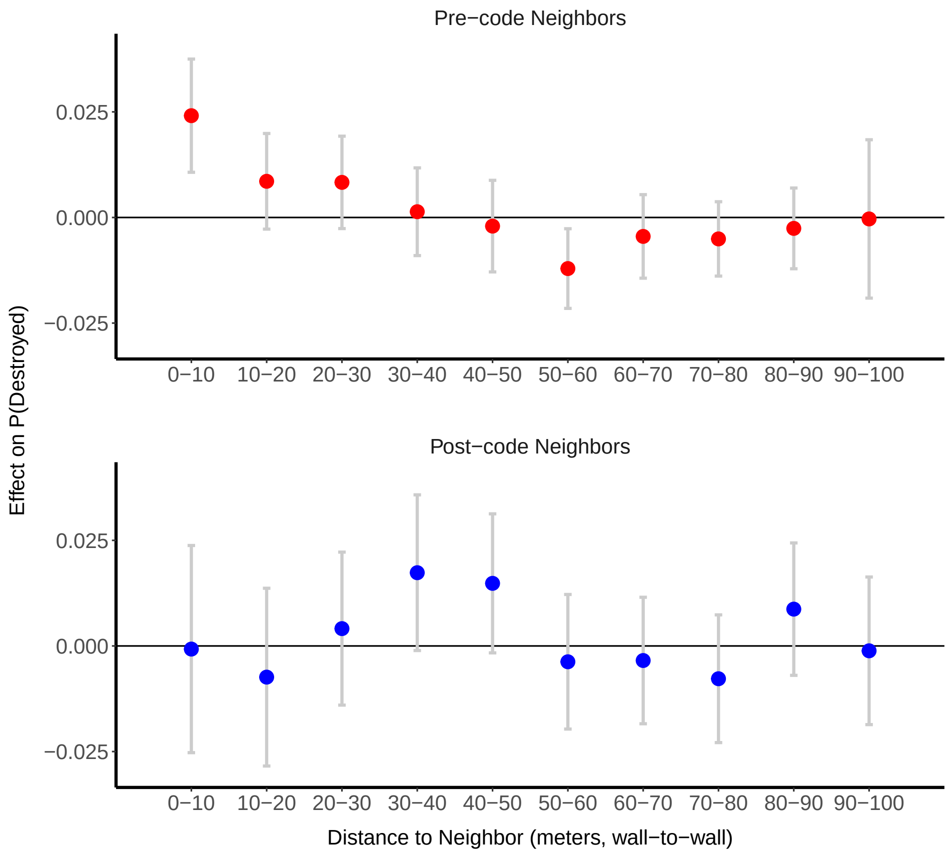
Notes: This figure shows the share of homes inside wildfire perimeters that were destroyed, according to the year that the home was built. The sample is limited to homes in State Responsibility Area. The blue lines show ten-year averages.

Figure 4: Estimated Vintage Effects by Building Code Jurisdiction



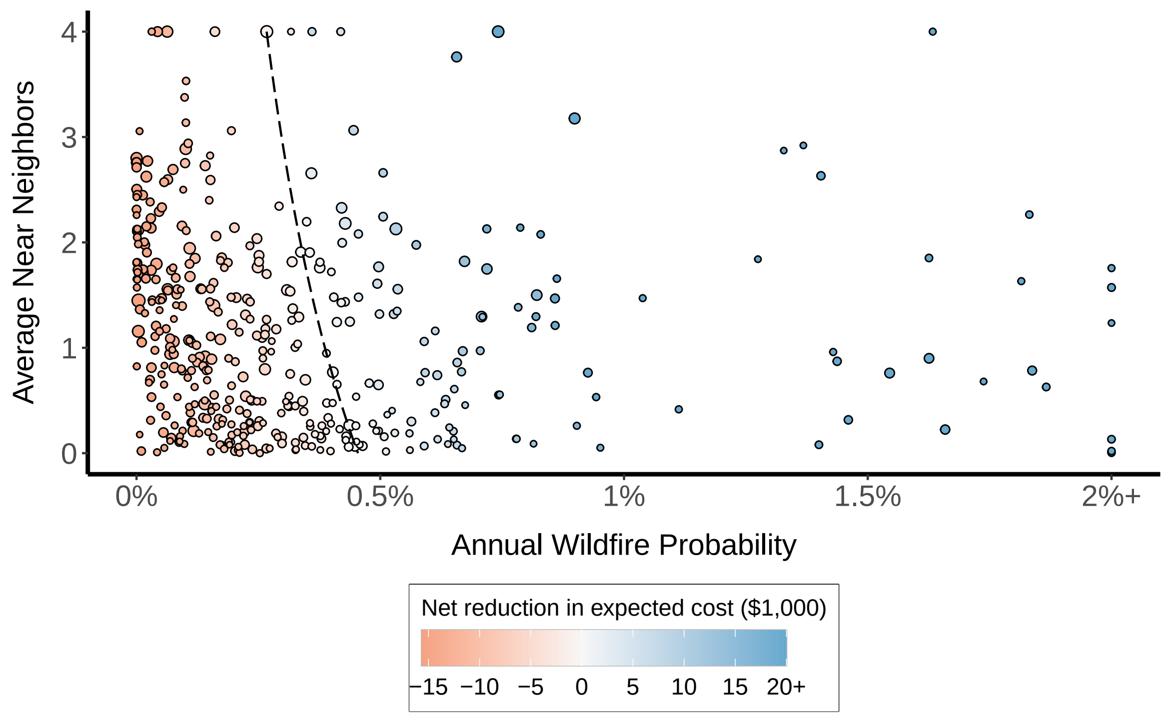
Notes: Figure plots point estimates and 95% confidence intervals from 3 separate OLS regressions of an indicator for Destroyed on bins of effective year built. Each regression includes street by incident fixed effects and other controls described in the text. Panel (a) shows homes in state responsibility area (SRA). Panel (b) shows homes in local responsibility area (LRA) inside state-recommended Very High Fire Hazard Severity Zones (VHFSZ). Panel (c) shows homes in states without wildfire building codes (AZ, CO, OR, WA) and LRA areas in California outside of state-recommended VHFHSZ. Standard errors are clustered by street. The histogram below each panel shows the relative number of observations in each bin.

Figure 5: The effect of neighboring homes on survival



Notes: Figure shows coefficients and 95% confidence intervals from a single OLS regression of "Destroyed" on the presence of pre- and post-code neighbors at various distances. The top panel shows estimates for indicator variables for the presence of one or more neighbors built without wildfire building codes. The bottom panel shows estimates for indicator variables for the presence of one or more neighbors built after wildfire building codes. The regression also includes own year built (in four year bins), street by incident fixed effects, and topographic controls. Distance to neighboring home is wall-to-wall distance. See text for details.

Figure 6: Lower-bound Net Benefits by Fire Hazard and Number of Neighbors



Notes: This figure plots the annual probability of a damaging wildfire and average number of close neighbors for a random sample of 100,230 California homes in areas subject to the Chapter 7A building codes. Markers represent zip-code averages. Marker color indicates average net benefits in the zip code using the cost-effectiveness measure, which is a conservative lower bound on total net benefits. Annual wildfire hazard is from Scott et al. (2020) and represents a snapshot as of 2014. Number of neighbors is the number of homes within a 30-meter centroid to centroid distance. Marker size is proportional to number of homes in the zip code. The dashed line shows a threshold for zero net reduction in expected cost. See text for discussion and alternative scenarios.

Table 1: Regression estimates of building code effects on own survival

	(1)	(2)	(3)	(4)	(5)
SRA * Before 1998	-0.022	-0.045	-0.027	-0.021	-0.029
	(0.033)	(0.041)	(0.029)	(0.037)	(0.020)
SRA * 1998–2007	-0.112***	-0.138***	-0.117***	-0.113***	-0.160***
	(0.034)	(0.043)	(0.031)	(0.039)	(0.022)
SRA * 2008–2016	-0.159***	-0.190***	-0.164***	-0.151***	-0.204***
	(0.036)	(0.044)	(0.033)	(0.041)	(0.027)
LRA VHFHSZ * Before 1998	-0.031	-0.048	-0.038	-0.028	-0.005
	(0.033)	(0.050)	(0.030)	(0.037)	(0.021)
LRA VHFHSZ * 1998–2007	-0.121***	-0.142***	-0.126***	-0.127***	-0.095***
	(0.034)	(0.048)	(0.032)	(0.038)	(0.025)
LRA VHFHSZ * 2008–2016	-0.159***	-0.178***	-0.162***	-0.163***	-0.130***
	(0.037)	(0.050)	(0.035)	(0.041)	(0.030)
No Codes * 1998–2007	-0.038	-0.029	-0.045*	-0.044*	-0.035
	(0.025)	(0.026)	(0.026)	(0.024)	(0.030)
No Codes * 2008–2016	-0.006	0.035	0.012	-0.010	-0.071
	(0.033)	(0.040)	(0.041)	(0.033)	(0.044)
Ground slope (degrees)	0.006***	0.005***	0.006***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lot size (acres)		-0.000			
		(0.000)			
Building square feet		-0.000			
		(0.000)			
Bedrooms		0.001			
		(0.003)			
Street FE	✓	✓			
Fuel model FE	✓	✓	✓	✓	✓
Street X 100 homes FE			✓		
Street X side of street FE				✓	
Incident FE					✓
Observations	48,843	38,991	48,843	48,843	48,843
R^2	0.62	0.63	0.63	0.66	0.39
Dep. Var. Mean	0.41	0.46	0.41	0.41	0.41

Notes: Table shows estimates and standard errors from five separate OLS regressions. The outcome variable is an indicator for Destroyed. Street fixed effects includes separate dummies for each street-by-incident. Incident fixed effects are dummies for each wildfire. Fuel model fixed effects are dummies for Anderson fire behavior fuel models. Standard errors are clustered by street.

Table 2: Neighbor Effects

	Destroyed			
	(1)	(2)	(3)	(4)
1 pre-code nearby homes	0.020***	0.023***	0.026***	0.027***
	(0.007)	(0.007)	(0.007)	(0.007)
2+ pre-code nearby homes	0.031***	0.039***	0.050***	0.051***
	(0.009)	(0.010)	(0.009)	(0.009)
1 post-code nearby home	0.001	0.002	0.010	0.001
	(0.013)	(0.013)	(0.012)	(0.013)
2+ post-code nearby homes	-0.001	0.001	0.003	-0.009
	(0.016)	(0.018)	(0.018)	(0.021)
Own Year Built	✓	✓	✓	✓
Topography	✓	✓	✓	✓
Street FE	✓	✓	✓	✓
Observations	38,226	23,564	44,923	26,842
R^2	0.64	0.68	0.63	0.68
Distances	Walls	Walls	Centroids	Centroids
Subsample		✓		✓
Dep. Var. Mean	0.40	0.49	0.40	0.51

Notes: Table shows estimates and standard errors from 4 separate OLS regressions. The outcome variable is an indicator for Destroyed, and each regression also includes dummy variables for own year built (in four year bins) and street-by-incident fixed effects. Columns (1) and (2) use wall-to-wall distances to assign neighbors, while Columns (3) and (4) use the centroid-to-centroid distance measure. Columns (1) and (3) use the full sample of single family homes, while columns (2) and (4) use a subsample in areas where our distance measures are likely to be particularly accurate. See text for details. Standard errors are clustered by street.

Table 3: Break-even Hazard under Risk Aversion and Alternative Costs

	Insured %	100	67		33	
			$\gamma = 2$	$\gamma = 5$	$\gamma = 2$	$\gamma = 5$
Cost Estimate	Source					
New Home						
$ 0	*HE-Low*	0	0	0	0	0
$ 4,029	*NAHB-Low*	0.10%	0.09%	0.08%	0.08%	0.05%
$15,660	*HE*	0.38%	0.36%	0.33%	0.30%	0.20%
$29,429	*NAHB-High*	0.71%	0.68%	0.63%	0.58%	0.41%
Retrofit						
$62,760	*HE*	1.50%	1.46%	1.40%	1.33%	1.15%

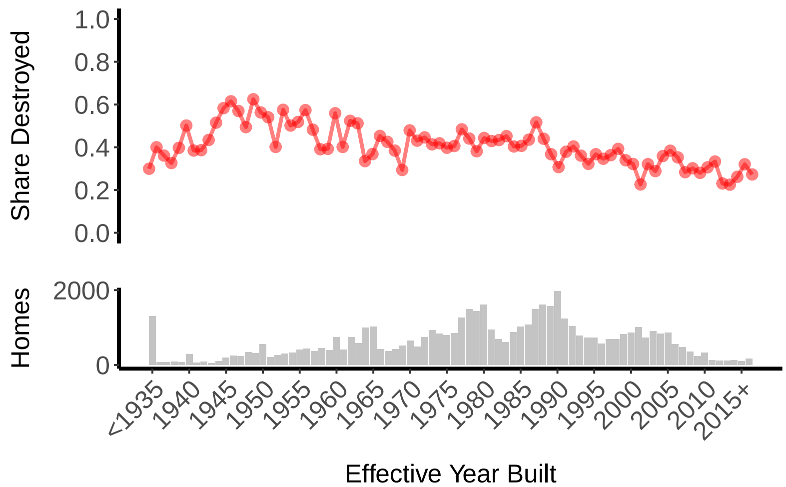
Notes: Table shows estimated minimum annual wildfire probability for which building standards yield positive net benefits under various assumptions about cost, share of losses insured, and risk aversion. Probabilities are reported as percentages (e.g., 0.32% per year). For partial insurance scenarios, γ is the coefficient of relative risk aversion. Calculations assume 1.2 near neighbors. See text for details of these calculations. Source code HE represents Headwaters Economics (2018) and NAHB represents Home Innovation Research Labs (2020).

Online Appendix to "Mandatory vs. Voluntary Adapation to Natural Disasters: The Case of U.S. Wildfires"

Patrick Baylis and Judson Boomhower

A Additional Data and Results

Appendix Figure 1: Year Built and Probability of Destruction – All Fires



Notes: Sample includes all ZTRAX single-family homes inside of observed wildfire perimeters. Red markers are share of homes of each vintage that are reported as destroyed in damage data.

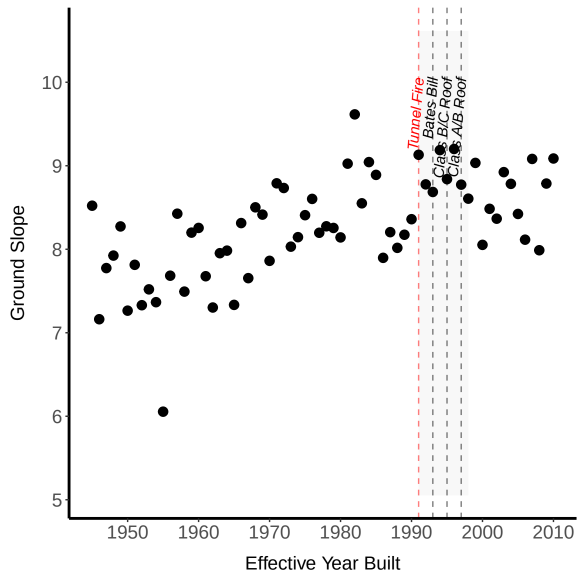
Appendix Table 1: Number of Homes per Code Area and Time Period

Area	Year Built	Number of Homes
SRA	Before 1998	20,544
SRA	1998–2007	3,815
SRA	2008–2016	827
LRA recommended VHFHSZ	Before 1998	14,087
LRA recommended VHFHSZ	1998–2007	2,515
LRA recommended VHFHSZ	2008–2016	474
LRA outside recommended VHFHSZ	Before 1998	3,513
LRA outside recommended VHFHSZ	1998–2007	212
LRA outside recommended VHFHSZ	2008–2016	37
Other states	Before 1998	1,974
Other states	1998–2007	601
Other states	2008–2016	244

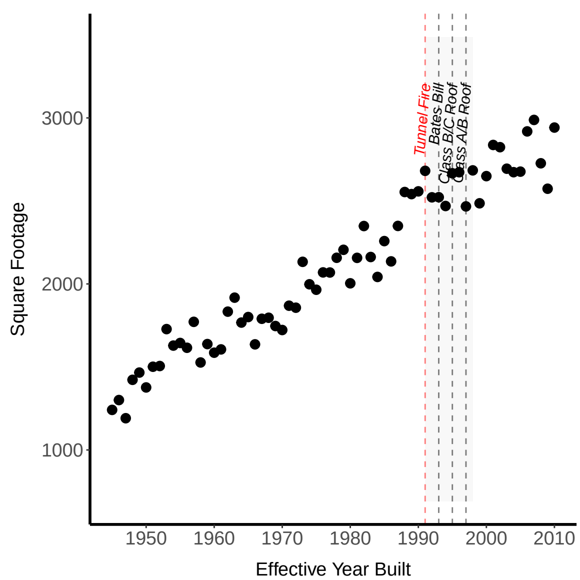
Notes: The No Codes treatment group includes the Other States and LRA outside recommended VHFHSZ groups. The Other States group excludes fires in areas with locally-adopted wildfire building codes (Appendix Table 6).

Appendix Figure 2: Other Characteristics by Year Built in Mandatory Code Areas

(a) Ground slope



(b) Building square footage



Notes: Means of other structure characteristics by effective year built for homes in SRA. Panel (a): ground slope at the home site from LANDFIRE (Rollins 2009). Panel (b): building square footage.

Appendix Table 2: Number of Neighbors by Distance

Neighbor Count	0	10	20	30	40	50	60	70	80	90+
Wall-to-wall Distance, All Neighbors										
0	25,535	28,266	23,936	19,907	19,557	20,480	21,770	23,293	25,039	10,729
1	7,904	9,035	8,824	8,909	10,004	10,518	10,248	9,805	9,316	1,027
2	8,177	3,339	4,297	5,517	6,370	6,065	5,784	5,429	4,828	1,088
3	382	817	2,243	3,509	3,506	3,148	2,735	2,363	1,986	1,229
4	75	373	1,472	2,290	1,722	1,296	1,095	880	689	1,426
5	13	182	698	1,167	630	430	346	244	173	1,557
6	0	61	390	499	209	115	90	58	44	1,576
7	0	9	172	223	64	29	15	12	9	1,696
8+	0	4	54	65	24	5	3	2	2	21,758
Mean	0.61	0.5	0.89	1.2	1.1	0.96	0.87	0.78	0.69	7.4
Wall-to-wall Distance, To-code Neighbors										
0	39,420	40,125	39,082	38,345	38,157	38,242	38,335	38,470	38,803	23,942
1	1,610	1,549	1,887	2,206	2,558	2,620	2,588	2,654	2,558	5,293
2	1,005	344	618	810	801	737	735	653	516	3,874
3	37	45	259	425	348	315	281	209	151	2,846
4	11	23	153	182	136	126	115	77	45	2,045
5	3	0	47	85	54	35	24	22	12	1,385
6	0	0	26	25	23	8	7	1	1	948
7	0	0	7	8	5	2	0	0	0	634
8+	0	0	7	0	4	1	1	0	0	1,119
Mean	0.09	0.059	0.12	0.15	0.15	0.14	0.13	0.12	0.1	1.4
Centroid Distance, All Neighbors										
0	128,963			31,821	28,094	24,606	23,935	24,775	25,911	6,967
1	13,416			11,172	11,351	10,694	11,381	11,930	11,812	1,173
2	7,955			5,307	5,615	6,758	7,709	7,524	7,139	1,485
3	516			1,195	2,602	4,168	4,300	3,850	3,530	1,592
4	114			555	1,415	2,418	2,021	1,583	1,374	1,906
5	11			206	703	1,110	720	497	417	2,134
6	3			50	338	426	203	137	120	2,260
7	6			16	145	110	45	24	21	2,351
8+	0			6	65	38	14	8	4	30,460
Mean	0.21			0.58	0.86	1.1	1.1	0.96	0.9	8.7
Centroid Distance, To-code Neighbors										
0	147,970			47,795	46,864	46,169	45,777	45,835	45,879	26,428
1	2,148			1,909	2,439	2,719	2,949	3,120	3,213	7,140
2	821			512	636	841	976	876	815	5,030
3	38			69	233	349	410	335	299	3,579
4	6			26	95	171	154	115	93	2,565
5	1			12	42	46	43	38	23	1,743
6	0			5	11	28	15	7	4	1,191
7	0			0	7	3	4	1	1	830
8+	0			0	1	2	0	1	1	1,822
Mean	0.026			0.066	0.1	0.13	0.14	0.13	0.12	1.5

Notes: This table shows the distribution of count of neighbors at various distances. "To-code neighbors" are neighbors built after WUI building codes. For the centroid distance measure, the first bin includes 0 to 30 meters.

Appendix Table 3: Controlling for spillovers in own-effect estimates

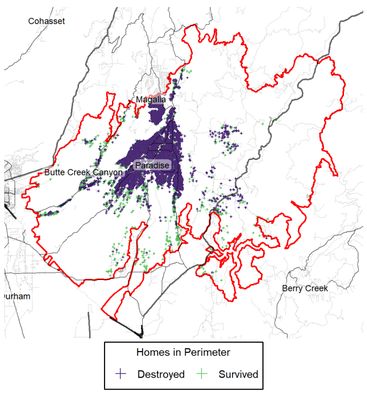
	(1)	(2)	(3)
1998–2007	-0.091***	-0.091***	-0.113***
	(0.008)	(0.008)	(0.010)
2007–2016	-0.129***	-0.128***	-0.145***
	(0.015)	(0.015)	(0.016)
Ground slope (deg)	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)
1 pre-code nearby homes		0.020***	
		(0.007)	
2+ pre-code nearby homes		0.029***	
		(0.009)	
1 post-code nearby home		0.001	
		(0.013)	
2+ post-code nearby homes		0.000	
		(0.016)	
Fuel Model FE	✓	✓	✓
Street FE	✓	✓	
Incident FE			✓
Observations	34,791	34,791	34,791
R^2	0.63	0.63	0.42

Notes: Table shows estimates and standard errors from three separate OLS regressions. Columns (1) and (3) are street fixed effects and incident fixed effects specifications. Column (2) is a street fixed effects regression that also controls for the number of pre- and post-code homes within 10 meters of wall-to-wall distance. The sample in all three columns is limited to California homes in SRA and LRA VHFHSZ areas (since we are only able to calculate wall-to-wall distances for California homes). We pool the SRA and LRA VHFHSZ code areas given the similar estimates in Table 1. Standard errors are clustered by street.

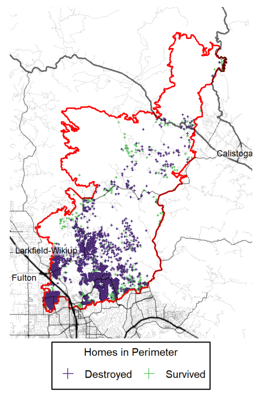
B Additional Maps

Appendix Figure 3: Additional Incident Maps

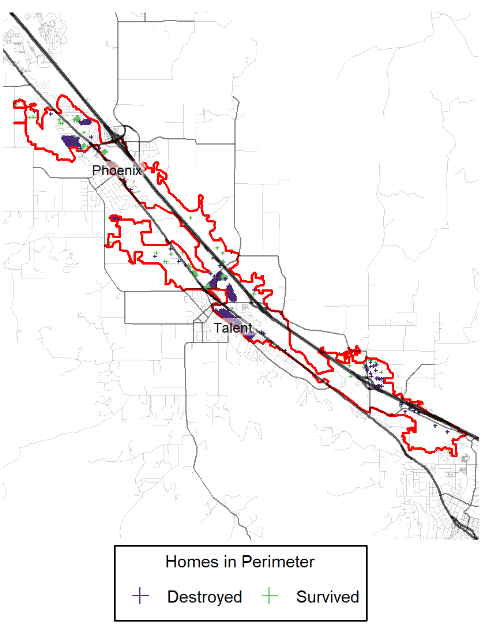
(a) Camp Fire (CA, 2018)



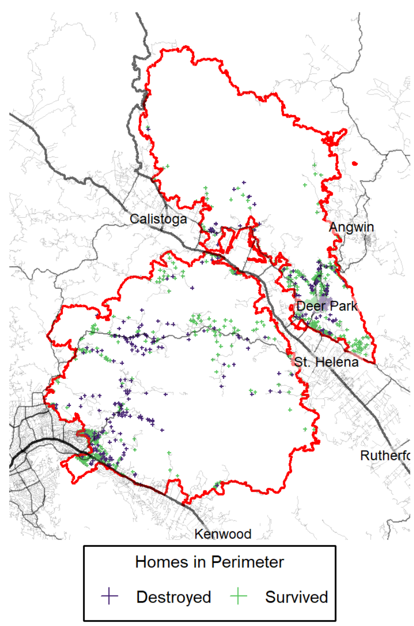
(b) Tubbs Fire (CA, 2017)



(c) Almeda-Obenchain (OR, 2020)



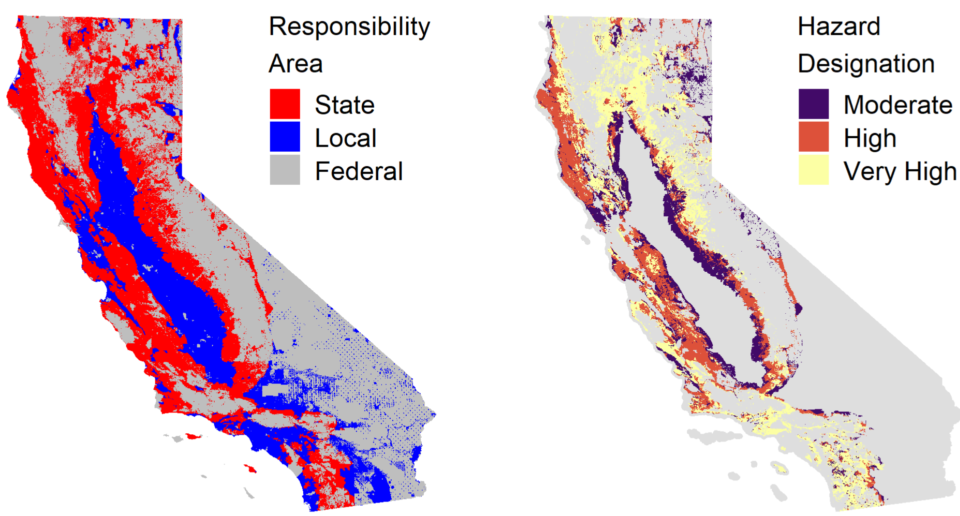
(d) Glass Fire (CA, 2020)



Notes: Additional examples of merged inspection, ZTRAX, and fire perimeter data. See Figure 2 notes for details.

Appendix Figure 4: Responsibility Areas and Fire Hazard Severity Zones in 2019

(a) Responsibility Areas (b) Fire Hazard Severity Zones



C Geocoding and Ground-truthing Homes and Damage Data

Rules for choosing street address-based locations

Section 2.2 explains how building footprints and parcel boundary GIS data are used to assign structure rooftop locations for the majority of homes in the data (87%). For the remaining 13%, street-address based geocodes from the ESRI premium geolocator are used. We use ESRI geocodes whenever any of these conditions exist for a given property:

1. Accurate parcel GIS boundary data are not available for the county.
2. The merge on assessor parcel number (APN) between all homes in a given incident and the parcel boundary data yields a merge rate below 95% (an indication of inconsistently-formatted APNs). For such incidents, all homes are located using ESRI locations.
3. A single parcel polygon contains 4 or more building footprint shapes. In our testing, this condition often indicates formerly-large parcels that were subdivided and developed subsequent to the date of the parcel boundary data and prior to the wildfire.

Ground truthing with aerial imagery

To ensure the quality of the location and damage assessment data, we evaluated a random sample of homes by hand using high resolution aerial images from NearMap as a ground truth (as in Figure 1). For each wildfire, we randomly chose 1 home (if any existed) with more than 10 neighbors within 200 meters and 1 home (if any existed) with fewer than 10 neighbors within 200 meters. We downloaded the NearMap image tiles containing these homes. Each downloaded image tile contains potentially other homes as well. We evaluated all homes in each image (stopping at 20 homes if there were more than 20 in one image).

Location: We assessed location accuracy using only *pre-fire* imagery (incidents with no available pre-fire imagery are excluded from the count). Rooftop locations were considered accurate if the assigned location was on top of the structure roof visible in the NearMap image. Even small deviations from the parcel rooftop were coded as errors, due to the need for accuracy in the neighbor analysis. Because we suspected that our footprint-based method would yield more accurate locations than street address-based geocoding, and that more rural areas would have poorer accuracy, we assessed accuracy separately for incidents geocoded with either method; and for areas with more or less than 10 neighbors located within 200 meters of a home.

Damage Reports: We assessed damage report accuracy using imagery taken within 365 days after the wildfire. If no imagery in this time window was available, the incident is excluded from the count. Damage reports were considered accurate if the reported structure outcome (Destroyed/Survived) matched the state of the structure visible in the NearMap imagery.

Appendix Table 4: Accuracy of Rooftop Locations and Damage Reports

	Error Rate	Homes	Images
Location Error Rates			
Footprint Geocodes, 10+ within 200 m	0.008	252	18
Footprint Geocodes, 0–9 within 200 m	0.069	72	19
Address Geocodes, 10+ within 200 m	0.275	51	3
Address Geocodes, 0–9 within 200 m	0.125	16	5
Damage Error Rate			
All	0.011	556	86

Notes: Error rate is the share of homes with incorrect locations or damage outcomes.

D Expected Utility and Cost Effectiveness

A more complete measure, *expected utility benefit*, accounts for the additional insurance benefits from mitigation due to the reduced probability of bearing uninsured losses. This section derives the expected utility benefit of universal mitigation relative to no mitigation, which is enough to identify the break-even wildfire hazards in Table 3. Since insurance premiums are actuarially fair in the model, insurers break even by construction and utility differences are fully represented in household expected utility. In the absence of mitigation investment, expected utility for a homeowner with utility function U and initial wealth (permanent income) w_0 is,

$$p^F p^D U(w_0 - L^U - k) + (1 - p^F p^D) U(w_0 - k) \tag{8}$$

Under a universal mitigation mandate, this same homeowner's private expected utility after undertaking mitigation is,

$$p^F(p_i^D - \sum_{j=1}^{N} \tau_{ij}) U(w_0 - L^U - \tilde{k} - m) + [1 - p^F(p_i^D - \sum_{j=1}^{N} \tau_{ij})] U(w_0 - \tilde{k} - m) \tag{9}$$

where $\tilde{k} = p^F(p^D - \tau_{ii})L^I$, the actuarially fair insurance premium after mitigation. We express expected utility for the gambles in (8) and (9) in terms of certainty equivalents CE^0 and CE^M respectively. The net expected utility benefit across households can then be expressed as $\sum_{i=1}^{N} CE_i^M$ - CE_i^0, or the sum of households' willingness to pay for the mitigation gamble as opposed to the no-mitigation gamble.

Implementing the expected utility calculation requires strong assumptions. Households have a constant relative risk aversion (CRRA) utility function $U(c) = \frac{c^{\gamma-1}}{\gamma-1}$. Permanent income is \$1,000,000. We further simplify the calculation of the expected utility measure by using a two-period model where households choose their mitigation investment at time 0 and then consume their wealth net of realized wildfire costs in period 1. To mirror the 40-year horizon of the risk-neutral cost effectiveness calculation, we discount period 1 costs using the mean of annual discount factors over 40 years ($\frac{1}{40} \sum_{t=1}^{40} \frac{1}{(1+0.05)^t}$). Future work could relax these simplifications by embedding our estimates into a life cycle model of consumption, savings, and mitigation which would capture savings behavior and differential ability to smooth losses according to age and other factors. Such a model goes well beyond the goal of the exercise in this section, which is to benchmark the degree to which uninsured loss exposure might affect the broad benefits of mitigation mandates.

E Voluntary Mitigation Takeup Without Building Codes

The net benefits of mandating universal mitigation in Section 5.2 depend on the share of homes that would have been voluntarily built to these codes in the absence of a legal requirement to do so. Because detailed data on structure characteristics are not available for most of the at-risk homes we observe, we do not have the data to assess this voluntary takeup rate for the full sample. However, recent damage inspection data from CAL FIRE make it possible to estimate this proportion for the subset of homes exposed to wildfire during the 2019 and 2020 fire seasons (in earlier years, damage inspection data are entirely or mostly limited to destroyed homes but these more recent fires also include information on a group of undamaged exposed homes). This is the best available information on mitigation takeup of which we are aware. To roughly estimate takeup of mitigation investments in the absence of building codes, we examine reported characteristics for homes built before 1990 (when no areas in our sample had binding wildland building codes).

Table 5 documents the proportions of these homes that were "fire-ready" across several structural features, including siding, eaves, vent screens, and windows. For each feature, the "Fire-ready?" columns count the number of homes that have features that are definitely fire-ready, not fire-ready, and unknown. The final column, "% Fire-ready", is the percentage of homes with fire-ready features (using only homes where fire-readiness could be determined). A significant limitation of this dataset is that more than half the homes in the dataset do not report sufficiently detailed information to allow us to determine whether they were built with fire-ready construction materials or techniques. In particular, when information on roofing is provided, it is often limited to a general description of the material used, not its fire resistance rating (which can vary within materials).

With these limitations in mind, we observe a large range in the % of homes that are fire-ready across features, from 29% for eaves to 54% for windows. In keeping with our other assumptions that deliver a conservative estimate of building code benefits, we take 1/3 – on the lower end of this range – as our estimate of the proportion of exposed homes that were built voluntarily to be fire-resilient in areas not subject to wildfire building codes.

Appendix Table 5: Pre-Building Codes Fire Readiness

Feature	Homes	Fire-ready? Yes	No	Unknown	% Fire-Ready
Siding	9,352	1,324	2,982	5,046	30.7
Eaves	9,352	967	2,420	5,965	28.6
Vent screens	9,352	1,830	2,057	5,465	47.1
Windows	9,352	2,232	1,890	5,230	54.1

Notes: Table estimates fire readiness characteristics for pre-1990 homes surveyed by CAL FIRE damage inspection teams in 2019 and 2020. Fire-ready siding is metal, brick, or vinyl, while not fire ready siding is wood. Non fire-ready eaves are those that are unenclosed. Non fire-ready vent screens are unscreened or screened with mesh larger than 1/8". Non fire-ready windows are single paned. For all features, unknown homes were those where the feature was marked as "Other" or "Unknown" in the original damage inspection data. The "% Fire-ready" column is the percent of homes that are determined to be fire ready for that feature, excluding homes for which fire-readiness could not be determined.

F Full List of Wildfires in the Dataset

This table lists the fires in the final merged dataset. It reports the count of single family homes destroyed and the count of single family homes inside the final fire perimeter (exposed). These counts may differ from reported counts of "structures lost" for individual incidents because we focus on single family homes and do not include outbuildings (sheds, detached garages, and other miscellaneous structures).

Appendix Table 6: Full List of Fires and Single Family Home Counts

	State	Year	Destroyed	Exposed	Share Destroyed
California					
CZU Lightning Cmplx	CA	2020	450	1,372	0.33
North Complex	CA	2020	396	621	0.64
LNU Lightning Cmplx	CA	2020	360	1,078	0.33
Glass	CA	2020	269	923	0.29
Creek	CA	2020	188	735	0.26
Slater	CA	2020	51	88	0.58
Bobcat	CA	2020	43	195	0.22
BEU Lightning Cmplx	CA	2020	36	128	0.28
Zogg	CA	2020	24	70	0.34
Laura 2	CA	2020	8	14	0.57
SQF Complex	CA	2020	8	42	0.19
Lake	CA	2020	7	28	0.25
Valley	CA	2020	4	73	0.05
Willow	CA	2020	4	13	0.31
Sheep	CA	2020	3	58	0.05
Bond	CA	2020	3	103	0.03
Stagecoach	CA	2020	2	10	0.20
Jones	CA	2020	2	15	0.13
SCU Lightning Cmplx	CA	2020	2	33	0.06
Gold	CA	2020	1	7	0.14
Quail	CA	2020	1	25	0.04
Oak	CA	2020	1	5	0.20
Blue Ridge	CA	2020	1	139	0.01
Branch	CA	2020	0	4	0.00
Pond	CA	2020	0	2	0.00
Kincade	CA	2019	36	170	0.21
Tick	CA	2019	16	605	0.03
Getty	CA	2019	8	128	0.06
Saddleridge	CA	2019	3	182	0.02
Mountain	CA	2019	2	8	0.25
Camp	CA	2018	8,247	10,279	0.80
Carr	CA	2018	742	1,672	0.44
Woolsey	CA	2018	656	6,831	0.10

Appendix Table 6: Full List of Fires and Single Family Home Counts *(continued)*

	State	Year	Destroyed	Exposed	Share Destroyed
Ranch	CA	2018	31	200	0.16
West	CA	2018	22	238	0.09
Klamathon	CA	2018	19	53	0.36
Holiday	CA	2018	9	33	0.27
Steele	CA	2018	8	15	0.53
Pawnee	CA	2018	6	27	0.22
Cranston	CA	2018	5	66	0.08
Meyers	CA	2018	3	4	0.75
Delta	CA	2018	3	21	0.14
Holy	CA	2018	1	147	0.01
Carder	CA	2018	1	1	1.00
Marsh	CA	2018	1	5	0.20
Silver	CA	2018	1	2	0.50
Creek	CA	2018	0	1	0.00
Tubbs Fire	CA	2017	3,730	4,607	0.81
Thomas	CA	2017	496	2,311	0.21
Nuns	CA	2017	380	1,396	0.27
Atlas	CA	2017	229	665	0.34
Redwood	CA	2017	106	185	0.57
Cascade	CA	2017	61	229	0.27
Sulphur	CA	2017	38	112	0.34
Helena	CA	2017	27	89	0.30
Creek	CA	2017	26	611	0.04
Laporte	CA	2017	25	87	0.29
Lilac	CA	2017	21	311	0.07
Detwiler	CA	2017	18	156	0.12
Ponderosa	CA	2017	9	15	0.60
Canyon 2	CA	2017	9	198	0.05
Wall	CA	2017	6	36	0.17
Skirball	CA	2017	5	76	0.07
Estate	CA	2017	2	5	0.40
Mission	CA	2017	2	14	0.14
Laverne	CA	2017	2	9	0.22
Hill	CA	2017	2	8	0.25
Railroad	CA	2017	2	6	0.33
Alamo	CA	2017	1	13	0.08
Stone	CA	2017	1	3	0.33
Cherokee	CA	2017	0	2	0.00
Canyon	CA	2017	0	24	0.00
Clayton	CA	2016	52	138	0.38
Erskine	CA	2016	51	546	0.09
Soberanes	CA	2016	15	54	0.28
Grade	CA	2016	4	11	0.36

Appendix Table 6: Full List of Fires and Single Family Home Counts *(continued)*

	State	Year	Destroyed	Exposed	Share Destroyed
Goose	CA	2016	1	5	0.20
Chimney	CA	2016	0	9	0.00
Valley	CA	2015	827	1,697	0.49
Butte	CA	2015	151	439	0.34
Round	CA	2015	31	130	0.24
Rocky	CA	2015	11	50	0.22
Tassajara	CA	2015	2	9	0.22
Cocos	CA	2014	30	156	0.19
Clover	CA	2013	12	20	0.60
Silver	CA	2013	4	68	0.06
Shockey	CA	2012	5	9	0.56
Ponderosa	CA	2012	2	4	0.50
Ponderosa	CA	2012	0	2	0.00
49er	CA	2009	63	125	0.50
Humboldt	CA	2008	47	189	0.25
Trabing	CA	2008	13	60	0.22
Martin	CA	2008	0	4	0.00
Witch	CA	2007	516	5,812	0.09
Grass Valley	CA	2007	152	432	0.35
Paradise2003	CA	2003	29	520	0.06
Other States					
Goodwin	AZ	2017	2	6	0.33
Yarnell	AZ	2013	79	212	0.37
EastTroublesome	CO	2020	272	573	0.47
CameronPeakFire†	CO	2020	72	552	0.13
MM 117 Fire†	CO	2018	7	85	0.08
Black Forest†	CO	2013	423	767	0.55
Waldo Canyon†	CO	2012	295	892	0.33
HighparkFire†	CO	2012	171	536	0.32
Almeda-Obenchain	OR	2020	414	599	0.69
HolidayFarm	OR	2020	325	594	0.55
BeachieCreek-Santiam	OR	2020	219	359	0.61
EchoMountainComplex	OR	2020	125	289	0.43
ColdSprings	WA	2020	10	70	0.14
OkanoganComplex	WA	2015	34	393	0.09
CarltonComplex	WA	2014	111	629	0.18
Eagle Road Fire	WA	2014	6	726	0.01

†Excluded from "other states" comparison group due to locally-adopted WUI building standards.

Appendix References

Rollins, Matthew G. 2009. "LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment." *International Journal of Wildland Fire* 18 (3): 235–249.