Building codes and community resilience to natural disasters

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April 2021

Natural disaster losses can be mitigated through investments in structure hardening. When property owners do not correctly perceive risks or there are spatial externalities, it may be beneficial to mandate such investments through building codes. We provide the first comprehensive evaluation of the effect of California's wildfire building codes on structure survival. We combine administrative damage data from several states, representing almost all U.S. homes destroyed by wildfire since 2007. We merge this damage data to the universe of assessor data for destroyed and surviving homes inside wildfire perimeters. There are remarkable vintage effects in resilience for California homes built after 1995. Using differences in code requirements across jurisdictions, we show that these vintage effects are due to state and local building code changes prompted by the deadly 1991 Oakland Firestorm. Moreover, we find that these improvements increase the survival probability of neighboring homes due to reduced structure-to-structure spread. Our results imply that property losses during recent wildfire seasons would have been several billion dollars smaller if all older homes had been built to current standards.

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1 Introduction

As natural disasters become more frequent and more severe, there is increasing attention to potential adaptive responses to mitigate economic impacts. One such margin of adaptation is "hardening" of homes and other structures in high hazard areas. A growing number of high-profile federal and state initiatives require or subsidize such investments. In theory, these policies can be justified by misperception of risk by property owners and/or by spillover benefits of mitigation across properties. But there is little empirical evidence about the degree to which these policies increase resilience compared to a counterfactual of purely voluntary takeup.

In this paper, we consider the case of wildfire building codes in California. California has some of the the most advanced and detailed mitigation requirements in the world for homes in areas with high fire hazard. We worked with state emergency management agencies and individual county assessors to assemble a database that includes almost all United States homes destroyed by wildfire between 2007 and 2020. We merge this damage data to assessor data for the universe of homes in affected areas. We use this new dataset to provide new evidence on the effects of California's building codes on structure survival, and on spillover benefits of mitigation across properties. A key advantage of our study is that we observe the full population of surviving and destroyed homes, unlike existing studies that primarily observe data for destroyed homes.

The rich dataset also allows us to deploy an explicit empirical design that requires substantially weaker identifying assumptions than existing work. Our preferred empirical approach is a fixed effects design that compares the likelihood of survival for homes of varying vintages located on the same residential street. These street fixed effects allow us to compare groups of homes that experience essentially identical wildfire exposures. This methodological contribution reduces noise and omitted variables bias introduced by the substantial variation in fire severity and average structure characteristics within any individual incident perimeter. Our empirical analysis leverages emerging tools in spatial analysis, including precise "rooftop" geocoding of structure locations and high-resolution aerial imagery.

We find remarkable vintage effects for California homes. A 2010 or newer home is about 15 percentage points (38%) less likely to be destroyed than a 1985 home experiencing an identical wildfire exposure. There is strong evidence that these effects are due to state and local building code changes prompted by the deadly 1991 Oakland Firestorm. The observed vintage effects are highly nonlinear and discontinuous, appearing immediately after these changes took effect. There are no similar effects in areas of California not subject to these code changes, or in other states.

We also find important benefits to neighboring homes, consistent with reduced structure-to-structure spread. These neighbor effects match anecdotal reports that home-to-home spread may be an important factor during urban conflagrations. Our results imply that, ceteris parabis, a home's likelihood of destruction during a wildfire falls by about 3 percentage points (8%) if its nearest neighbor was built under the modern wildfire codes. This benefit is even larger when homes have multiple close neighbors built to modern codes.

These results have immediate policy implications. The state of California, for example, is actively implementing policies to require or incentivize home hardening in wildfire-prone areas. Assembly Bill 38, which took effect in 2020, introduced a large-scale grant program to support wildfire safety retrofits for existing housing. The law specifically calls for support of "cost effective" retrofits, a concept to which the evidence in this study is essential. Similarly, California's 2021 Wildfire and Forest Resilience Action Plan calls for large-scale increases in state support for home hardening and defensible space.[1] Additionally, policymakers are confronting pressing issues of insurance rate reform in response to large losses during the 2017 and 2018 wildfires. One key debate in this area is the degree to which individual investments improve structure survival, and should thus be rewarded through insurance pricing. This paper's evidence on the effectiveness of such investments from real wildfire events directly responds to this knowledge gap. Finally, the clear risk spillovers that we measure between neighboring homes underscore the need for policy approaches that can address these externalities.

This paper is related to a small literature on natural hazard mitigation. For wildfires, several studies in the engineering and ecology literature estimate benefits of various mitigation actions such as removing vegetation near homes and upgrading roofs,

1. California Natural Resources Agency, California Environmental Protection Agency, and Department of Forestry and Fire Protection. "California's Wildfire and Forest Resilience Action Plan: A Comprehensive Strategy of the Governor's Forest Management Task Force." January 2021.

windows, and other home components (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). These studies paint a conflicting picture of the effectiveness of various potential investments. None of them directly measure the effects of building codes or other policy changes. In economics, Shafran 2008; Champ, Donovan, and Barth 2013; Dickinson et al. 2015; Wagner 2020 consider the uptake or effectiveness of risk mitigation activities for wildfire or flooding.

From a methodologial perspective, our work connects to a separate literature in environmental economics on the effectiveness of building codes in reducing energy consumption (Jacobsen and Kotchen 2013; Levinson 2016; Kotchen 2017). Our approach to measuring code effects is similar to the approaches in these papers, although our focus on disaster resilience is quite different.

This study adds to our understanding of these issues in four ways. First, we focus on evaluating building code policies, where previous work studies homes where owners have or have not chosen to install various fire safety technologies. Thus, our study is able to estimate benefits of the policy relative to an explicit counterfactual of not mandating these investments and relying instead on voluntary takeup. Second, we provide the first empirical estimates of the spillover benefits of wildfire mitigation investments to neighboring properties. Third, we apply the toolkit of modern applied microeconomics to introduce an explicit empirical design in a causal framework. Previous work is primarily descriptive or relies on regression adjustment. Finally, we compile a comprehensive dataset of structure-level outcomes in wildfires across states that, to our knowledge, is the most complete accounting in existence. This large-scale dataset allows us to examine structure loss and survival in a more general and granular way than previous studies, which have tended to be case studies of one or a few fires. Beyond the results in this study, this new dataset will enable future work on the economic impacts of catastrophic wildfire risk.

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

2 California's Wildfire Building Codes

Among U.S. states, California has the most detailed building standards for wildfire resistance in high hazard areas. Code requirements vary 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 Oakland Hills Firestorm of 1991, which killed 25 people and caused $1.5 billion in property damage, focused the public and policymakers on wildfire safety and led to a series of legislative actions. 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 recommend Very High Fire Hazard Severity Zones (VHFHSZ) where new building codes would apply. Local governments could choose whether to adopt these recommended hazard zones in LRA areas. 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 (73%) local governments either adopted the VHFHSZ regulations or claimed to have promulgated equally strong existing rules.[2]

On the heels of the Bates Bill, Assembly Bill 3819 of 1994 increased requirements for ignition-resistant roofs. Roofing materials are rated Class A, B, C, or unrated.[3] Starting in 1995, the law required Class B ignition-resistant roofs on homes built or re-roofed in all SRA areas and in LRA areas that accepted the state's proposed VHFHSZ designations. In 1997, this requirement stepped up to Class A ignition-resistant roofs in the highest-hazard areas. Finally, Assembly Bill 423 in 1999 simplified enforcement of these roofing codes by outlawing the use of unrated roofing materials throughout the state.

California increased its code requirements again in 2008 with the so-called "Chapter

2. For an excellent qualitative study of local VHFHSZ adoption decisions, see also Miller, Field, and Mach (2020).

3. 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 speeds. The material must not ignite for 90 minutes.

7A" requirements of the California Building Code. These requirements include detailed standards for building components like decks and eaves, as well as requirements for managing vegetation around the home. The Chapter 7A codes apply to all homes built in 2008 or later in SRA areas and in designated LRA VHFHSZ areas.

3 Data and Spatial Analysis

This section reviews the key datasets and data processing steps. A detailed account of the database construction is included in the online appendix.

Damage inspection data

We assembled a database of administrative records for homes destroyed or damaged by wildfire in the United States. In California this information is managed by CAL FIRE. In other states, we worked with individual county assessors, who track these damages for the purpose of updating property tax assessments. To our knowledge, the resulting database is the most complete accounting ever compiled of homes lost to wildfire. It includes the large majority of homes destroyed by wildfire in the United States since 2007.

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. We focus on "destroyed" as our primary outcome and report results for the other damage categories in the online appendix. We augment the DINS data with data on the earlier 2003 and 2007 fire storms in San Diego provided by San Diego County.

To complement the California data, we solicited damage inspection data for wildfires in other states during the same period. Using ICS-209 incident reports, we identified the 15 counties outside of California with the greatest number of structures lost since 2010. We then contacted county assessors in each of these counties to request damage data. So far, we have received usable data from 11 of these counties.

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 extensive remodels), building square footage, lot size, and other housing characteristics. The merge from damage data to ZTRAX uses assessor parcel numbers. 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.

Identifying and validating rooftop locations

We combine several sources of spatial data to identify the precise location of every home in our dataset. First, we limit the population of ZTRAX homes to all homes in zip codes where at least one home was destroyed. We merge this homes data to parcel boundary maps from county assessors. We then use comprehensive building footprint maps from Microsoft to identify the largest structure on each single family parcel.[4] 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 calculated rooftop locations for each structure. Yellow markers show homes that are reported as destroyed in the damage data.

To quality check the calculated property locations and the damage report data, we use high-resolution aerial imagery from NearMap. The base image in Figure 1 shows an example. The detailed imagery allows us to manually confirm structure locations. 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

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

data. We have done extensive manual checking of a random sample of homes and found the data to be highly reliable. Detailed results of our checks are summarized in the online appendix.

Currently, we have implemented this rooftop geocoding method for almost all California counties. In a small number of California counties with unreliable parcel boundary data, and in all counties outside of California, we instead geocode home locations using the ESRI StreetMap Premium geolocator product. This alternative approach yields structure locations for 98% of homes in ich returns structure locations for 98% of homes. Our quality checking shows that these locations are also highly reliable in most cases.

Spatial merge to wildfire perimeters and code jurisdictions

We restrict the dataset to homes located inside within a 20-meter buffer around final wildfire perimeters. This defines the population of exposed homes during each incident to be all single family homes inside these buffered perimeters. 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, LRA) and fire hazard that together determine building codes in a given location in California. Currently, we use the most recent SRA definitions and fire hazard zones available from CAL FIRE. These maps have changed somewhat over time, which likely introduces some misclassification in our analysis. We are working with CAL FIRE to get access to digital versions of historical maps.

Identifying nearest neighbors

We identify the 15 nearest neighbors for each home in the final dataset. We restrict the neighbor definition to homes inside the wildfire perimeter and within 1,000 meters, so that some homes have fewer than 15 neighbors. We identify two sets of neighbors: one based on all nearby homes, and another limited to homes on the same street. We validate these neighbor locations during the quality checking of structure locations described earlier. Appendix Figure **??** shows an example of the same-street neighbor assignment for a home inside the perimeter of the 2017 Tubbs fire in Santa Rosa, California. The underlying aerial image (taken before the fire) shows that the implied neighbor ordering and distance closely matches the actual arrangement of homes along the street.

Data Summary

The final dataset includes 49,435 single family homes exposed to 91 wildfires in California, Oregon, Washington, and Arizona between 2007 and 2020. Forty percent of these (19,753) were destroyed. Table 1 summarizes information for a subset of the largest fires, and Appendix Figure A1 shows the distribution of year built and fraction destroyed by year built.

4 Empirical Strategy

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 (shown in red). 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, response timing, landscape vulnerability, structure characteristics, and potentially numerous other factors. This heterogeneity adds noise to empirical analysis of structure resilience. Moreover, it may introduce bias if year built or other structure traits also vary within burned areas. We address these challenges using an empirical design that compares the likelihood of survival for homes on the same residential street, taking advantage of the address information and large number of unburned comparison structures available in the assessor data.

4.1 Own-structure survival

Event study figures

We begin our regression analysis with the following event study-style model for home i on street s within fire perimeter f,

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

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. We estimate Equation 1 separately for homes in SRA, LRA areas that opted in to VHFHSZ designations, and a pooled comparison group that includes areas of California not subject to state codes along with homes in other states. We pool these two comparison groups to maximize our ability to measure any effects in these somewhat smaller samples.

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. Our main specification groups all homes on the same street and zip code as one street. We also show results for an approach that further segments houses into groups of no more than 25 homes along each street, ordering homes by house number.

The additional control variables X_i include structure characteristics from the assessment data and landscape characteristics for the home site from USDA Forest Service LANDFIRE.[5] The primary effect of these control variables is to improve precision by explaining some of the residual variation in structure survival on each street.

Difference in differences

We calculate overall effects of the building codes using a difference-in-differences (DiD) model that limits the sample to years close to the policy change, and collapses time periods into before and after 1995. This DiD regression includes three groups: SRA, LRA VHFHSZ, and the pooled comparison group of other California homes and

5. The structure characteristics are lot size, building square footage, number of bedrooms, and number of bathrooms. The LANDFIRE variables are slope steepness and vegetation type at the home location.

homes outside California. Our main speciication includes two time periods centered on 1995, but we estimate alternative specifications that also capture the additional effect of the 2008 Chapter 7A standards.

4.2 Structure to structure spread

To measure the effect of mitigation investments 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,

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

Like Equation 1, this specification controls for own year of construction. The additional regressors and coefficients $\sum_{j=1}^{j=J} \rho_j D_j$ capture the effect of the jth nearest neighbor being built after 1995 ($D_j = 1$). We implement several different versions of this basic neighbor regression. Our first preferred specifications tests the effects of the nearest home. An additional specification tests the effects of *both* of the two nearest neighbors having been built under the codes.[6]

This regression identifies the causal effect of mitigation by neighboring homes if the age of 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, and by the direct controls for own-structure vintage. However, one might still worry that even conditional on these controls, the age of a home's neighbors may predict other wildfire risk factors. We investigate these concerns using a placebo test that measures the effect of homes located five or six homes away on structure survival. These properties located "a few doors down" are far enough away to present little direct ignition threat, but should be expected to otherwise be subjected to all of the same potential omitted variables as the home directly next door.

We report results for each neighbor separately, as written in Equation 2. However, our preferred specification pools information for the nearest two or three neighbors

6. Laboratory and field evidence on home ignitions suggest there may be little benefit to mitigation by the second-nearest neighbor if the closer neighbor still presents an ignition risk.

into summary variables (e.g., age of oldest neighboring structure, or number of neighboring structures built before 1995). In addition to increasing statistical power, this pooling is consistent with the logic of defensible space, in that protecting a home requires eliminating when potential ignition sources are eliminated on all sides of the house.

5 Results and Discussion

5.1 Own-structure survival

5.1.1 Graphical Evidence

Figure 3 shows the raw mean of *Destroyed* for SRA homes in each year of construction from 1940 to 2016. These simple averages show that about 35% of homes built prior to the effective date for AB 3819 we destroyed by the 2007–2020 wildfires analyzed in this study. Immediately after the AB 3819 roof requirements begin to be enforced in 1995, that share drops by about ten percentage points. The share destroyed continues to smoothly decline in later construction years. Additionally, homes built earlier than about 1985 are somewhat less likely to be destroyed than homes built just prior to the roof requirements. This may reflect the fact these older homes are likely to have been re-roofed at least once, with these roof replacements possibly happening after AB 3819 (and thus falling subject to its requirements for ignition-resistant materials).

Figure 4 shows means for other structure characteristics by effective year built in SRA areas. Predictors of wildfire hazard, such as the slope of the home site (Panel a), do not change for homes built after 1995. Similarly, building characteristics like building square footage (Panel b) also do not change sharply in 1995 in the way that survival probability does. The constant upward slope over time in building square footage mirrors national trends in the size of new homes over this period.

Moving on to regression analysis, Figure 5 presents estimates from Equation 1 for homes in SRA and LRA-VHFHSZ areas. The red markers are estimates and 95% confidence intervals. The horizontal axis plots the left-most year in each two-year vintage bin. The lowest bin includes all homes older than 1951, and the highest bin includes all homes newer than 2015. The gray histogram shows the density of observations across these bins. Panel (a) considers the group of SRA homes from the previous plot of raw means. The regression-adjusted vintage effects are flat prior to about 1993, and then begin to decrease rapidly during the 1995–1999 period when the various roof mitigation rules were rolled out in SRA areas.

Panel (b) of Figure 5 shows LRA areas with VHFHSZ designations. These areas again show extremely flat trends in resilience prior to the Tunnel Fire and the Bates Bill. Immediately after the Bates Bill taking effect in 1992, the figure shows the beginning of gradual improvements that persists for about 12 years. This pattern is consistent with the Bates Bill process (or independent local initiatives) gradually improving structure quality in these locally-managed areas.

Figure 6 shows vintage effects for the pooled group of homes not subject to California's codes. Due to the smaller sample, we use ten-year bins. There is no evidence of any kind of similar improvement in resilience after 1992 or 1995 as in the SRA and LRA-VHFHSZ figures.

5.1.2 Difference in Differences Estimates

Table 2 reports difference-in-differences estimates of the effect of building codes on own structure survival. Column (1) shows that the average effect is 8.5 percentage points in SRA areas and 9.0 percentage points in LRA-VHFHSZ areas. These estimates are robust to a number of checks, including omitting the comparison group (so that estimates are identified only by before-after differences), applying finer "street" definitions that group together no more than 25 adjacent homes, controlling for structure age (defined as year of fire minus effective year built), and controlling for additional home characteristics. The final column adds an additional time threshold to capture the introduction of the Chapter 7A standards in 2008.

5.2 Spillovers to neighboring properties

This section discusses spillover effects to neighboring homes in SRA and LRA VHFHSZ areas. Before presenting estimates for Equation 2, we begin with a graphical presentation of the effect of neighbors on own-structure survival as a function of distance between roofs and age of the neighboring structure. The results are in Figure 7. These estimates come from a single regression of *Destroyed* on street fixed effects, own year built, and an additional set of dummy variables that capture the presence of older and new homes at various distances away. The red estimates show the effect of having at least one pre-1995 home located at a given distance. At distances less than 30 meters, pre-1995 neighbors increase own-structure loss probability by about two percentage points. Beyond this short distance there is no effect of older neighbors. The gray estimates show the effect of newer homes. Regardless of distance away, post-1995 neighbors do not increase the likelihood of structure loss.

Table 3 reports regression estimates from Equation 2. The sample is limited to California homes in SRA or LRA-VHFHSZ areas. Column (1) shows that the effect of the nearest neighboring home being built after 1995 is about 1.5 percentage points on average. The remaining columns of Table 3 restrict the sample to homes on streets with average lot sizes of 1 acre or smaller. These denser neighborhoods are where structure-to-structure ignition is most likely. The effect of the nearest neighbor increases to about 3.3 percentage points in this subsample. Column (3) shows that this effect grows to 5.4 percentage points if both the nearest and the next-nearest structure were built after 1995.

Columns (4) and (5) present the placebo test based on homes located 5 or 6 doors down. These neighbors' ages have no effect on own-structure survival. This result further allays any concerns about neighborhood-level omitted variables that could be correlated with neighbors' ages, supporting the conclusion that the effects we observe in our neighbor regressions are due to increased likelihood of structure to structure fire spread from adjacent homes. Finally, Columns (6) and (7) show effects using neighbor definitions that only consider homes on the same street. The treatment effect increases, while the placebo result continues to show no effect.

6 Conclusion

Improving community resilience to natural disasters is an increasingly urgent challenge. In this paper, we create a new, comprehensive dataset of outcomes and property characteristics for destroyed and surviving homes in U.S. wildfires. We use that data to provide new estimates of the effect of building vintage on structure resilience, the role of building codes, and the spillover effects of hazard mitigation for neighboring homes. Our empirical approach is based on highly localized within-street comparisons that compare nearby homes experiencing essentially identical wildfire exposures.

Our results imply that structure characteristics play a major role in wildfire outcomes. Our main estimates show that a structure built to 2012 standards is 17 percentage points, or about 35%, less likely to be destroyed than a pre-1995 home facing the same risk. The timing of these improvements is closely tied to the effective date of the Bates Bill and subsequent increases in roofing standards and other rules. Moreover, we do not see similar improvements in structure resilience in states and jurisdictions not subject to these building codes. Together, these pieces of evidence strongly suggest that building codes are behind the large vintage effects we measure.

The results also show that hardening homes yields benefits for neighboring properties. Holding constant own year built and other factors, a home whose two nearest neighbors were all built after 1995 is about 5 percentage points less likely to be destroyed when a wildfire occurs. Even if homeowners were fully informed and rational about wildfire risk, these externalities would argue for public policy interventions to improve community-level resilience.

The economic significance of the effects that we measure will only continue to grow as wildfires grow more frequent and severe. A simple back-of-the-envelope calculation illustrates the amounts at stake. Our data show that about 85% of the homes destroyed in the 2017 and 2018 California wildfires were built prior to 1995, meaning that pre-1995 homes represented about \$32.5 billion in property losses during those two years. If those homes had been built to 2012 standards, our estimates imply that the avoided property losses during those two years would have been about \$11 billion.[7] This calculation ignores other important benefits, including lives saved, reduced public spending on firefighting to save homes, and less frequent need for disruptive Public Safety Power Shutoffs that temporarily eliminate electricity service during high fire-risk periods.

Our estimates can be combined with estimates of construction costs to understand the cost-effectiveness of these investments. For newly constructed homes, the benefits we measure clearly pass a cost-benefit test, particularly because the cost of achieving them is low. The consulting firm Headwaters Economics found in a recent study that there is little cost difference associated with constructing a wildfire resistant home relative to a typical home, although this study does not account for the value

7. Details of this calculation: Munich RE NatCatSERVICE reports \$38 billion of property damage in wildfires during 2017–2018. \$38 billion $*$ 85% $*$ 35% = \$11.3 billion.

of aesthetic differences (Headwaters Economics 2018). Thus, our study implies that there would be large net benefits from strengthening wildfire building codes in other states to match those in California. The cost-effectiveness of retrofits for existing homes is a more complex question since such upgrades may be costly and time-consuming. Given cost estimates for retrofitting homes to current standards, our estimates could be applied to generate cost benefit ratios. Further work to identify the costs and resilience benefits of individual upgrade investments is an important priority for future research.

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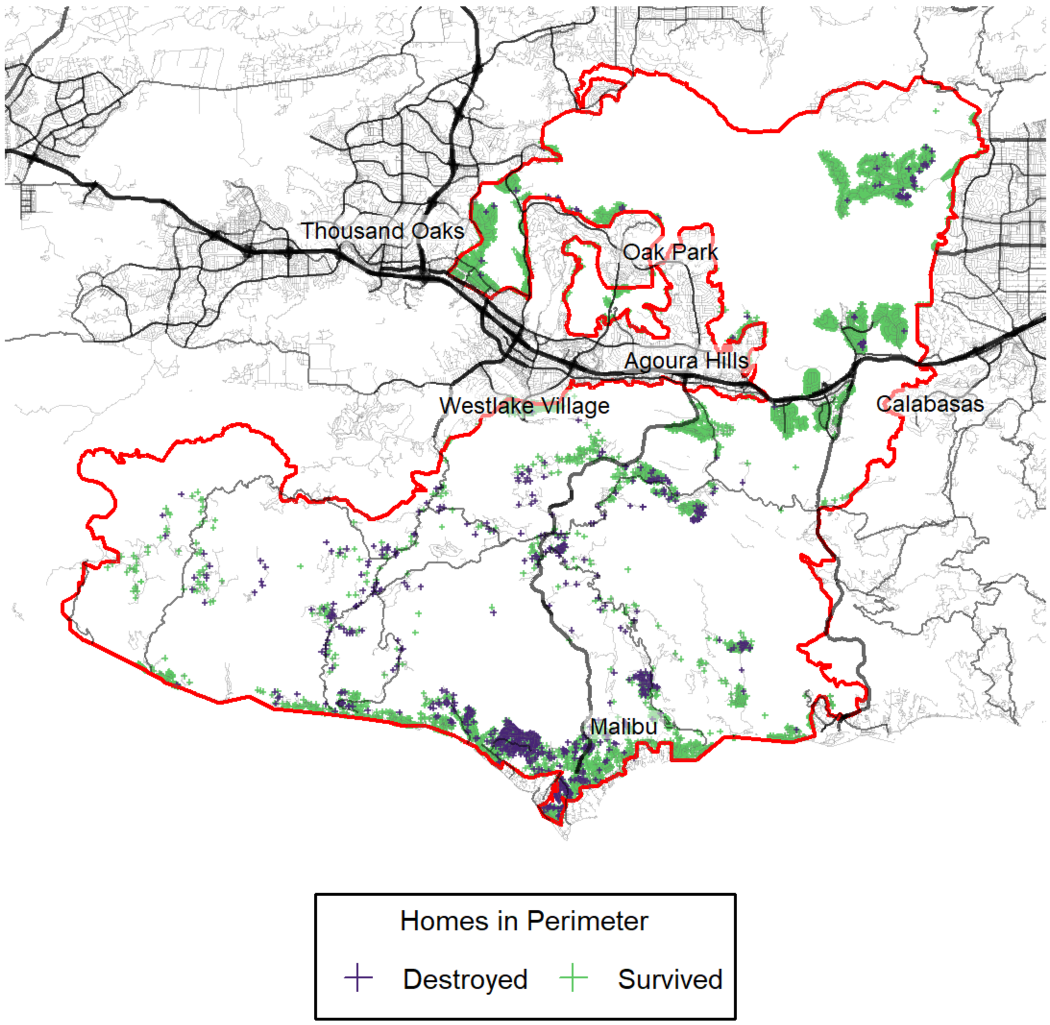
Figure 1: Identifying and validating roof locations

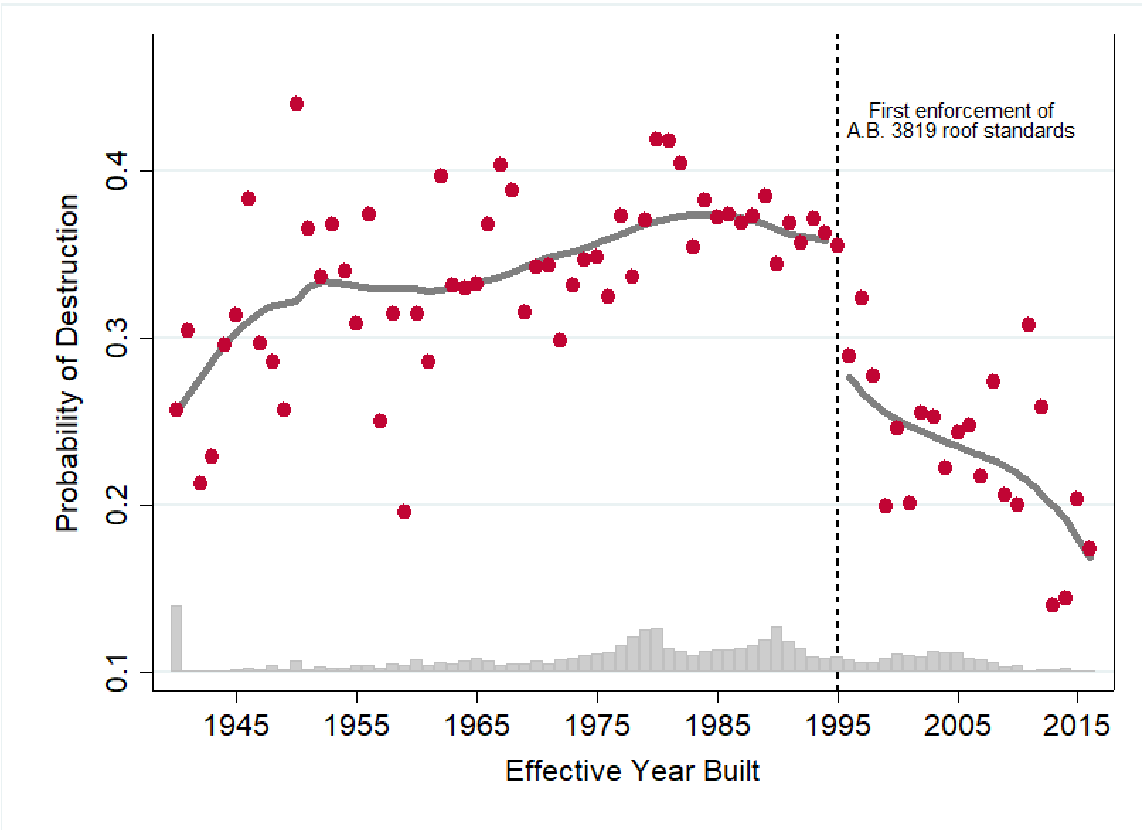
Notes: Redding, California in the area of the Carr Fire (2018). Circular markers are geocoded structure locations for the ZTRAX assessment data. Yellow markers show structures reported as destroyed in the damage inspection data; purple markers are all other ZTRAX homes. Blue building shapes and gray parcel outlines are the Microsoft building footprint data and assessor parcel boundary data used to identify rooftop locations (see text for details). The background imagery is high-resolution aerial imagery after the Carr Fire, provided by NearMap.

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



Notes: 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.

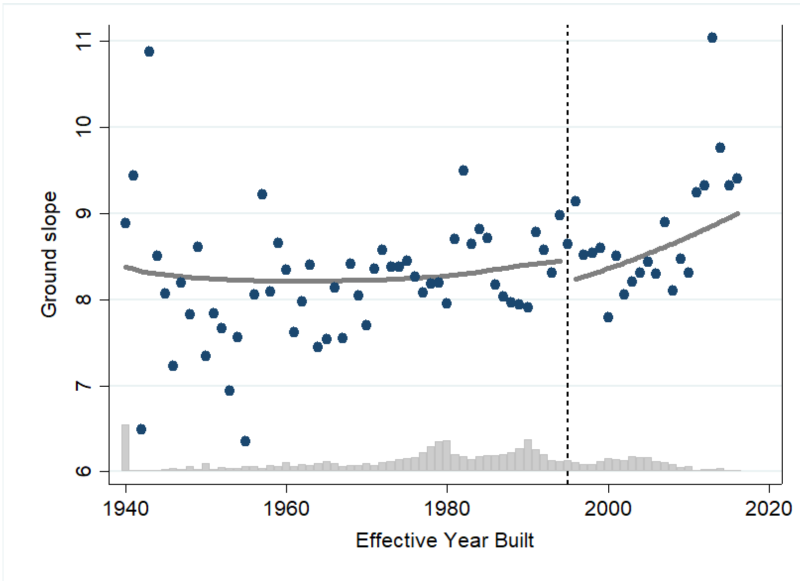
Figure 3: Share Destroyed by Year Built in Mandatory Code Areas



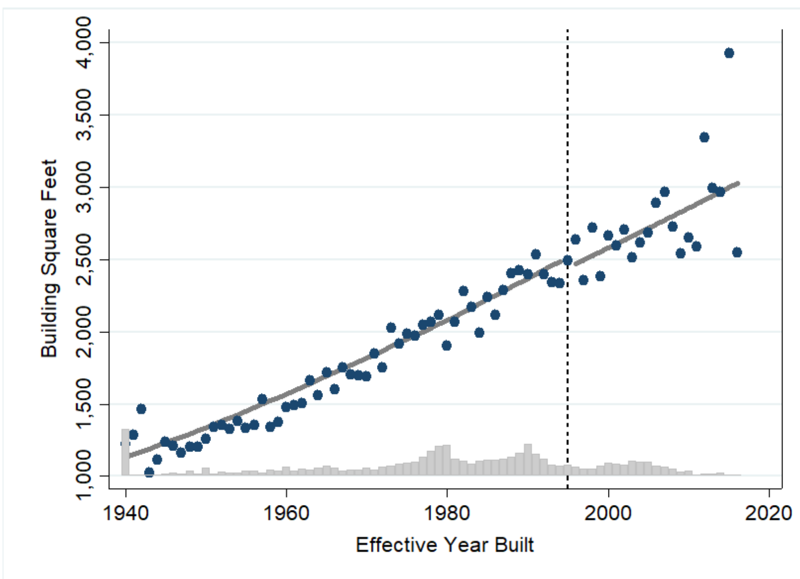
Notes: This figure shows the share of homes inside wildfire perimeters that were destroyed, according to the year that the home was built or remodeled. The sample is limited to homes in State Responsibility Area. The black lines show separate kernel regression fits before and after 1995. The gray histogram shows the relative number of homes in the sample from each year.

Figure 4: Other Characteristics by Year Built in Mandatory Code Areas

(a) Ground slope



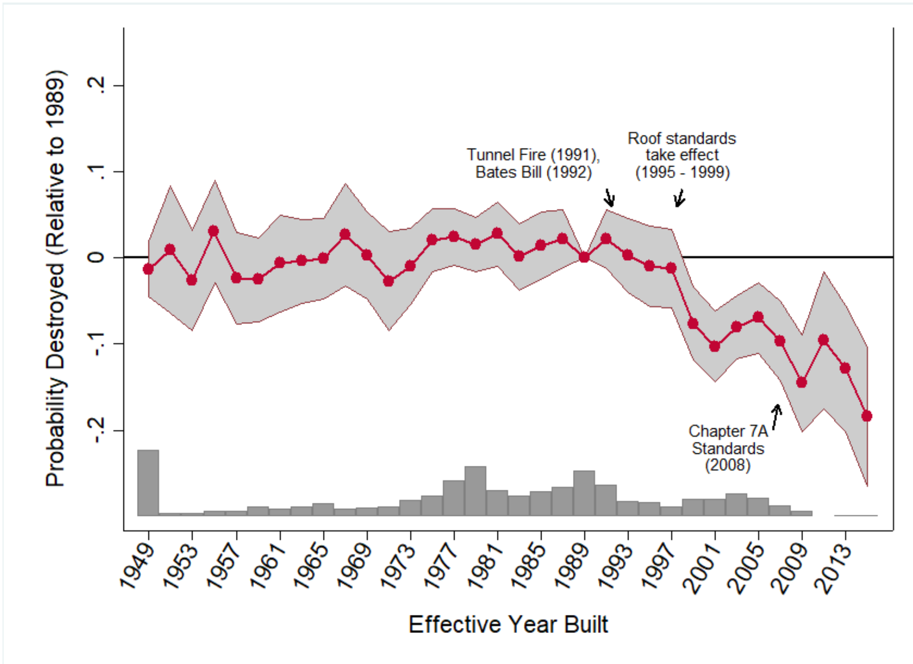
(b) Building square footage



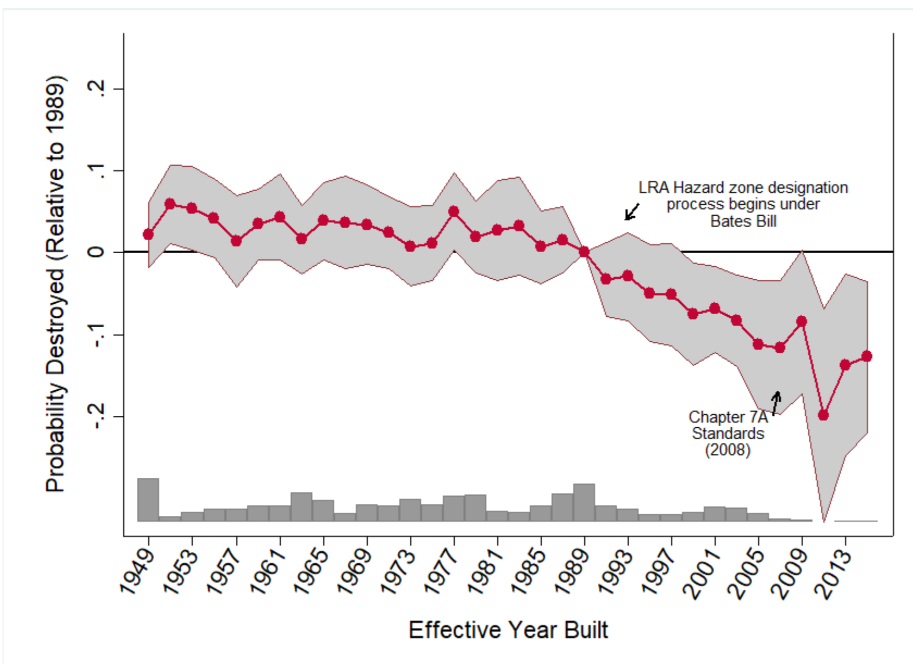
Notes: Means of other structure characteristics by effective year built for homes in State Responsibility Area. Panel (a) shows means of ground slope at the home site and panel (b) shows means of building square footage.

Figure 5: Estimated Vintage Effects in Mandatory and Recommended Code Areas

(a) Mandatory Code Areas (SRA)

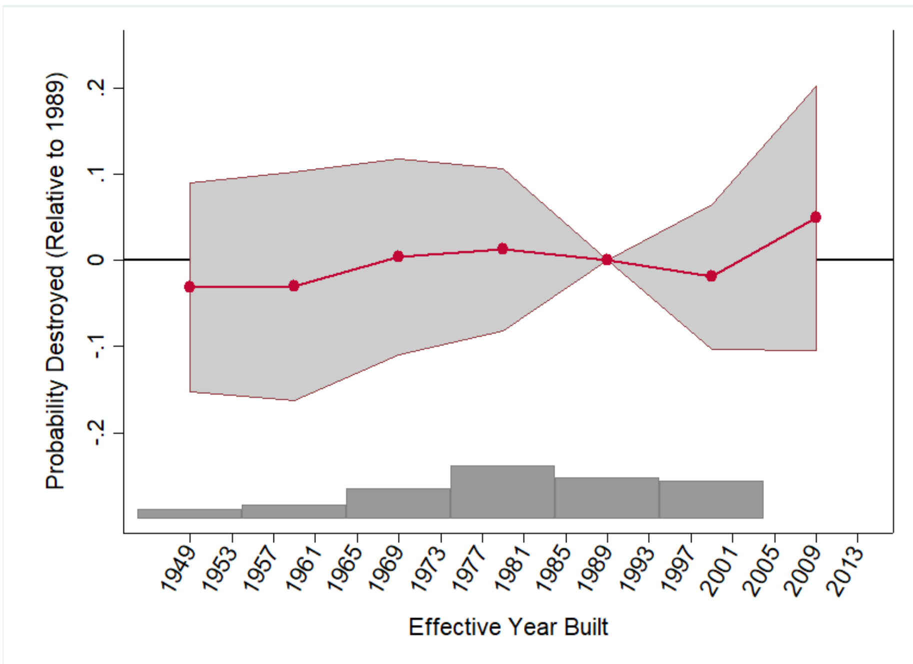


(b) Opt-in Code Areas (LRA VHFHSZ)



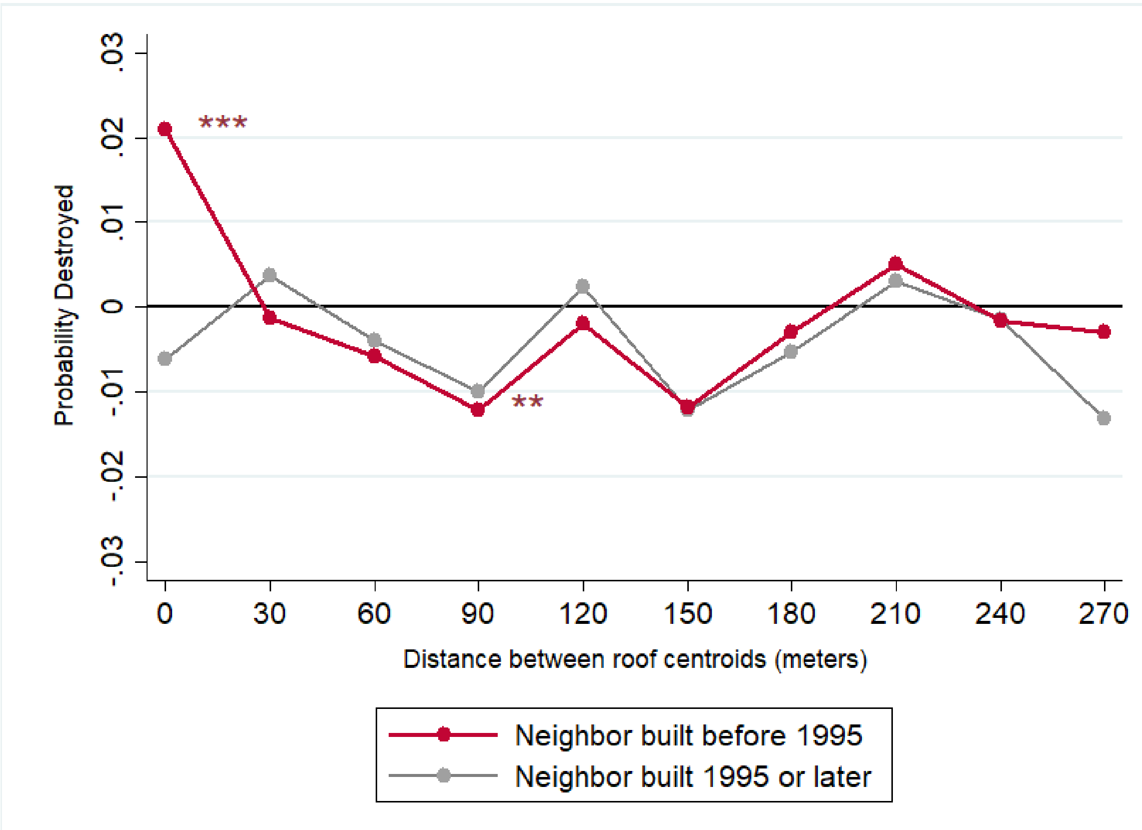
Notes: Figure plots point estimates and 95% confidence intervals from 2 separate OLS regressions of an indicator for Destroyed on two-year bins of effective year built. Each regression includes street by incident fixed effects. Panel (a) is limited to state responsibility area (SRA). Panel (b) shows homes in local responsibility area (LRA) inside of designated Very High Fire Hazard Severity Zones. Standard errors are clustered by street.

Figure 6: Estimated Vintage Effects in Areas without Codes



Notes: Figure plots point estimates and 95% confidence intervals from an OLS regressions of an indicator for Destroyed on ten-year bins of effective year built, with street by incident fixed effects. The sample includes homes inside wildfire perimters in Oregon, Arizona, and Washington; as well as California homes in local responsibility area outside of designated Very High Fire Hazard Severity Zones.

Figure 7: The effect of neighboring homes on survival



Notes: Figure shows estimates from a single OLS regression. Red line is the effect on survival of a pre-1995 home located a given distance away. The dashed gray line shows point estimates for the effect of a 1995 or later neighbor on survival. Stars represent statistically significant estimates at the 1% (***) and 5% (**) levels. The regression also includes dummy variables for own year built (in four year bins) and incident by street fixed effects.

Table 1: Example Fires for California and Other States

State	Name	Year	Destroyed Single Family Homes	Single Family Homes In Fire Perimeter	Share Destroyed (%)
		Panel A. California			
California	Camp	2018	8,247	10,279	80
California	Tubbs Fire	2017	3,730	4,607	81
California	Valley	2015	826	1,693	49
California	Carr	2018	747	1,681	44
California	Woolsey	2018	655	6,825	10
California	Witch	2007	511	5,760	9
California	Thomas	2017	496	2,311	22
California	CZU Lightning Cmplx	2020	450	1,373	33
California	North Complex	2020	399	628	64
California	Nuns	2017	370	1,363	27
California	LNU Lightning Cmplx	2020	364	1,109	33
California	Glass	2020	275	960	29
California	Atlas	2017	229	665	34
California	Creek	2020	193	1,147	17
California	Other California Fires (N=67)		1,072	6,779	16
		Panel B. Other States			
Oregon	Almeda-Obenchain	2020	414	603	69
Oregon	HolidayFarm	2020	312	559	56
Oregon	BeachieCreek-Santiam	2020	217	352	62
Oregon	EchoMountainComplex	2020	125	289	43
Arizona	Yarnell	2013	85	219	39
Washington	CarltonComplex	2014	16	57	28
Washington	OkanoganComplex	2015	9	108	8
Washington	ColdSprings	2020	8	60	13
Arizona	Goodwin	2017	3	8	38

Notes: This table describes the destructiveness of the worst 15 California fires in our dataset, and all Oregon, Washington, and Arizona fires. An additional 67 California incidents are grouped as "Other California Fires".

Table 2: Regression estimates of building code effects

	(1) Street FE	(2) Treated Only	(3) Finer Street FE	(4) Addl. Controls	(5) Limit Window	(6) Age Controls	(7) Plus Ch. 7A
After 1995	0.008		0.018	-0.007	-0.001	0.048*	0.005
	(0.026)		(0.025)	(0.030)	(0.036)	(0.029)	(0.026)
After 1995 * SRA	-0.085***	-0.077***	-0.099***	-0.086***	-0.073*	-0.067**	-0.072***
	(0.027)	(0.010)	(0.027)	(0.032)	(0.039)	(0.028)	(0.028)
After 1995 * LRA VHFHSZ	-0.090***	-0.085***	-0.104***	-0.095***	-0.057	-0.073**	-0.078***
	(0.029)	(0.018)	(0.029)	(0.035)	(0.040)	(0.030)	(0.029)
After 2008							0.033
							(0.030)
After 2008 * SRA							-0.092***
							(0.035)
After 2008 * LRA VHFHSZ							-0.083**
							(0.042)
SRA	0.013	-0.045	0.015	0.018	0.023	-0.011	0.011
	(0.066)	(0.098)	(0.064)	(0.074)	(0.071)	(0.075)	(0.066)
LRA VHFSZ	0.015		0.012	0.028	0.002	0.011	0.013
	(0.025)		(0.024)	(0.057)	(0.030)	(0.026)	(0.025)
Topography	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property characteristics	No	No	No	Yes	No	No	No
Street fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes
Finer street fixed effects	No	No	Yes	No	No	No	No
R^2	0.64	0.60	0.68	0.65	0.71	0.66	0.64
Homes in CA SRA	14,196	14,196	14,196	9,897	6,955	12,587	14,196
Homes in CA LRA VHFSZ	8,003	8,003	8,003	5,951	4,958	7,825	8,003
Homes in other areas	5,368	0	5,368	4,168	3,311	4,898	5,368
Mean of Dep. Var.	0.37	0.31	0.37	0.43	0.37	0.38	0.37

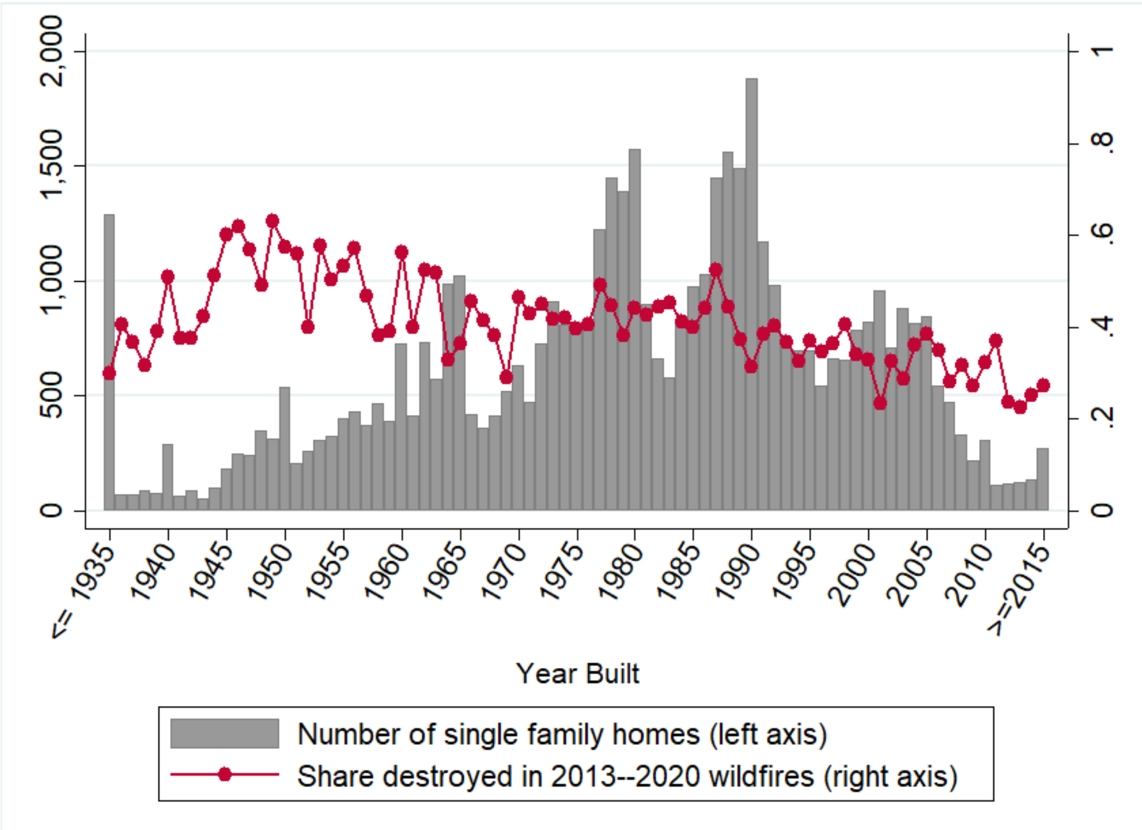
Notes: Table shows estimates and standard errors from 7 separate OLS regressions. The sample is limited to homes built in 1980 or later. "Homes in other areas" is a pooled comparison group that includes homes in other states (OR, AZ, WA) plus LRA areas in California with no state-recommended hazard zones. The "Limit window" specification is limited to homes with effective year built between 1987 and 2003. "Age controls" includes a 4-th degree polynomial in structure age (incident year − effective year built). Standard errors are clustered by street.

Table 3: Neighbor Effects by Relative Position

	All lot sizes	1 acre lots or smaller					
	All Neighbors	All Neighbors	All Neighbors	All Neighbors	All Neighbors	Same Street	Same Street
Nearest House	-0.015*	-0.033***					
	(0.008)	(0.012)					
Nearest 2 Houses			-0.054**			-0.088***	
			(0.027)			(0.033)	
5 Doors Down				-0.002			
				(0.012)			
5 and 6 Doors Down					-0.010		0.010
					(0.022)		(0.039)
Own Vintage	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Street fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.65	0.71	0.71	0.71	0.71	0.69	0.69
N	39,261	21,024	21,024	21,024	21,024	17,877	17,877

Notes: Table shows estimates and standard errors from 7 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 incident-by-street fixed effects. Standard errors are clustered by street.

Appendix Figure A1: Year built and probability of destruction: All states

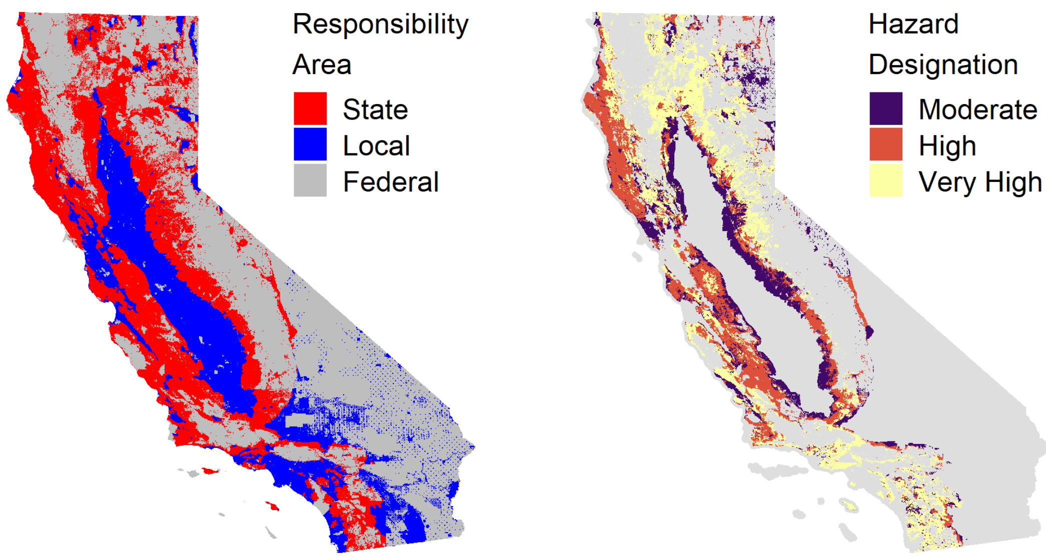


Notes: Sample includes all single-family homes in the ZTRAX assessment data located inside of wildfire perimeters in our dataset. The red markers show the fraction of homes of each vintage that are reported as destroyed in damage inspection data.

Appendix Figure A2: Responsibility Areas and Fire Hazard Severity Zones

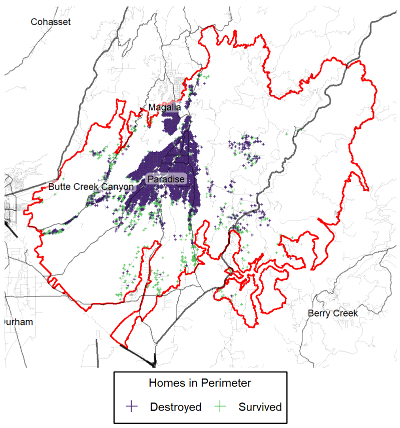
(a) Responsibility Areas

(b) Fire Hazard Severity Zones

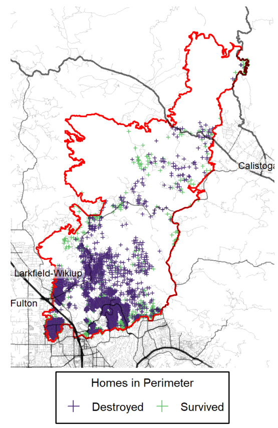


Appendix Figure A3: Additional Incident Maps

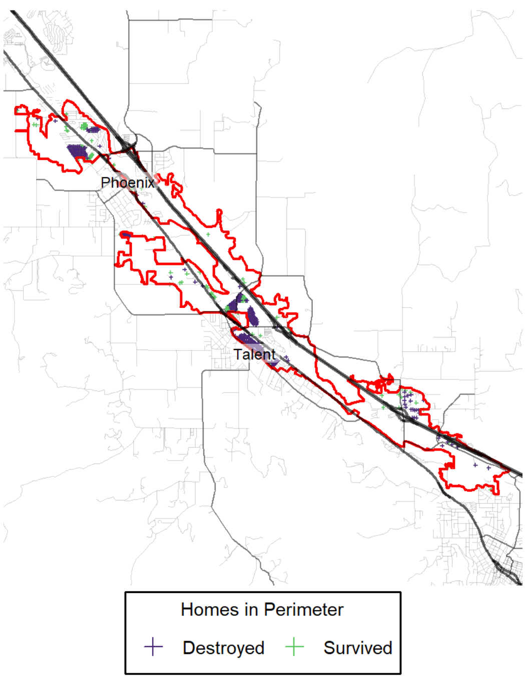
(a) Camp Fire (2018)



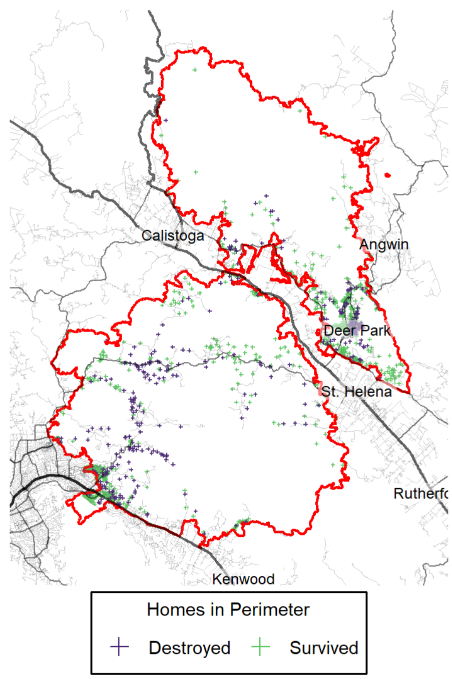
(b) Tubbs Fire (2017)



(c) Almeda-Obenchain (2020)



(d) Glass Fire (2020)



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