The Equilibrium Effects of Wildfires: Evidence from the California Housing Market

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Abstract

Destructive wildfires lead to significant changes in housing markets. In this paper, I explore the equilibrium effects of wildfire exposure in California's housing market. The effect of exposure is unclear ex ante because wildfires negatively impact both the housing supply and demand. I determine whether supply or demand effects are stronger by estimating the net exposure effect using 20 years of housing transaction and wildfire data. After a wildfire, prices for properties within the fire perimeter decline by up to 55% but fully recover to the pre-fire level three years after the fire. I explore the short-run decline by using property-level damage data and determine that the price decline is attributable to both declining housing quality and worsening local amenities. Then I show that improving neighborhood quality through increased construction and recovering local amenities helps prices to rebound. This paper exhibits that wildfires impact housing markets primarily through demand effects.

JEL: Q51, Q54, R21

Keywords: wildfires, climate change, natural disasters, housing markets, adaptation, valuation of environmental effects, resilience

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1 Introduction

Increased warming and drying because of climate change has created more variance in the typical fire season and resulted in more frequent and severe wildfires (Abatzoglou and Williams 2016). From 1990 to 2020, development in the wildland-urban interface (WUI) increased substantially with there being a 47% expansion in the number of homes in the WUI in the United States (US Forest Service Research and Development 2023). The combination of climate-driven wildfires and increased development in the WUI has triggered some of the most destructive wildfires in California's history with 75% of the most destructive happening since 2015 (FIRE 2025b).[1,2] With more frequent destructive wildfires being a relatively recent phenomenon, it is important to understand how housing markets are reacting to these new climate shocks.

I study the equilibrium effects of wildfires in the housing market. I estimate a net effect of wildfire exposure on housing transaction prices to determine if supply or demand effects are driving changes in the housing market. I disentangle the effects further by exploring a housing quality, local amenity, and supply effect and calculating the associated costs. This quantification contributes to the understanding of the mechanisms behind the housing market changes. I introduce the different effects in a simple description of one property: for a house in a neighborhood impacted by a wildfire, the house is either damaged or undamaged. If the property is damaged, the net effect on prices is composed of a housing quality effect, an amenity effect, and a supply effect. The housing quality effect is a demand-side effect where the property is actually burned. The property is then less desirable and potentially not habitable which drives prices down. If the fire also damages local amenities, the neighborhood quality declines which lowers demand and pushes prices down. Finally, the fire reduces housing supply which drives prices up. Thus, a market experiences demand effects, namely housing quality and amenity effects, and supply effects. For an undamaged property, the

[1]CAL FIRE defines destructive as the number of structures destroyed.

[2]For example, the 2025 Los Angeles fires saw $140 billion in total losses while destroying 12,000 homes and killing 31 people (Jones et al. 2026).

net effect is composed of the same effects except for the housing quality effect since it is not burned. In the two scenarios, supply and demand both decrease which makes the net price effect ambiguous. In this paper, I estimate the change in housing prices, quantify the housing quality effect, and bound the amenity effect. Then, I calculate the associated costs and explain through what mechanisms the price changes occur.

I implement 20 years of California housing and wildfire data to explore wildfire equilibrium effects. Following Wing, Freedman, and Hollingsworth (2024), I employ a stacked event study research design in the hedonic context which permits the estimation of short and medium run effects. I control for time-invariant property characteristics with repeat-sales data. I compare properties within the fire perimeter to those outside but within 10 kilometers of the perimeter and estimate the net effect of wildfire exposure on property transaction prices. After a wildfire occurs, properties within the fire perimeter experience a large decline in prices by as much as 55% relative to the month preceding the fire. This negative effect indicates that demand effects are outweighing supply effects.

I then examine what is driving the price decline by separately estimating the exposure effect for damaged and undamaged properties in the fire. Damaged properties see a decline in prices by 69%, and undamaged properties face a 30% decline one year after the fire. The greater negative effect on damaged homes indicates that fire exposure reduces the housing quality of sold properties. The smaller but still negative effect on undamaged homes indicates that local amenities have worsened and impact prices more than a fire-induced reduction in housing supply. I quantify the housing quality effect and find the upper bound of the amenity effect using these estimates and calculate the associated costs. The average housing quality costs for a fire are $650 million, while the lower bound of the amenity costs are even larger at over $800 million. I then highlight local damage as a mechanism of the amenity effect by showing that when conditioning on the property's damage status, high shares of nearby damaged homes reduce prices by up to 62%.

While wildfire exposure leads to large losses, prices recover to pre-fire levels three years

after the fire. This recovery is driven by improving housing quality and amenities which raises overall neighborhood quality. I use residential building permit issuances to show that construction activity increases after a wildfire and reaches pre-fire levels four years later. This construction indicates that there is increasing housing supply and improving housing quality. I show that transacted properties after the fire are newer which confirms that housing quality is improving. Then, I show that local amenities are recovering by looking at neighborhood greenery which recovers fully three years after the fire. Even though housing supply increases with construction, the rise in demand driven by improving housing quality and amenities is pushing prices up. The large initial price decline followed by the price recovery indicates that after a wildfire, transaction prices move in accordance with changes in demand rather than changes in supply.

1.1 Contribution to Literature

The hedonic method, formalized in Rosen (1974), is one of the most widely used approaches to value environmental goods, including natural disasters (Albouy et al. 2016; Bishop et al. 2020; S. Lee, Wan, and Zheng 2026; Zhang, Phaneuf, and Schaeffer 2022). However, fewer studies analyze goods like wildfires that directly affects the housing supply. Due to this unique feature of wildfires, this work must account for the changes in supply and the shifting hedonic price function (Banzhaf 2021; Haninger, Ma, and Timmins 2017; Klaiber and Smith 2013; Kuminoff, Parmeter, and Pope 2010; Kuminoff and Pope 2014; Muehlenbachs, Spiller, and Timmins 2015). I expand the work on hedonics and environmental hazards by addressing changes in the quantity and quality of housing supply while employing a quasi-experimental hedonic approach. I provide the first estimate of the net valuation of wildfire exposure over time and determine that demand effects are stronger than supply effects. Moreover, I separately quantify the effect of declining housing quality and worsening amenities by using property-level damage data.

There is a plethora of excellent work on a variety of wildfire topics including smoke

exposure, self-protection and insurance, fuel treatments, and municipal finances.[3] The strand of literature this work most pertains to is that of property values and wildfires, and I make two key contributions. Existing studies that estimate the effect of wildfires on property prices find mixed results that depend on the spatial scale and timing (Dong 2024; Hennighausen and James 2024; Huang and Skidmore 2024; Mueller, Loomis, and González-Cabán 2009; Shi et al. 2022). I reconcile these differences by using comprehensive data on 20 years of housing and wildfires in conjunction with a stacked event study approach that permits within-fire comparisons to obtain short and medium-run net effects of wildfire exposure. I show that on average there are large price declines for properties within the fire perimeter but no net price effects for nearby properties outside the perimeter. I also exhibit that these declines are temporary, and prices recover three years after the fire. This work shows that demand effects drive these changes and explain through what mechanisms these changes occur.

I also separately determine the negative effects attributable to declining housing quality and local amenities by using property-level damage data. Other work sheds light on non-housing quality effects like wildfire smoke, neighborhood features, or fire characteristics (He, Ortiz-Bobea, and Wu 2026; Huang and Skidmore 2024; Malliaris et al. 2026). This is the first study to separately provide estimates of declining housing quality and local amenities that are due to wildfire exposure. I also estimate the associated costs of these effects and find substantial losses. Issler et al. (2026) approaches post-wildfire recovery similarly by exploring how property-damage status affects rebuilding and sales prices. This work estimates the temporal and spatial dynamics of prices after wildfire exposure and quantifies the damages caused by different effects.

The rest of this paper is structured as follows. Section 2 provides information on wildfires in California, how they interact with the housing market, and a case study. I lay out a conceptual framework to illustrate the different effects of wildfire exposure in Section 3.

[3]See Baylis and Boomhower (2023), Baylis and Boomhower (2026), Boomhower, Fowlie, and Plantinga (2023), Gellman, Walls, and Wibbenmeyer (2025), G. Lee and Beatty (2025), Liao and Kousky (2022), Strabo and Matthew N Reimer (2026), and Strabo, Bryan, and Matthew N. Reimer (2026)

In Section 4, I describe the housing and wildfire data. Section 5 illustrates how I define treatment and control and what econometric method I use for the empirical portion of the paper. In Section 6, I present results on the net effects of wildfire exposure and explain the price decline and recovery. Finally, Section 7 provides a discussion on policy and concludes.

2 Background

Historically, California's wildfire season ranged from early summer (May/June) to late fall (October/November). However, climate change has lengthened dry seasons, created more variation in rainfall, and increased temperatures thus extending the typical California fire season. With more variation in rain and longer droughts, there is a larger build up of vegetation that then dries out and creates copious wildfire fuel. Combining these conditions with high wind events, like the Santa Ana winds in Southern California, results in the perfect conditions for wildfires to start and spread quickly. The 2025 Los Angeles wildfires were preceded by heavy rains in February 2024, then drought conditions the rest of the year. Once the fires started, extreme Santa Ana winds quickly spread the fire and embers and led to 31 deaths, the destruction of over 15,000 structures, and billions of dollars in damages (FIRE 2025b; Li and Yu 2025). In general, wildfire size and total acres burned has increased in the last two decades.[4]

Wildfires interact with housing markets differently than other disasters. First, many wildfires are caused by human activity, so the chance of wildfire ignition is correlated with human activity (Kestelman 2023).[5] As populations grow in the WUI, human activity in wildfire-prone landscapes increases which elevates the chances of wildfires. Moreover, a lack of knowledge of wildfire risk may be contributing to increased wildfire exposure. Unlike floods which have the Federal Emergency Management Agency (FEMA) Flood Maps that

[4]See appendix Figures A1 and A2.

[5]In the entire sample of California fires, 33% are caused by lightning, 44% are caused by human activity, and 23% of the causes are unknown. In the fires used in my analysis, 6% are started by lightning, 55% are caused by human activity, and 40% of the causes are unknown.

support the National Flood Insurance Program, wildfires do not have a standardized national program that makes homeowners aware of fire risk. If a property is in a Special Flood Hazard Area, it is required to have flood insurance. This is not the case for properties located in places at risk for wildfires. In California, a property owner can acquire fire insurance through a private provider or through the California FAIR Plan. The FAIR Plan is self-described as an "insurer of last resort" when other options in the traditional insurance market are not available. Since fire insurance is not required, the full wildfire risk is not salient to homeowners.

Private insurers also increase premiums and drop fire coverage as the frequency of destructive fires increases. California residents then turn to the FAIR Plan which has become overburdened with almost an $800 billion risk pool covering about 700,000 properties across the state (St. John 2026). The ability to rebuild is dictated by the property-owner's insurance plan or lack of, so the rising insurance costs have tangible impacts on post-fire recovery. Finally, there is substantial damage heterogeneity within fires. There are many instances of properties right next to each other where one is completely destroyed, and the other is untouched. Fire-resistant infrastructure, geography, or changes in wind direction are reasons why this damage heterogeneity occurs. Overall, wildfires are unique in that they are primarily caused by human activity, the risks may not fully be known, and the resulting damages are spatially unpredictable.

2.1 Case study: Camp Fire (2018)

I illustrate the impacts of wildfires on housing markets through a case study of the 2018 Camp Fire, California's most destructive and deadliest wildfire. The Camp Fire killed 85 people and destroyed 18,804 structures. It further displaced many residents and resulted in short-run changes in housing prices (Hennighausen and James 2024). As of 2023, only one third of the pre-fire population had returned with only about 32% of the structures having been rebuilt (Bliss 2023; Chabria and Garrison 2023). I plot the raw annual mean

transaction price per square foot in Figure 1 to highlight the housing market dynamics over time. I split the sample by whether the property was in the fire perimeter or outside of it but within 10 kilometers (km). Before 2018, the prices per square foot for both types of properties follow a similar trend. However, when the fire occurs in November 2018, prices for in-fire properties decline while prices for out-of-fire properties continue to follow the same trend for a few years after the fire. This figure highlights that prices are associated with wildfire exposure. It is worth recalling that this is California's most destructive fire, so it is not clear if housing markets will respond similarly in other contexts.

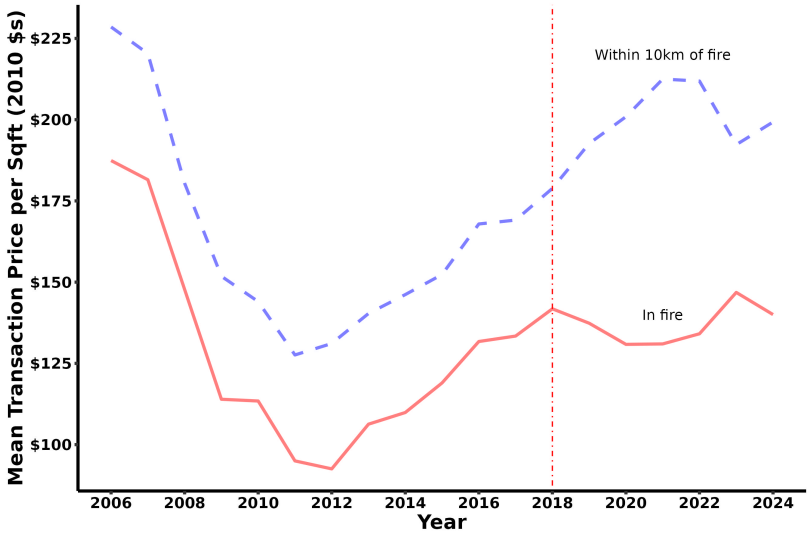


Figure 1: Mean transaction price/square foot for the Camp Fire. The annual mean transaction price per square foot is plotted for properties associated with the 2018 Camp Fire. Properties within the fire perimeter are denoted by the red line, and those outside of the perimeter but within 10 km are denoted by the blue dashed line. Prices are normalized to 2010 dollars.

3 Conceptual Framework

In this section, I explicitly define the effects that impact housing prices. The net effect on housing prices is composed of demand and supply effects. As described in Section 1, I break these down into three effects. The housing quality (HQ) effect is when a property is physically damaged by a fire which leads to an inhabitable and less desirable property. This

effect has a non-positive impact on housing prices. Then, there are two neighborhood-level effects that impact housing prices: the amenity (A) and the supply (S) effects. I define the amenity effect as the impact of wildfire exposure on neighborhood quality through damaging local amenities which has a non-positive impact on prices. I define the supply effect as the destruction of local housing stock because of the wildfire which has a non-negative impact on prices. There is no effect on prices through the supply effect if no properties are destroyed. If a property is damaged, the total change in price is defined as $\Delta P_D = HQ + A + S$. If a property is undamaged, then the total change in price is defined as $\Delta P_U = A + S$. Given my data, I cannot explicitly disentangle the amenity and supply effects, but I can determine which is larger by estimating ΔP_U. If ΔP_U is positive then the supply effect is stronger, and if it is negative then the amenity effect is stronger. The equations and sign assumptions of the effects are presented below where ΔP_D and ΔP_U are estimable. It is worth noting that these definitions and sign assignments are specific to the wildfire shock in the short-run, where the change in housing supply that is associated with the wildfire is non-increasing.[6]

$$\Delta P_D = HQ + A + S \tag{1}$$

$$\Delta P_U = A + S \tag{2}$$

$$HQ \leq 0, A \leq 0, S \geq 0 \tag{3}$$

The magnitudes of the three effects are unknown, and the effects have opposite signs. Therefore, the net effect of wildfire exposure on prices is unknown ex ante as illustrated in Figure A1. I first estimate the net effect which determines whether the demand or supply effect is stronger. Then, I disentangle the net effect into the housing quality effect and the sum of the amenity and supply effects by estimating effects separately for damaged and undamaged properties. I assume that damaged and undamaged properties face the same

[6]When considering recovery, the changes in price would be post-wildfire from a pre-recovery price to post-recovery price. The signs of the effects change. In this paper the focus is on the wildfire impacts on prices and not recovery impacts on prices.

amenity and supply effects. Even if a property is destroyed, the land still retains value. Therefore, it is a reasonable assumption that the supply effect still pushes the price of a damaged property up. Then, subtracting Equations 1 and 2 yields the housing quality effect: $\Delta P_D - \Delta P_U = HQ$.

While the amenity and supply effects cannot be separated, I show that the estimated change in price for undamaged properties is an upper bound for the amenity effect. In the empirical analysis, I make within-fire comparisons. Let ΔP_{U1} denote the change in price for undamaged properties in the scenario where only one housing market is affected by the wildfire. Let ΔP_{U2} denote the change in price for undamaged properties in the scenario where there are multiple housing markets affected by the wildfire. If the impacted area is only one housing market, then the supply effect is the same for all properties in the area. Therefore, the supply effect is removed in a within-fire analysis, and $\Delta P_{U1} = A_1$ where A_1 is the amenity effect in the one-market scenario. If there is more than one housing market, then the supply effect is not dropped in a within-fire analysis and the resulting change in price for undamaged properties is the same as before: $\Delta P_{U2} = A_2 + S$ where A_2 is the amenity effect in the multiple-market scenario. Setting ΔP_{U1} equal to ΔP_{U2} reveals that $A_1 \geq A_2$ since $S \geq 0$. Hence, the one-market scenario provides the upper bound for the amenity effect. Since $A \leq 0$ by definition, the amenity effect is at least as, if not more, negative, than any estimated effect for undamaged properties. Therefore, the associated costs for the amenity effect are a lower bound.

To illustrate these effects, I plot an example of supply and demand curves for a neighborhood impacted by a wildfire in Figure 2. Curves denoted with a 0 superscript are pre-fire curves, and those denoted with a 1 superscript are post-fire curves. When the fire occurs, the supply curve shifts from S^0 to S^1. On the demand side, the pre-fire demand curve is D^0. A property in the fire perimeter is either damaged or undamaged. For undamaged properties, the demand curve shifts to D_U^1. For damaged properties, the demand curve shifts even further to D_D^1. In this example, I assume the amenity effect is larger than the supply effect,

so the net change in price for undamaged properties is $\Delta P_U = P_U^1 - P^0 < 0$. If the supply effect is larger, the net change in price for undamaged properties is positive. For damaged properties, the change is $\Delta P_D = P_D^1 - P^0 < 0$. If the supply effect is larger than the sum of the amenity and quality effects, then the net change in price for damaged properties is positive. The housing quality effect is the difference between ΔP_D and ΔP_U. In the next section, I define the data that allows me to identify the illustrated effects.

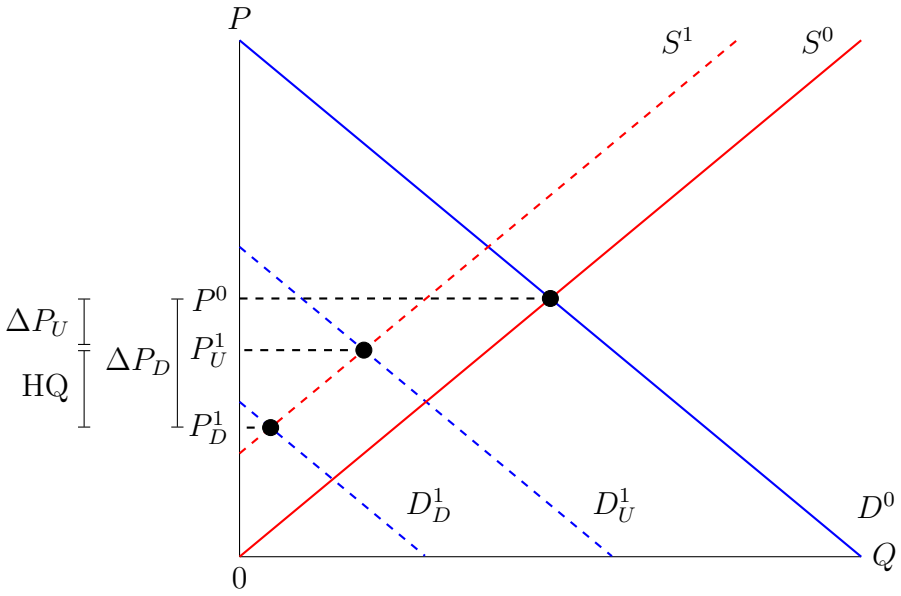


Figure 2: Supply and demand graph illustrating wildfire exposure effects. Supply and demand curves are plotted for before and after fire exposure. Undamaged properties face a smaller demand shift than damaged properties. The price effect for undamaged properties is $\Delta P_U = A + S$, and the price effect for damaged properties is $\Delta P_D = HQ + A + S$. The two price effects are estimable. The housing quality effect, HQ, is identified by taking the difference between ΔP_D and ΔP_U.

4 Data

4.1 Housing

The primary housing data comes from ATTOM. I use the Recorder, Tax Assessor, and Assessor History datasets (ATTOM Data 2025b; ATTOM Data 2025c; ATTOM Data 2025a).[7] The Recorder data is collected from the county recorder's office and contains information on transaction price, transaction date, type of transaction, and information on the buyers and sellers. In addition to data on housing transactions, I use tax assessor data which is collected from the county tax assessor's office. This data contains information on the assessed property value, property characteristics, and location information. The Tax Assessor data only contains information for the most recent assessment. I use the Assessor History dataset to obtain previous housing characteristics. This data contains the same information as the Tax Assessor data but for previous tax assessments.

I link transactions to the housing characteristics of the most recent assessment before the transaction using the assessed year, transaction date, and assessor's parcel number (APN). I restrict the sample to owner-occupied residential properties and drop non-arm's length transactions, quit claims, and foreclosures. My main housing characteristics of interest are age, number of bedrooms, number of bathrooms and property type (e.g. single family versus townhouse). To address outliers and unrealistic housing characteristics, I drop properties that are either missing these variables or have values that are in the 1st and 99th percentiles of a characteristic of interest. Transaction prices are normalized to 2010 dollars, and I drop missing transaction values and those below $\$50,000$ and above $\$3,690,000$ (99th percentile). I also drop properties built before 1900. There are 518 addresses with missing latitude and longitude values, so I geocode those using R's "tidygeocoder" package. I further restrict the sample by only keeping properties that have sold at least twice from 2004 to 2024 and drop those that were sold more than once in a single month. I drop properties that were impacted

[7] These datasets are accessed via subscription to the private data provider, Dewey (https://www.deweydata.io)

by more than one fire during this time.[8] The resulting dataset is a repeat sales pseudo-panel of property transactions where I observe the transaction date, transaction price, property type, address, and property characteristics. There are over two million transactions for almost 400,000 properties. Table 1 contains the summary statistics for the primary housing data. About 1% of the transactions occur within the fire perimeter, while the average home was built in 1980. Moreover, a majority of the sample (77%) is single family residences.

Variable	Mean	St. Dev.	Min	Max
In Fire	0.01	0.08	0.00	1.00
Sale Price	458,795.50	297,571.80	34,460.20	3,823,794.00
Log Sale Price	12.87	0.58	10.45	15.16
Bath Count	2.34	0.77	0.01	5.00
Bedroom Count	3.16	0.92	1.00	6.00
Age	33.90	20.88	0.00	124.00
Year Built	1980.66	20.34	1900	2,023
Number of Sales	2.43	0.69	2.00	8.00
Single Family	0.77	0.42	0.00	1.00
Multifamily	0.003	0.06	0.00	1.00
Condo/Townhouse	0.21	0.41	0.00	1.00
Other Housing	0.02	0.12	0.00	1.00
Number of properties	399,789			
Number of transactions	2,020,059			

Table 1: Summary statistics for main analysis data. This table provides the summary statistics for the data used in the main analysis of this paper. Housing transactions occurred from 2004 to 2024. Transaction prices are normalized to 2010 dollars. In Fire is a binary variable indicating if a property is within a fire perimeter or not. Single Family, Multifamily, Condo/Townhouse, and Other Housing are binary variables indicating the type of property. The multifamily category consists of buildings like apartments, duplexes, and triplexes. The Other Housing category consists of buildings like mobile homes and manufactured homes. The 0.01 seen in Bath Count minimum does not mean there was 1% of a bath. Decimals are used to indicate partial baths (e.g. just a toilet and sink and no bathtub).

[8] 156 properties ($< 1\%$)

4.2 Wildfires

I use the Fire Perimeters and Damage Inspection (DINS) datasets from The California Department of Forestry and Fire Protection (CAL FIRE). Fire responsibility in California is split between Local Responsibility Areas (LRA), State Responsibility Areas (SRA), and Federal Responsibility Areas (FRA). CAL FIRE is responsible for wildfires and fire management in the SRAs. They actively run a fire prevention program which "includes brush clearance, prescribed fire, defensible space inspections, emergency evacuation planning, fire prevention education, fire hazard severity mapping, and fire-related law enforcement activities" (FIRE 2025a).

The Fire Perimeters data is created through the Fire and Resource Assessment Program (FRAP) with the help of the United States Forest Service Region 5, the Bureau of Land Management, the National Park Service, and the Fish and Wildlife Service to provide information on current fuel conditions within burned areas. They record historic wildfire perimeters for timber fires greater than 10 acres, brush fires greater than 50 acres, grass fires greater than 300 acres, and any wildland fires that result in three or more destroyed residential or commercial properties or a fatality. While CAL FIRE is only responsible for the SRAs, there are fires in the LRAs and FRAs in this data. The dataset provides the fire name, fire ID, start date, containment date, size of the fire, cause of the fire, and the perimeter shapefile. In some cases, a fire is reported by multiple agencies which results in multiple observations for a fire. In my data I only keep unique observations to eliminate duplicates. I restrict my sample to fires that are 300 acres or greater that occurred from 2004 to 2024 and had at least one property within the fire perimeter. The 159 fires used in the main analysis are shown in Figure 3. The fires are spread throughout the state with larger concentrations near populated areas.

The DINS data is collected in post-fire inspections for California fires starting in 2013. It provides property-level information on location, the damage level, structure type, property attributes, and which fire it is associated with for properties within 100 meters of the fire

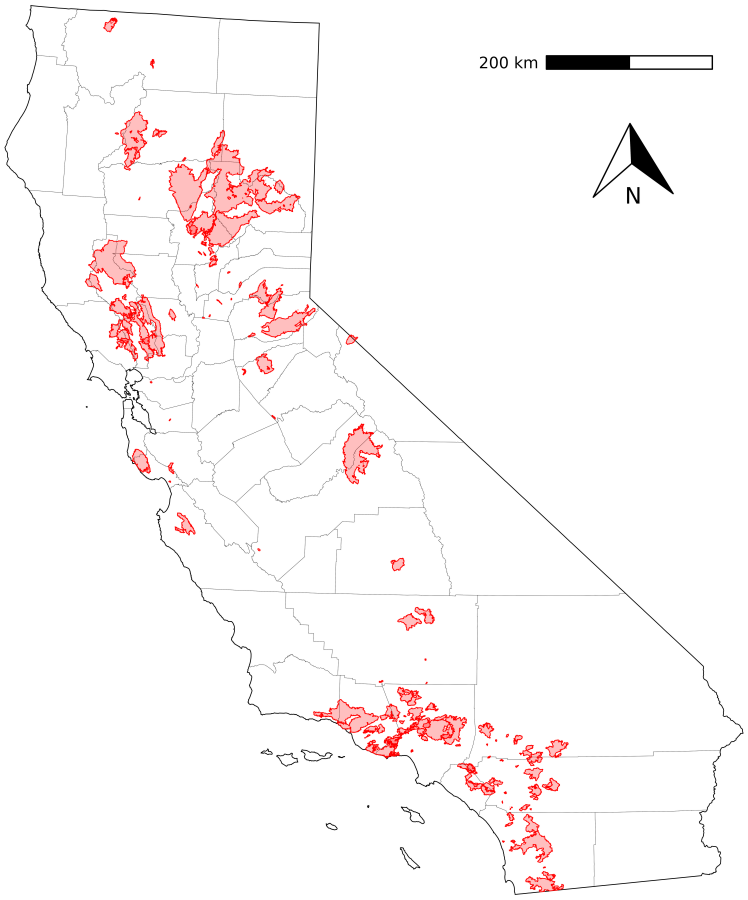


Figure 3: Map of wildfires in the analysis. The 159 fires from the CAL FIRE Fire Perimeters data that are used in the main analysis are plotted here. These are fires from 2004 to 2024 that are larger than 300 acres and had at least one property within the fire perimeter. Counties are outlined in gray. The projection used is EPSG: 32611 "WGS 84 / UTM zone 11N".

perimeter.[9] Before 2018, they only collected information on damaged properties, but since 2018 they also record information on undamaged properties within the fire perimeter. For damage data before 2013, I use data from Baylis and Boomhower (2026). The authors collected and cleaned data going back to 2003 from San Diego County and the CAL FIRE staff. Like the DINS data, this data contains the APN, address, whether the property was destroyed or not, and the fire it is associated with. To combine both damage datasets, I distinguish between damaged and undamaged rather than different levels of damage.[10] These fire datasets allow me to see whether housing transactions took place within the fire perimeter, before or after the fire, and for a subset of fire events, I can see which properties were damaged and undamaged. Figure 4 shows the 2018 Camp fire that impacted multiple communities in Butte County, CA, most notably Paradise. Within the Camp Fire perimeter, I plotted locations of properties that I have transaction data for. The blue circles are properties that were within the perimeter but not damaged. The red triangles are properties that were damaged. The right-hand figure highlights the damage heterogeneity that can occur across space within a fire. The Camp Fire example exhibits multiple instances of undamaged and damaged properties being directly next to each other.

While the damage data contains fires from 2003 to 2024, it does not contain information on every fire in the fire perimeter dataset and undamaged properties before 2018. As a result, the data is sparse for earlier years and leads to power issues in subsequent analysis. To overcome this problem, I supplement the actual damage data with predicted damage data. I use the annual ATTOM Assessor and DINS data and run a least absolute shrinkage and selection operator (LASSO) regression where the outcome variable is an indicator variable for if the property is damaged or not, and the predictor variables are the change in assessed value, minimum and maximums of property characteristics, and changes in property characteristics from before and after the fire. This specification determines how property changes before and after the fire influence the likelihood of being denoted as damaged. I run a logistic regression

[9]The damage data does not account for smoke damage or if an undamaged building is habitable.
[10]In the DINS data, 89% of damaged homes were completely destroyed.

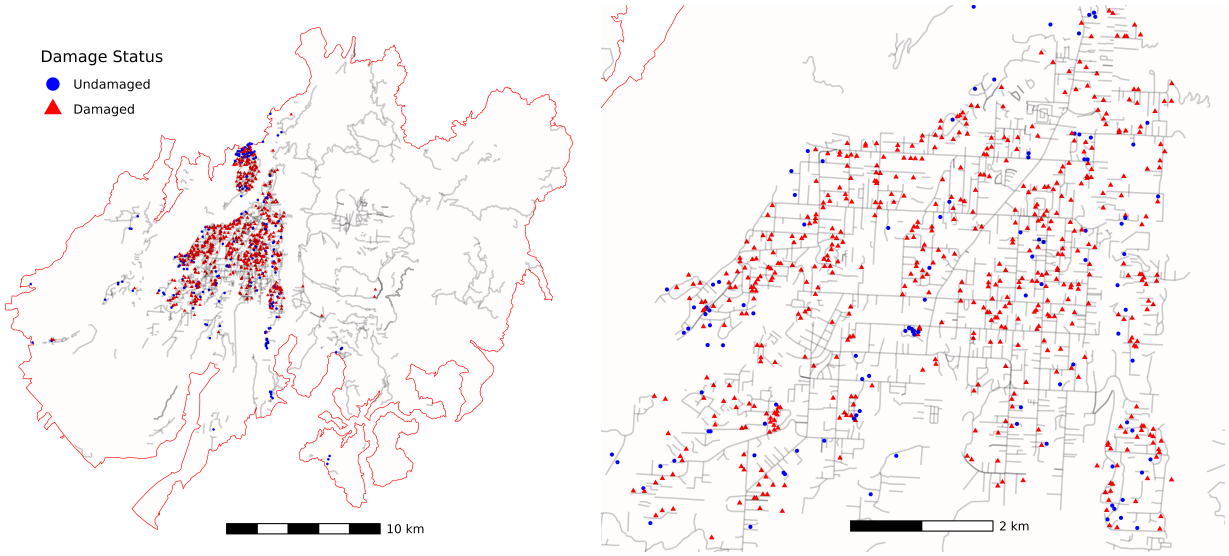


Figure 4: Map of damaged and undamaged properties in the Camp Fire (November 2018). The Camp Fire (2018) perimeter is on the left with damaged properties as the red triangles and undamaged properties as blue circles. The right-hand figure zooms in to Paradise, CA within the fire perimeter. The data comes from the CAL FIRE DINS data. The gray lines are roads.

with ten folds where the training sample has 15,766 properties, and the holdout sample has 1759 properties. Appendix Figure A5 shows the cross-validation curve and denotes the lambda that results in the minimum mean cross-validated error and that which provides the most regularized model such that the cross-validated error is within one standard error of the minimum.[11] The number of selected variables is denoted by the numbers on the top of the plot. I proceed with the lambda that leads to the minimum mean cross-validated error. The predictor variables with non-zero coefficients are presented in Table A1. When testing the prediction on the holdout data, the correlation between the predicted damage status and actual damage status is 73%. 87% of the damage statuses are predicted correctly with damaged properties being predicted correctly 75% of the time and undamaged properties 95% of the time. I augment the actual damage data with predicted data for fires that do not appear in the actual data. The original damage analysis data contains 62 fires and 681,777

[11]The lambda that results in the minimum mean cross-validated error is 0.00006306975, and the lambda that provides the most regularized model such that the cross-validated error is within one standard error of the minimum is 0.003780932.

transactions for 206,569 properties. The augmented data contains 120 fires and 1,712,942 transactions for 355,483 properties.

4.3 Supplemental Data

I also incorporate data on building permits, normalized difference vegetation index (NDVI), and neighborhood-level data on income and whether the neighborhood is urban or rural. I obtain building permit data from Builty through a subscription to Dewey. The data is web scraped from online sources. It contains the address, file date, permit issuance date, and final date. I focus on the permit issuance date. It also contains a description of what the permit is for (e.g. room addition). I use data for residential permits in California from 2004 to 2024 and geocode latitude and longitude using the Census geocoder and ArcGIS geocoder through "tidygeocoder". I then spatially merge the permit locations with shapefiles for California census block groups and aggregate the number of permits issued to the month-census block group level. Then I spatially merge the aggregated data with the wildfire data.

In addition to building permit data, I use NDVI data to analyze the impact of wildfires on neighborhood greenness. I use NDVI as a measure of greenery to proxy for neighborhood quality. NDVI is a measure of vegetation greenness that comes from satellite imagery that ranges from -1 to 1 with more greenery being associated with higher values. To analyze the impact of wildfires on neighborhood greenness, I obtain NDVI measures at the census tract level from Google Earth Engine.[12] Then, I aggregate the data to the month-census tract level and use data from 2004 to 2024. I normalize the data by subtracting the mean and dividing by the standard deviation. I then merge the NDVI data with the wildfire data.

Finally, I also use Census data on census tract median household income and whether the neighborhood is urban or rural. I obtain the income data from the 5-year American Community Survey (ACS) through the R package "tidycensus" for the years 2005 to 2024.[13] I merge the tract-level income data with census tract shapefiles and then merge it with the

[12] I use the Landsat Collection 2 Tier 1 Level 2 8-Day NDVI Composite.

[13] Specifically I have versions for 2005 to 2009, 2010 to 2014, 2015 to 2019, and 2020 to 2024.

housing data, so a property is assigned the annual median household income of the census tract it is located in. Similarly, I obtain the urban-rural designation from the 2020 US Census Bureau TIGER Directory. I merge the housing data with this data to designate whether a property is located in an urban or rural area. I spatially merge the data with the fire data.

5 Methodology

5.1 Defining Treatment

To define treatment and control groups, I first merge the wildfire perimeter data and housing transaction data based on location. I merge all properties that fall within 10 kilometers (km) of a wildfire perimeter to that wildfire regardless of timing. If the property is within the fire perimeter and the transaction is not in the month right before the fire, I consider it a treated property. If it is outside the fire perimeter but within 10 km or within the fire and transacted in the month directly preceding the fire, I consider it a control property. In the main analysis, I restrict the control group to properties 1 to 10 km from the fire because it is possible that a property can be outside the fire perimeter but experience damage because of flying embers. Hence, properties within the fire perimeter are compared to those between 1 and 10 km from the fire with the assumption that these properties are similar in terms of characteristics and price. Table A2 in the appendix illustrates the similarity of the two groups before treatment. To illustrate the identifying variation, I plot the Camp Fire's perimeter, the 1 to 10 km buffer, and the treated and control units for one year before and after the fire in Figure 5. Units vary substantially by space, clustering in denser urban areas. Assuming the prices of the control and treated properties would have followed similar trends absent wildfire exposure, the differences in post-fire prices reveal the effect of fire exposure on transaction prices.

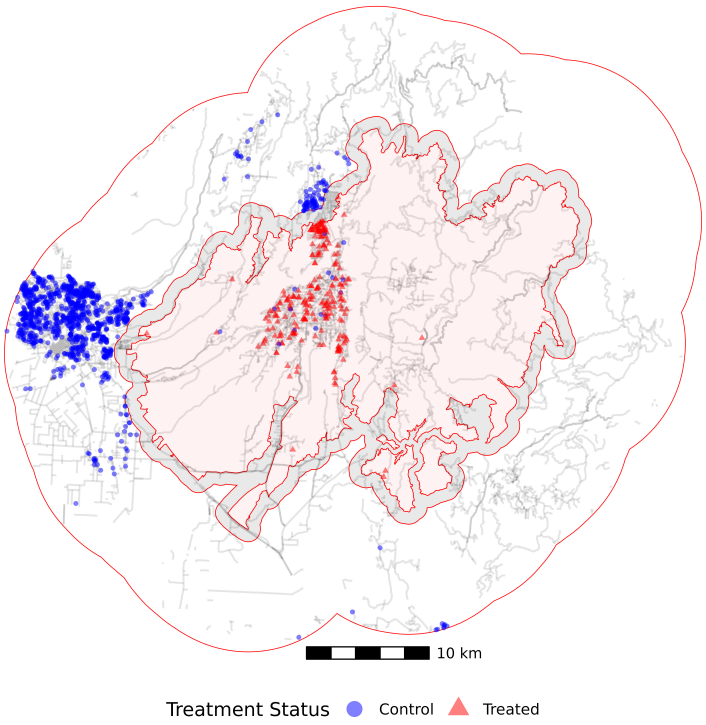


Figure 5: Map of treated and control units in the Camp Fire (November 2018). This map highlights how treatment and control are assigned over space and what observations are being compared in the analysis. The Camp Fire perimeter, a 1 to 10 km buffer, and treated and control units are plotted. Each dot represents a transaction. Transactions from one year before and after the Camp Fire are exhibited in this figure. The blue circles represent control units: transactions that took place outside the fire perimeter at any time (between 1 and 10 km from the perimeter) and transactions that took place within the fire perimeter one month before the fire (October 2018). The red triangles represent treated units: transactions that occurred within the fire perimeter at any point except the month right before the fire.

5.2 Empirical Strategy

To empirically estimate the effect of wildfire exposure on housing transaction prices, I follow Wing, Freedman, and Hollingsworth (2024) and employ a stacked event study where event time is monthly. This approach is beneficial in two ways. First, like other staggered adoption designs, this approach addresses both the issue of heterogeneous treatment effects and comparing early versus late treatment adopters which may be violating the parallel trends assumption (Callaway and Sant'Anna 2021). Further, the stacked approach in Wing, Freedman, and Hollingsworth (2024) weighs observations to correct for bias that arises in the standard stacked event study design. Through weighted least squares, this approach allows estimation in one stacked regression where causal inference techniques can be used. In my context, each fire is its own sub-experiment, so properties within the fire perimeter are compared to those outside the perimeter of that same fire.

The main estimating equation is

$$ln(p_{ityscf}) = \sum_{\substack{\tau=k \\ \tau \neq -1}}^{K} \beta_\tau Fire_{if} \times ET^\tau_{ft} + \gamma X_{ity} + \alpha_{if} + \delta_{tf} + \eta_{cyf} + \varepsilon_{itycf} \tag{4}$$

where the outcome of interest is the log of property i's transaction price in month t in year y while in census geography c (tract in the main specification) and in fire f. $Fire$ indicates if property i is in the fire perimeter of fire f. ET indicates the month relative to the fire f. For example, if a fire happened in August 2007 and a property within the fire perimeter transacted in November 2007, then both $Fire$ and ET^3 are equal to one since the transaction happened three months after the fire. If a sale happened in the same month as the fire, its event time is zero. X is property i's characteristics in month-year ty, specifically the number of bedrooms, bathrooms, age, age squared, and type of property (single family, multifamily, condo, other). Since my sample only contains properties that have sold more than once, I include a property fixed effect, α, which accounts for property characteristics that are constant over time (e.g. lot size). δ is a transaction month of year fixed effect to

account for seasonality in the housing market. η is a neighborhood-transaction year fixed effect to address local features specific to that year. For example, this may include school district quality, local demographics, or access to natural amenities. I interact all fixed effects with the fire. The reference period for this analysis is the month immediately before the fire. Event times outside the window of interest are controlled for with end cap indicators. When running heterogeneity analyses, I interact another indicator variable with $Fire$ and ET. Otherwise, the estimating equation remains the same. Standard errors are clustered at the fire level throughout the paper.

6 Results

6.1 Impact of Wildfire Exposure on Housing Prices

In this section, I analyze the effect of being within the fire perimeter on log transaction prices. Figure 6 exhibits the results from estimating Equation 4 with twelve months in the pre period and 36 months in the post-period.[14] The dashed red line in period zero indicates when the fire happened. In the year leading up to the fire, prices are unaffected which validates the parallel trends between the treated and control groups. However, once the fire happens, prices decline sharply by 39% as early as two months after the fire. They decline the most eight months after the fire at 55%.[15] Prices remain depressed until two years after the fire and then begin to increase. They reach pre-fire levels before the three-year mark and fully recover as seen in Figure A10. It is important to note that the dates used for the housing transactions are when the transactions were finalized. This process usually takes one to two months after agreeing on the sale; therefore, the estimated coefficients can approximately represent the effect of the decision two months previously. This context helps explain why strong effects do not appear until month three. These results indicate that being

[14]Results for different control groups and specifications are presented in the appendix.

[15]To convert the log points to percent changes, I use the following formula: $(e^{\beta} - 1) \times 100$ where β is the log points estimate from Equation 4. For the coefficient of -0.791, the calculation is $(e^{-0.791} - 1) \times 100 = 55$

located within the fire perimeter is negatively capitalized in housing transaction prices which highlights that the demand effects are outweighing supply effects. However, this decline is only temporary, and it is unclear what is driving the decline.

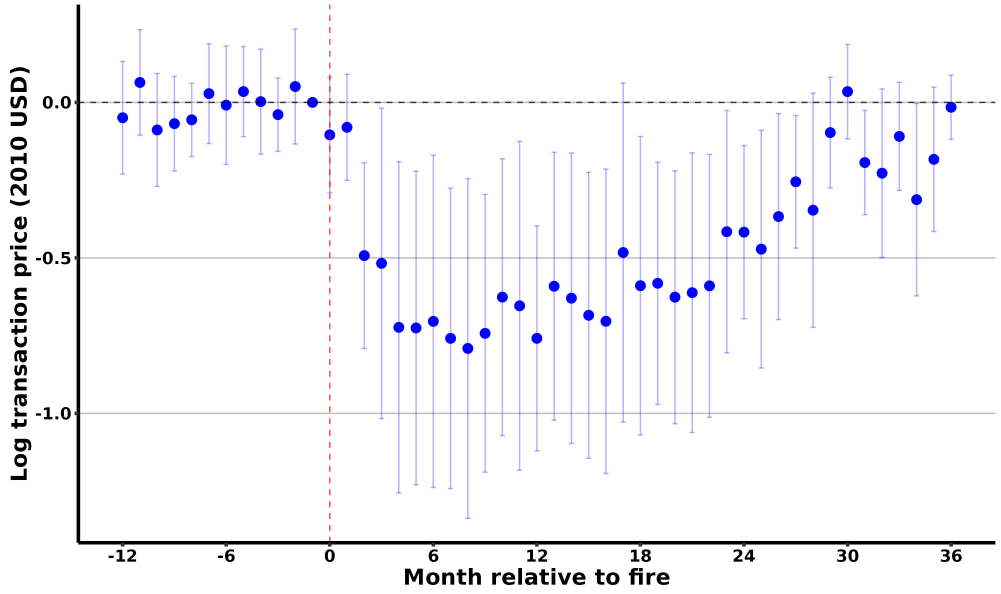


Figure 6: The effect of being in the fire perimeter on log transaction prices. This figure plots point estimates and 95% confidence intervals for the event study. 12 months are used for the pre-period, and 36 months are used for the post-period. Fires that take place before 2005 and after 2021 are dropped to allow for fires where the whole pre-period and post-period can be observed. Treated units are transactions within the fire perimeter that took place at any point between 2005 and 2021 except for transactions in event time -1. Control units are transactions between 1 and 10 km from the fire perimeter or those within the perimeter that took place in event time -1. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

6.2 Spatial Spillovers

I explore whether there are spatial spillovers that are biasing the estimates since treatment is based on space. In this section, I conduct a similar analysis to Equation 4. However, rather than interacting event time with the indicator for whether the property is in the fire or not, I interact it with a variable for what distance bin the property is in. Since treatment is based on space, interacting event time with the fire binary variable does not allow me to

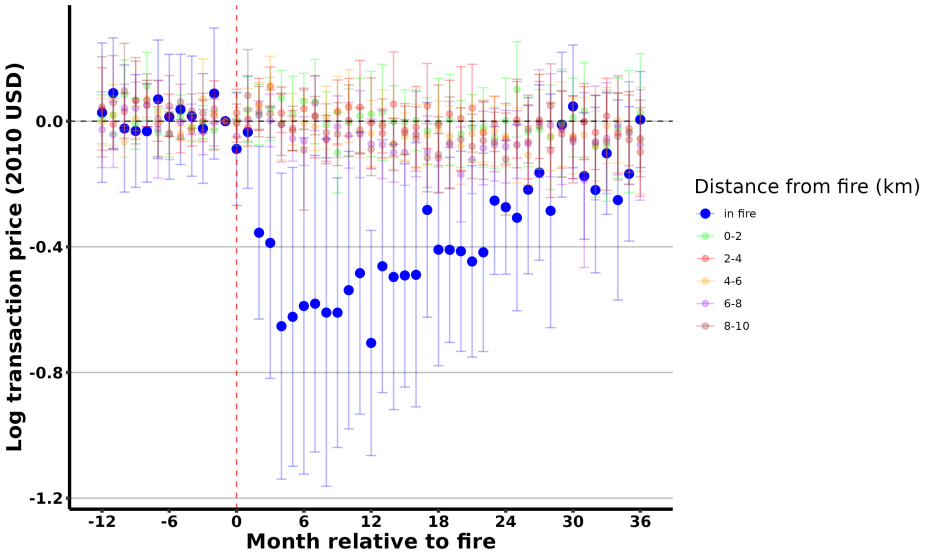
see the effects of the fire on prices outside the perimeter. Hence, this set up is not a typical event study, but rather using proximity to the fire, it shows the effect of the fire on prices in the given distance bin. Figure 7 provides two specifications of this distance analysis: long distance bins out to 10 km and short distance bins out to 1 km.

Both the long and short distance bin figures show that the price effects are concentrated in the fire perimeter. There is not enough to say that there are no price effects outside the fire perimeter since demand from residents inside the fire perimeter may be pushing prices up, while a decrease in demand due to a decline in local amenity quality may be pushing prices down. The net effect appears to be no change in prices because of the fire. In the subsequent sections, I assume there are no spatial spillovers and focus on the effects within the fire perimeter.

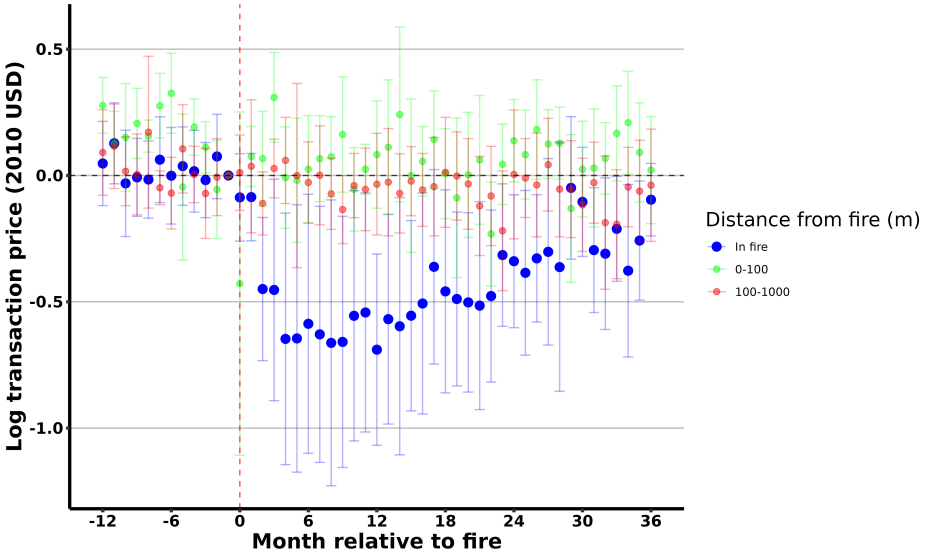
6.3 Explaining the Price Decline

6.3.1 Identifying the housing quality, amenity, and supply effects

In this section, I explain why the price declines in the short-run. I determine whether direct fire exposure is the only mechanism that drives prices down by quantifying the housing quality (HQ) effect and the sum of the amenity (A) and supply (S) effects. I incorporate the property-level damage data which allows me to see whether a property within the fire perimeter is physically burned by the fire or not. As previously discussed, this data of actual and predicted property damage status contains 120 fires, 1,712,942 transactions, and 355,483 properties. Not all fires that are in the main analysis data are present here. The specification remains similar to Equation 4, but now the event time and fire variables are interacted with a binary variable indicating if the property is damaged in that particular fire or not. This is a heterogeneity analysis that breaks down the results in Figure 6 by damaged and undamaged properties. In Figure 8, damaged properties face large declines in prices after the fire, seeing a 69% decline one year after. Undamaged properties also see a decline in prices. About one year after the fire, prices have declined by as much as 30%. Prices remain relatively



(a) Long distance bins out to 10 km



(b) Short distance bins out to 1 km

Figure 7: The effect of event time on log transaction price by distance bin. This figure plots point estimates and 95% confidence intervals for the event study split by distance bins. In (a) the groups are in fire, 0-2 km, 2-4 km, 4-6 km, 6-8 km, and 8-10 km from the fire perimeter. In (b) the groups are in fire, 0-100m, and 0-1000m from the fire perimeter. The in fire indicator cannot be used as in the main results since anything outside the perimeter would become zero. 12 months are used for the pre-period, and 36 months are used for the post-period. Fires that take place before 2005 and after 2021 are dropped to allow for fires where the whole pre-period and post-period can be observed. The control group (reference period) for each distance bin is the month directly preceding the fire, and the treated group is any other event time within the window of analysis. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

below pre-fire levels until two years after the fire which is a faster recovery than damaged properties by about one year. The decline in prices for undamaged properties indicates that the amenity effect is stronger than the supply effect. While the drop in prices for undamaged properties is not as large as that of damaged properties, it highlights that declining housing quality is not the only factor contributing to the changes in price after the fire.

Then, I use these results for damaged and undamaged properties to quantify the housing quality effect, and the sum of the amenity and supply effects. The sum of the amenity and supply effects is equivalent to the effect of exposure on undamaged properties, so for one year after the fire, $A + S = -30\%$. This -30% is an upper bound for the amenity effect, so it is possible that the price declines associated with the amenity effect are actually larger in absolute value than 30%. As seen in Section 3, the housing quality effect is obtainable by differencing the effect of damaged homes and that of undamaged homes. The effect in log points one year after the fire is -1.17 for damaged properties and -0.37 for undamaged properties. Hence, the housing quality effect in log points is -0.8 which is equivalent to a decline of 55%. These findings indicate that both worsening housing quality and local amenities are contributing to the post-fire price decline.

6.3.2 Housing Quality and Amenity Costs

In this section, I use the previously obtained quality and amenity estimates from twelve months post-fire to calculate the short-run costs. Since the undamaged property effect is the upper bound for the amenity effect, for this exercise I denote $A^{UB} = \Delta P_U = A + S$ and refer to the associated costs as amenity costs. I use the following equations to calculate the costs for the housing quality and amenity effects:

$$costs_{HQ} = n_{dam} \times p_{dam} \times |HQ| \tag{5}$$

$$costs_{A^{UB}} = (n_{undam} \times p_{undam} \times |A^{UB}|) + (n_{dam} \times p_{dam} \times |A^{UB}|) \tag{6}$$

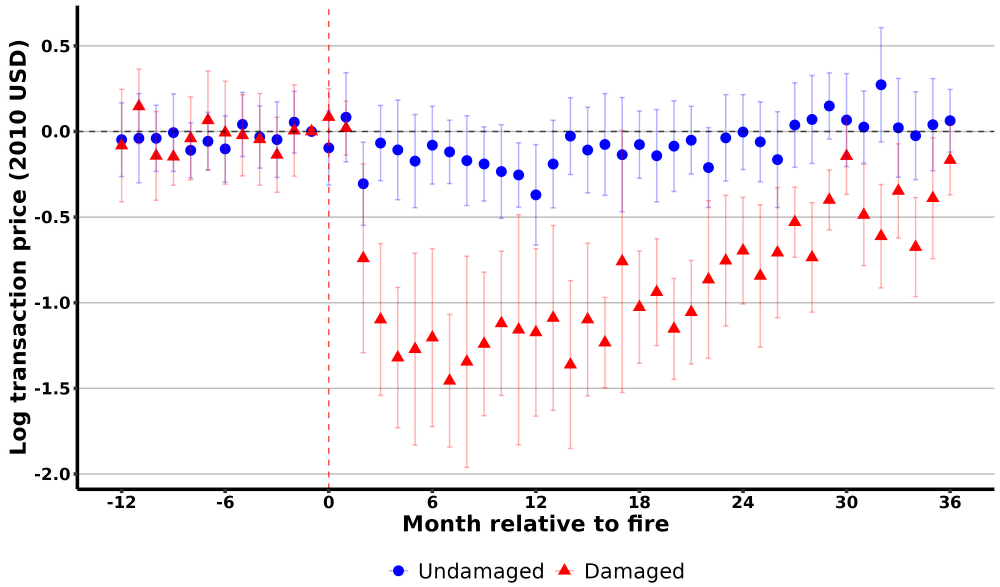


Figure 8: The effect of fire exposure on log transaction price by damage status within fire. This figure plots point estimates and 95% confidence intervals for the event study split by whether the property is damaged or undamaged in the fire perimeter. Fires that take place before 2005 and after 2021 are dropped. The reference period for both damaged and undamaged properties is the preceding month. The control group is properties between 1 and 10 km from the fire perimeter. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

where n denotes the number of properties in the fire perimeter for either damaged or undamaged properties, p is the median pre-fire transaction price for damaged or undamaged properties, HQ is the housing quality effect, A^{UB} is the sum of the amenity and supply effects, and the *dam* and *undam* subscripts indicate whether the group of interest is damaged or undamaged properties.[16] For these calculations, $HQ = -55\%$ and $A^{UB} = -30\%$. It may be expected that damaged properties lose the entirety of their value, but it is important to remember that the value of the remaining structure and land are still accounted for in the transaction price.

For each fire, I obtain the values for costs associated with housing quality and amenity effects. Table 2 presents the breakdown of these costs for both the dataset of actual damage data and the dataset including predicted damage data. For the actual damage data, the average housing quality and amenity costs are close in value at about $250 million with the maximum values being in the billions of dollars. The costs are larger when using the predicted data, specifically the housing quality costs average about $660 million while amenity costs average about $800 million with total costs being an order of magnitude larger than with the actual data. A benefit of the predicted damage data is that it provides data on undamaged properties that were not accounted for in the DINS data. Moreover, the predicted data provides information on fires that are not included in DINS. Hence, the predicted data provides more complete cost estimates. Overall, the total costs are substantial, and amenity costs are just as large, if not larger, than housing quality costs. As previously mentioned, I use the upper bound of the amenity effect, so these amenity costs are actually a lower bound since benefits (increasing price) from the supply effect can be reducing the total price decline. This is a significant level of costs that is not being accounted for when determining the total damages of wildfire exposure.

[16] Using 2010 dollars, damaged homes before a fire had a mean (median) transaction price of $400,758 ($276,604) while undamaged homes had prices of $522,899 ($412,086).

A. DINS (49 fires)					
Costs (millions $)	Mean	Median	Min	Max	Total
Housing Quality	254.16	37.21	6.08	2091.41	9657.92
Amenity	241.59	71.74	3.41	1461.31	7972.35
Total	463.95	75.08	8.88	3552.72	17,630.27
B. Predicted Damage (80 fires)					
Costs (millions $)	Mean	Median	Min	Max	Total
Housing Quality	656.68	152.41	2.93	12,956.84	42,027.77
Amenity	812.36	292.60	3.97	10,684.08	26,807.74
Total	1075.56	208.24	5.53	23,640.92	68,835.51

Table 2: Wildfire costs based on estimates from Figure 8. This table provides summary statistics for housing quality and amenity costs using estimates from Figure 8. Data on damage counts comes from either CAL FIRE's DINS data or the predicted damage data described in Section 4. To obtain the amenity costs, pre-fire median transaction prices for damaged and undamaged properties are multiplied with their respective counts and then by the upper bound of the amenity effect 12 months after the fire (31%). To obtain the housing quality costs, pre-fire median transaction prices for damaged properties are multiplied by the number of damaged properties and by the housing quality effect 12 months after the fire (55%). Median transaction prices are in 2010 dollars. Fire counts may differ from event study plots due to there not being pre-fire properties of a certain type for a given fire. In estimation, fires without the necessary observations are given zero weight so dropped.

6.3.3 Local damage as an amenity effect

The results show that costs because of declining local amenities exist and can be quite substantial. In this section, I focus on one aspect of local amenities, local damage. Using the property damage data, for each property within each fire, I draw a circle with a 500 meter (m) radius around the property. I then count the number of damaged properties in that circle to obtain the share of damaged properties nearby. Figure 9 illustrates this calculation with a random selection of properties in Paradise, CA. The share of damaged properties around a property is a proxy for local amenity quality. The more damage there is, the worse the amenity quality is. I condition on property damage status, so the effect is only nearby damage.

To answer this question econometrically, I run a variation of the main estimating equation, Equation 4. Now, the fire and event time variables are interacted with a binned variable indicating the share of damaged properties within 500 meters of the property. The chosen bins are below 90% and 90% and above. For properties that see any damage within 500 meters of them, 81% face more than 90% damage, and 40% face 100% damage. Hence, the bins are chosen to explore some of the variation in the high damage range. Furthermore, an indicator variable for whether the property of interest was damaged is included. Therefore, I estimate the effect of only nearby damage on property prices. In Figure 10, the results of this estimation are presented. For properties with less than 90% damaged properties around them, there is not an effect on their prices. It is not until the share of damage is above 90% that there is a decline in prices. These results indicate that even when controlling for the damage status of a given property, local damage around a property still leads to a decline in transaction price, in particular when the damage share is substantial. Overall, as the local neighborhood quality declines, prices also decline. This finding indicates a decline in demand as the neighborhood quality gets worse. Overall, the initial decline in prices after a fire is composed of both the housing quality and amenity effects. The increase of local damage and degradation of neighborhood quality play important roles in the amenity effect

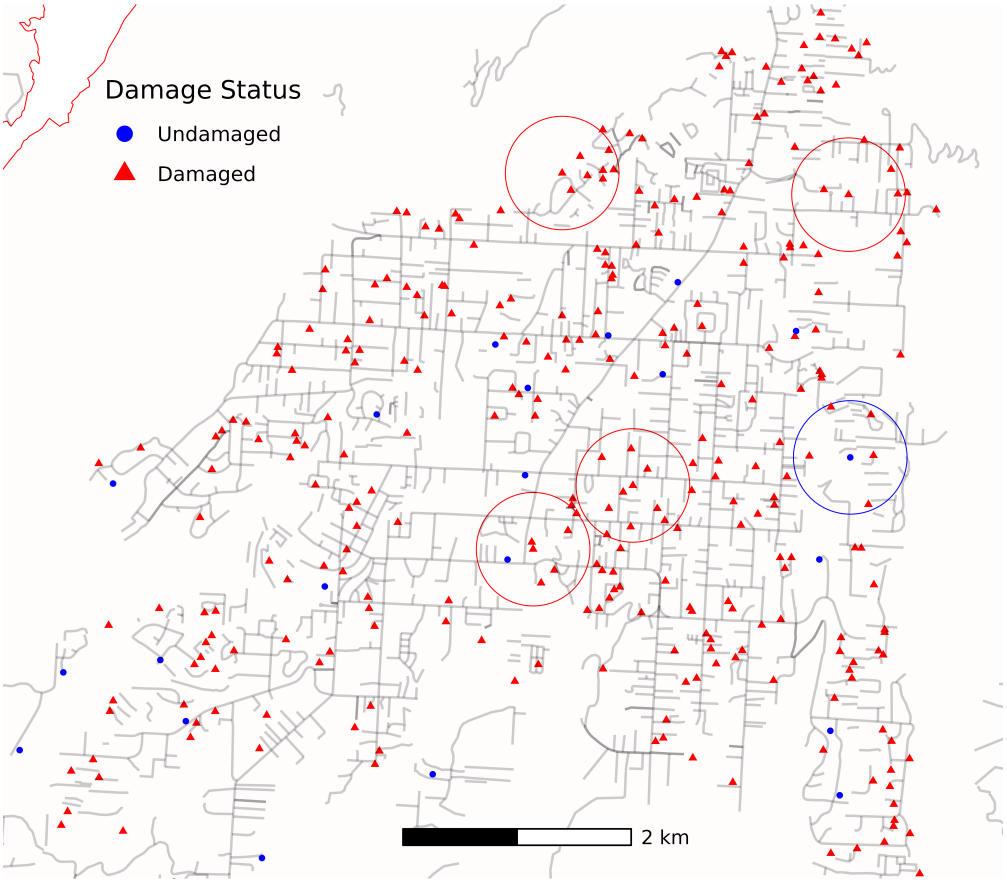


Figure 9: Map of examples of local damage calculation. This map shows a randomly selected sample of damaged and undamaged properties in Paradise, CA (Camp Fire). Blue circles indicate undamaged properties, and red triangles indicate damaged properties. Five properties were randomly selected to illustrate the 500 meters radius circle drawn around each property. The share of damaged properties is obtained by adding the number of damaged properties within 500 meters of the property and dividing by the total number of properties in that same area.

that pushes prices down and leads to substantial costs.

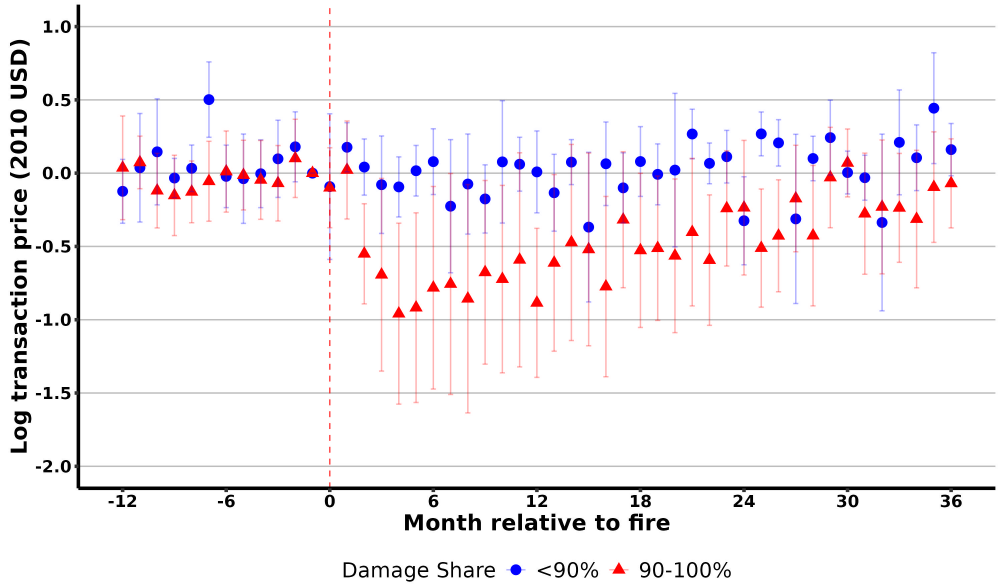


Figure 10: The effect of local damage on log transaction price. This figure plots point estimates and 95% confidence intervals for the event study split by the share of damaged properties nearby. Damage status of the property of interest is controlled for. Fires that take place before 2005 and after 2021 are dropped. The reference period for all groups is the preceding month. The control group is properties between 1 and 10 km from the fire perimeter. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

6.4 Explaining the Price Recovery

While there are large price declines, this effect is not permanent. In this section, I shed light on why prices recover by looking at residential building permits, local amenities, and the composition of transacted homes. Throughout this section, I conduct the analysis at the neighborhood level (either census block group (CBG) or census tract) rather than comparing individual properties. Since the number of houses within fires compared to outside of fires can differ substantially, looking at a census geography where the number of houses falls within a certain range (typically 240 to 1,200 housing units for a CBG) results in more comparable groups. I denote a census geography as treated if its geographic center (the centroid) is within the fire perimeter. Control census geographies are those whose centroids

are within 10 km of the fire perimeter but not within it.[17] Geographies that have a majority of their area within the fire are being compared to those that have a majority of their area outside the fire. This treatment definition is necessary to compare housing clusters with a similar number of housing units. An example of treated and control units for the Camp Fire is presented in Figure A15. Similar to Equation 4, I estimate a stacked event study but now use a Poisson model for outcomes that are count data and have zeros.

$$outcome_{ityf} = exp(\sum_{\substack{\tau=k \\ \tau \neq -1}}^{K} \beta_\tau Fire_{if} \times ET_{ft} + \alpha_{if} + \delta_{yf} + \varepsilon_{iyf}) \tag{7}$$

outcome is either the number of permits issued, the normalized value of the local amenity, or the number of transactions that occurred in a given geography and time period. α is a fixed effect for census geography-fire, and δ is a (permit or sale) month-year-fire fixed effect.

6.4.1 Building Permits

I use Equation 7 to estimate the effect of wildfire exposure on neighborhood-level building permits. *outcome* is the number of permits issued in month t, year y, in CBG i in county c and look at 36 pre-months and 60 post-months. Figure 11 shows the impact of wildfire exposure on the number of residential building permits issued in a CBG. The number of issued permits peaks in the month directly after the fire at about 84% and steadily declines to pre-fire levels in year four. These results indicate a rapid increase in permitting activity after a fire supporting the idea that there is an increase of demand for the affected neighborhood. The increase in building permits mirrors the impact of fire exposure on prices where there is a short-run decline followed by a recovery to pre-fire levels three years after the fire. Together, these results indicate an improvement in neighborhood quality. Since prices increase with construction, the demand effects from improving neighborhood quality are outweighing supply effects that result from increased construction.

[17] Some geographies that are both in and out of the fire will be treated while others will be control units.

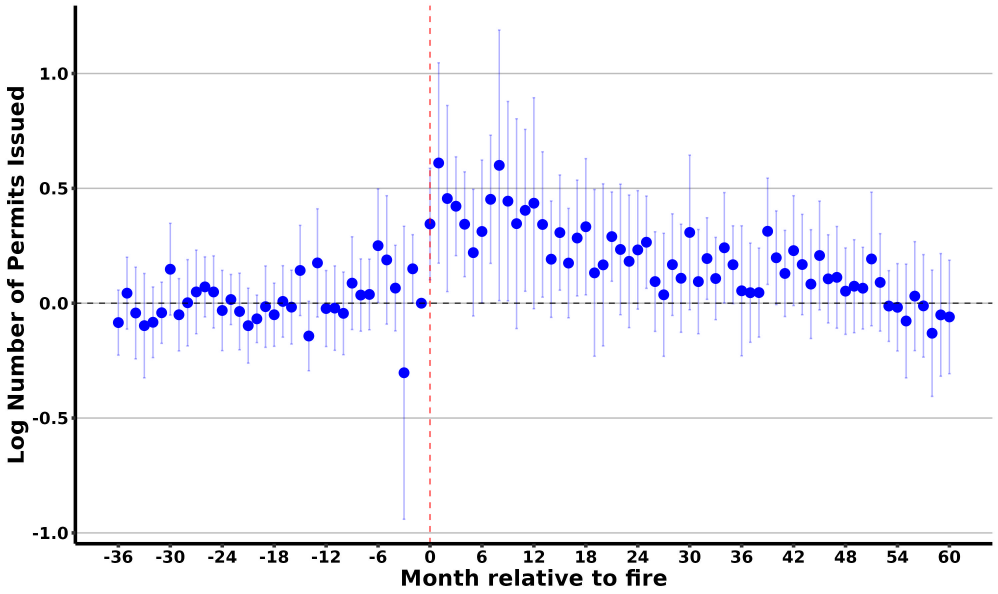


Figure 11: The effect of fire exposure on number of permits issued in a CBG at the monthly level. This figure plots point estimates and 95% confidence intervals for the event study estimated with a Poisson regression. Fires that take place before 2007 and after 2019 are dropped. The reference period is the preceding month. The control group is CBGs outside the fire perimeter but within 10 km. Fixed effects for CBG and permit issuance month are interacted with a fire indicator. Standard errors are clustered at the fire level.

I merge the permit data with the property damage data by address to look at the composition of the types of permits that are being issued to damaged homes over time. In Figure 12, I show the composition of permits issued to damaged properties at the annual level. Before the fire, the number of permits remains stable with utilities comprising a majority of the issued permits. However, in the year of the fire, the number of permits issued increases substantially. Utilities are still a majority of the issued permits, but the share of demolition and accessory structure permits increases significantly relative to the pre-fire levels.

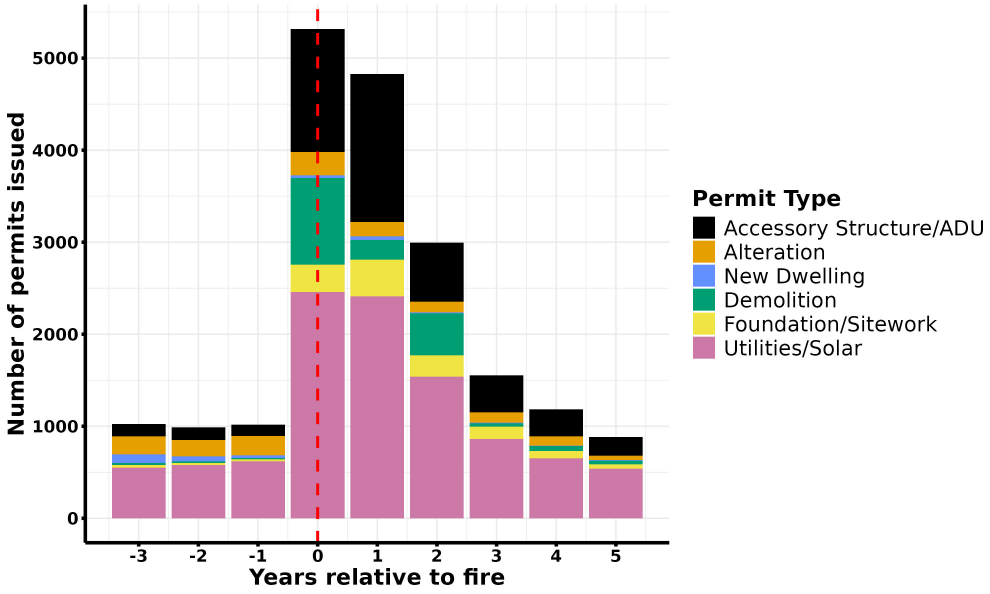


Figure 12: The annual composition of permits issued to damaged properties relative to the year of the fire. This figure plots the composition of issued permits to properties that were damaged in a fire. The x-axis shows the year relative to the year of the fire in year 0.

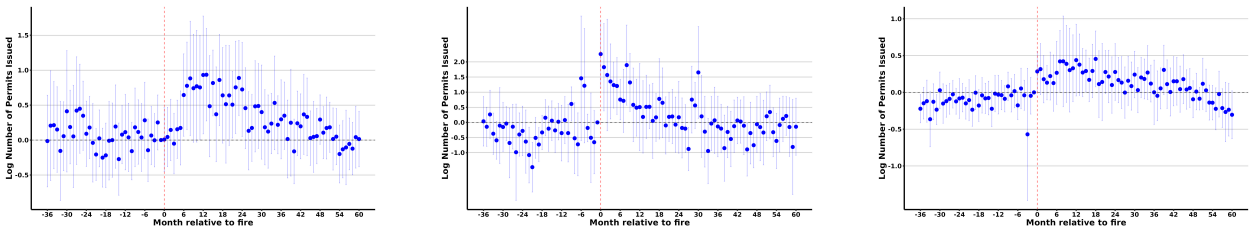
To confirm this descriptive finding, I run a subsample analysis by type of permit focusing on utilities, demolitions, and accessory structures. Figure 13 shows demolitions spike immediately after the fire at an 858% increase which coincides with the clearing of damaged properties. Then demolitions return to the pre-fire level two years later. Utilities also increase by as much as 57% and remain elevated for almost four years indicating the reconnecting of utilities for impacted properties. Finally, accessory structure permits, which include accessory dwelling units and other detached structures on the property, increase six

months after a fire by as much as 153% and remain elevated for four years afterward. An alternate dwelling unit (ADU) is a habitable unit on the property that is different from the main dwelling unit. These results indicate the clearing out of damaged properties, followed by the reconnecting of utilities, and then the building of smaller structures on the same property. There are two primary reasons as to why accessory structure permits are increasing. First, ADUs are a cheaper relative to the main dwelling unit which is important if homeowners are waiting for insurance payouts to rebuild. Second, ADU permits are quicker to obtain and provide temporary housing. This became evident with the 2025 Los Angeles fires where the governor issued an executive order to make it easier to obtain ADU permits, and many people turned to this option (Adeniyi 2025).[18] Because of the lower costs and permit issuance time, accessory structures are an attractive option to remain on one's property while waiting for the main dwelling to be completed. It is worth noting that these results do not provide evidence that properties are being rebuilt one for one in the short to medium term. Thus the increase in demand is not being driven by a direct increase in housing stock, but rather by increased construction activity in the neighborhood which supports the idea that demand effects from neighborhood quality improvements are outweighing supply effects from increased housing stock.

6.4.2 Neighborhood Amenity: Normalized Difference Vegetation Index (NDVI)

The previous results exhibited that the neighborhood is improving through construction. In this section, I analyze a neighborhood amenity to determine whether improving amenities are aiding local demand. Local vegetation and green space is capitalized into housing prices. I use NDVI as a measure of greenery to proxy for amenity quality. I normalize NDVI by subtracting the mean and dividing by the standard deviation. I present the event study of the impact of wildfire exposure on tract-level NDVI standard deviation in Figure 14. Before the wildfire, tracts that will see a wildfire face an increase in vegetation which dries out and

[18]See this link for the executive order: https://www.gov.ca.gov/2025/02/13/governor-newsom-cuts-more-red-tape-by-further-streamlining-permitting-laws-to-accelerate-rebuilding-los-angeles/



(a) Accessory Structures (b) Demolitions (c) Utilities

Figure 13: The effect of fire exposure on the number of permits issued in a CBG at the monthly level by permit type. This figure plots point estimates and 95% confidence intervals for the event study estimated with a Poisson regression. Fires that take place before 2007 and after 2019 are dropped. The reference period is the preceding month. The control group is CBGs outside the fire perimeter but within 10 km. Fixed effects for CBG and permit issuance month are interacted with a fire indicator. Standard errors are clustered at the fire level.

creates fuel right before the wildfire occurs. After the fire, vegetation decreases by about 0.25 standard deviations which is a change of about 0.03 on the NDVI scale. Greenness remains below the pre-fire level before fully recovering three years after the fire which mirrors the price recovery in the main results. This return to the pre-fire level highlights that one type of neighborhood amenity is recovering which complements the increase in building activity and indicates that demand is increasing as neighborhood quality is improving.

6.4.3 Transaction Composition

I analyze the composition of homes that are transacted by using cross-sectional property transaction data. All analysis is done at the annual level with three pre-years and five post-years. First, I look at if fire exposure impacts the number of transactions where I use Equation 7 with the number of sales as the outcome variable. I aggregate to the CBG level to obtain the number of transactions by CBG for each event time. Figure 15 exhibits that there are no significant changes in the number of transactions happening after a fire. This finding may rule out the idea of a large number properties being purchased by a single commercial entity due to depressed prices.

Next, I regress housing characteristics on fire exposure using the cross-sectional data to

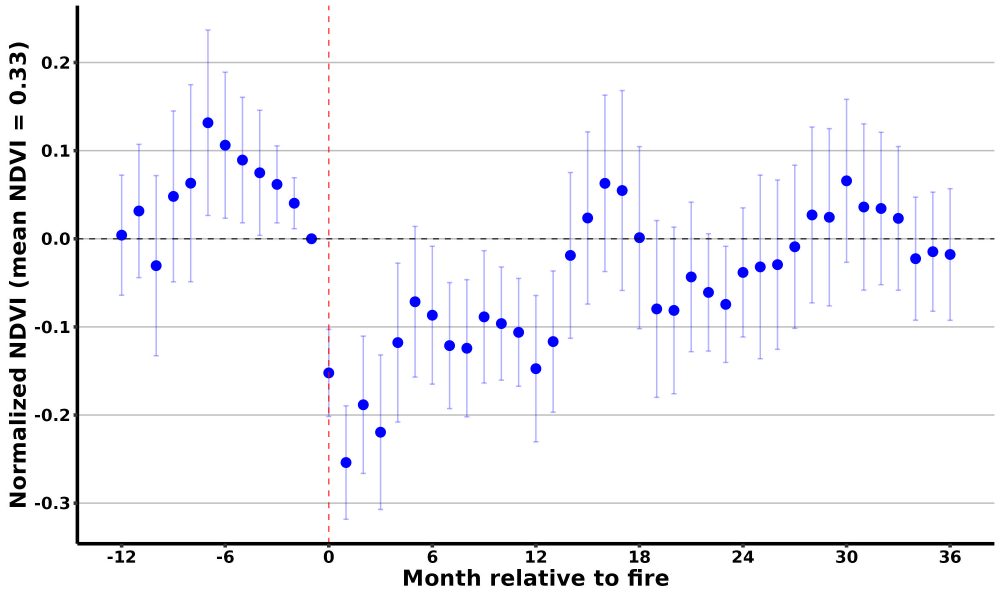


Figure 14: Changes in census tract NDVI. This figure plots point estimates and 95% confidence intervals for the event study looking at the effect of wildfire exposure on census tract NDVI standard deviation. Fires that take place before 2005 and after 2021 are dropped. The reference period is the preceding month. Treated census tracts have their centroid within the fire perimeter. The control group is census tracts whose centroid is outside a fire perimeter but within 10 km. Fixed effects for tract-month of year and county are interacted with a fire indicator. Standard errors are clustered at the fire level.

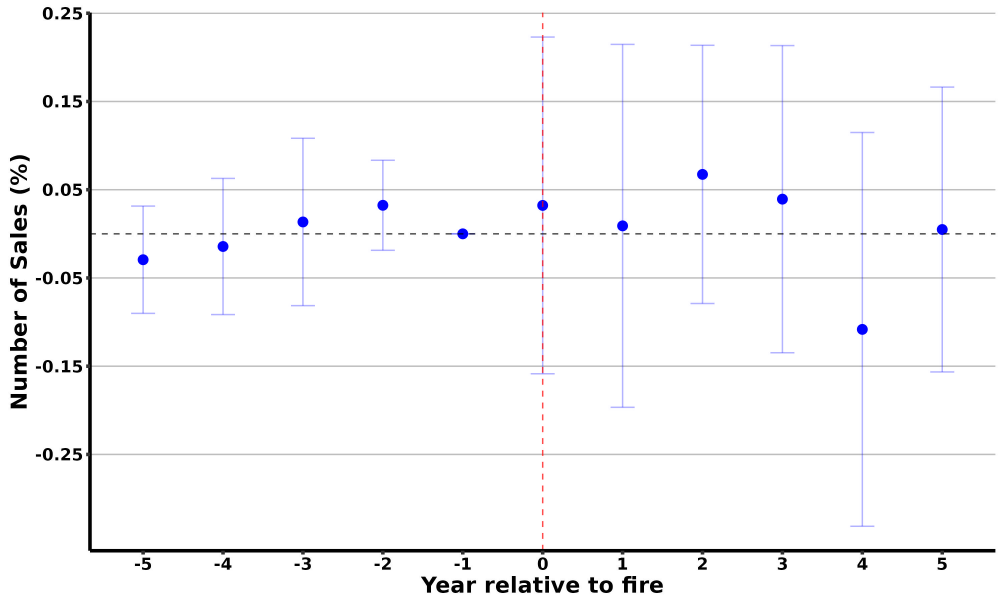


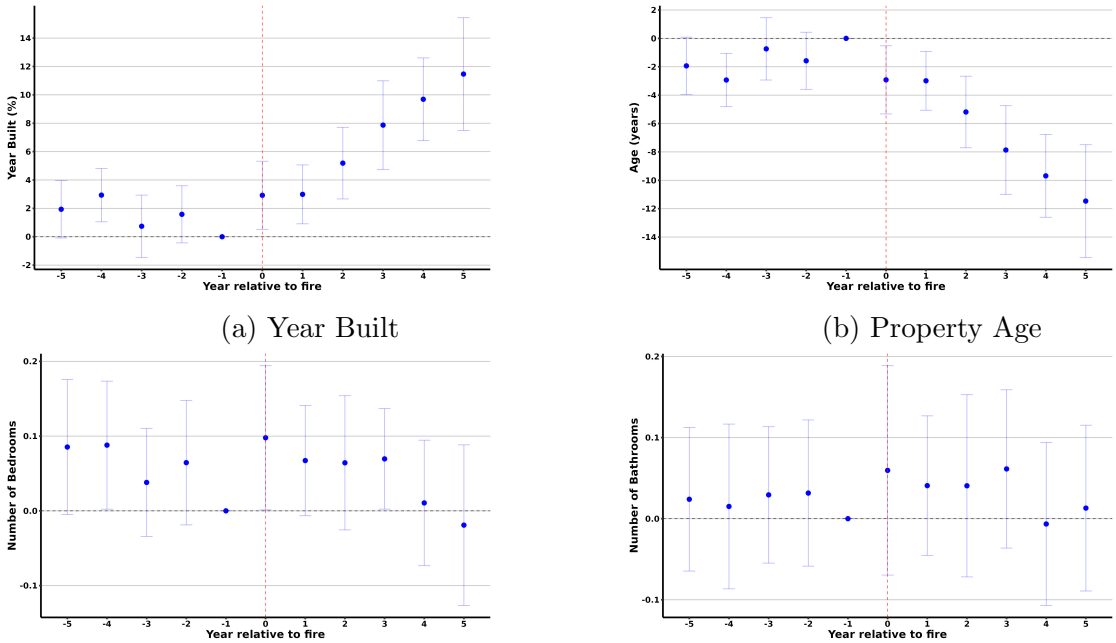
Figure 15: The effect of fire exposure on number of sales in a CBG using cross-sectional data. This figure plots point estimates and 95% confidence intervals for the event study estimated with a Poisson regression. Fires that take place before 2009 and after 2019 are dropped. The reference period is the preceding year. The control group is CBGs outside the fire perimeter but within 10 km. Fixed effects for CBG and sale year are interacted with a fire indicator. Standard errors are clustered at the fire level.

look at whether the composition of properties sold is changing. I look at year built, age, number of bedrooms, and number of bathrooms. The specification is similar to Equation 7, but I estimate an OLS model where the outcome variable is the level of different housing characteristics. The top plot in Figure 16 exhibits that after a fire, the year built increases which means that newer structures are being built and transacting. Figure 16 also shows the mirror image of year built by looking at age. The age of properties that are sold after the fire is less than pre-fire. To understand if properties are changing, I also look at the effect on the number of bedrooms and bathrooms in the bottom plots of Figure 16. The number of bedrooms increases in transacted properties up to three years after the fire, but these results are not statistically different from zero. The estimates for the number of bathrooms are above zero three years after the fire but again are not statistically different from zero. While the estimates are not statistically significant, the overall pattern suggests that the characteristics of properties sold may be changing. Overall, this section reveals that sales remain stable after the fire, and newer properties that potentially have more rooms are sold. Coupled with the permit results, some properties are being rebuilt, and those that are selling are on average newer. These findings indicate an improvement in housing and neighborhood qualities drives demand and outweighs any supply effects from increased housing stock, thus helping prices to rebound.

6.5 Heterogeneity

I conduct a heterogeneity analysis to explore whether certain fire or property characteristics result in different price effects. The monthly analysis paints a clear picture of short-run dynamics, but for the heterogeneity analysis, I increase the size of the pre-period and post-period to three and five years respectively and run the analysis at the annual level to analyze medium and long-run dynamics.[19] I first look at fire characteristics, specifically the fire size

[19] I use the monthly event times to create annual event times. For example, month event times 0 to 11 are annual event time 0. Month event times -1 to -12 are annual event time -1. In general, annual event times are calculated by taking the floor of the monthly event time divided by 12.



(a) Year Built

(b) Property Age

(c) Number of Bedrooms

(d) Number of Bathrooms

Figure 16: The effect of fire exposure on property characteristics. This figure plots point estimates and 95% confidence intervals for the event studies with year built, property age, number of bedrooms, and number of bathrooms as the outcome. Fires that take place before 2009 and after 2019 are dropped. The reference period for both damaged and undamaged properties is the preceding year. The control group is properties between 1 and 10 km from the fire perimeter. Fixed effects for CBG and sale year are interacted with a fire indicator. Standard errors are clustered at the fire level.

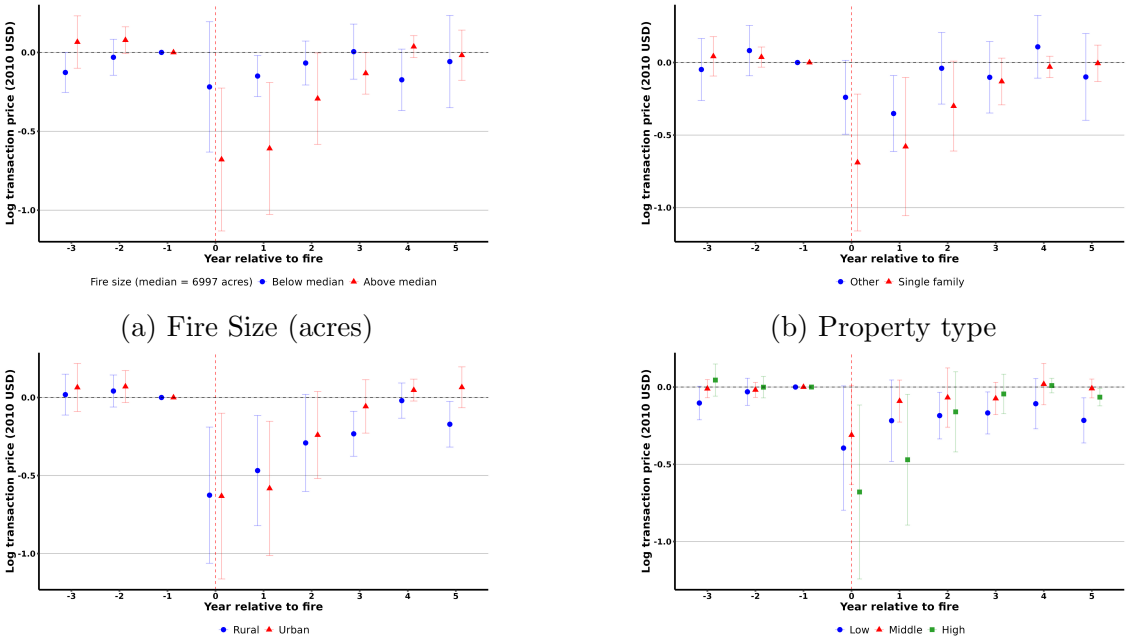
(in acres). In the first plot in Figure 17, using the main analysis data, I split the sample by properties that were exposed to fires that are larger than the sample median (6997 acres) and those that were in smaller fires.[20] Larger fires are associated with a larger price decline. However, in both cases, the prices recover to the pre-fire levels and remain there. It is worth noting that fire size does not always indicate how damaging a fire was. In some cases, fires will continue to burn if they are not a threat to people (in more rural areas).

Next, I explore whether property or neighborhood characteristics impact the results. At the property level, I look at the type of property (single family versus other) and at the neighborhood level, I look at whether a property is in an urban or rural neighborhood and whether it is in a richer or poorer neighborhood. I categorize properties by whether they are single family homes or other (e.g. duplex, condominium, townhouse, mobile home, etc.). In the second plot of Figure 17, single family homes face a sharper initial decline in prices. Single family homes are usually in wealthier areas, so these properties may face steeper amenity effects as well. However, the confidence intervals of both types of properties contain the point estimates of the other types, so it is difficult to conclude if there are any significant differences. Both types of properties return to pre-fire price levels four years after the fire. When comparing urban versus rural properties in the third plot of Figure 17, there is no discernable difference in effects. Urban properties appear to recover slightly before rural properties, but again it is difficult to conclude if there is actually a difference. Finally, in the last plot of Figure 17, I split the sample by census tract median household income within a fire by using the 5-year ACS.[21] While all properties face a price decline, higher income properties experience a larger decline. Middle and high income properties fully recover by four years after the fire while low income properties remain below the pre-fire level. It is possible that higher income neighborhoods face a larger percent decline in prices because their amenity effect is larger because of higher quality local amenities that are capitalized

[20] I take the unique properties within the sample and obtain the median from those rather than all fires that occurred in California.

[21] In the full sample, the first tercile is \$2499 to \$57,551.37, the second is \$57,551.37 to \$90,278.00, and the third is from \$90,278.00 to \$250,001.00.

into the transaction price. These higher income locations may also have more resources to aid in the recovery after fire exposure compared to lower income locations. While the evidence is not statistically significant, it appears that wealthier residents are facing a steeper decline but are able to fully recover as opposed to less wealthy residents. Overall, neighborhood income is the only factor that may be associated with different recovery outcomes.



(a) Fire Size (acres)

(b) Property type

(c) Urban versus rural property

(d) Neighborhood income

Figure 17: The heterogeneity effects of fire exposure on log transaction price. This figure plots point estimates and 95% confidence intervals for event studies split by fire size, property type, urban versus rural properties, and census tract income tercile. Fires that take place before 2007 and after 2019 are dropped. The reference period is the preceding year. The control group is properties between 1 and 10 km from the fire perimeter. Fixed effects for property, month of year, and county-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

7 Conclusion

Wildfires are a direct shock to local housing supply. In this work, I illustrate the net effect of wildfire exposure on the housing market. Fire exposure leads to a sharp decline in transaction prices of up to 55% for all properties within the fire perimeter. This net decline indicates that

demand for the affected area is decreasing, and the resulting demand effects are outweighing any changes in prices attributable to supply effects. Then, I estimate exposure separately for damaged and undamaged properties which allows me to quantify a housing quality effect of -55% and an upper bound on the amenity effect of -30%. There are substantial costs associated with both effects, and amenity costs are larger than housing quality costs.

While this price decline is steep and leads to large costs, it is not permanent. Prices begin to recover about two years after the fire and reach pre-fire levels three years afterward. Building permit activity increases immediately after the fire with demolition, utility, and accessory structure permits comprising a majority of the rise. Neighborhoods improve in quality by clearing out the damaged housing stock and building additional structures in the form of cheaper and easier to build accessory structures. Improving local amenities also complement the price recovery as seen with increasing greenery after an initial decline. Analyzing the composition of properties sold reveals that after the fire, the number of properties sold does not change, but properties are newer on average. These results highlight that even though housing supply is increasing, demand effects from improving neighborhood quality are stronger which drives prices up.

These results can inform policy decisions. It is worth noting that the suggestions provided here make a normative assumption that rebuilding should occur in the burned areas which may lead to a moral hazard issue if people are incentivized to rebuild in high fire risk locations. First, I showed that prices recovered as building permits were issued. Therefore, lowering the barriers to obtaining permits can help the price to recover more quickly. Moreover, the impact of local damage plays a significant role in the price effect. Providing a way to rebuild in clusters can result in spillover effects that help prices to rebound faster. Finally, while a focus of this work is on the amenity effect, declining housing quality from being burned is still a substantial cost. Defensive space that prevents and mitigates structure damage may be the most effective way to prevent further fire spread and damage.

Overall, this work helps to better understand the local housing supply and demand

dynamics that are present after wildfires. This understanding of the post-fire dynamics and different effects can help to inform future research and policymakers on how to support adaptation to wildfires and other climate hazards. While this paper answers important questions, there is still room for future work. This paper only bounds the amenity effect and does not explicitly quantify the supply effect. Richer data on housing supply can help to disentangle the two effects. Moreover, it remains unclear how the demographic composition of neighborhoods changes after a fire. Future work can attempt to address this by obtaining homeowner data or migration data. Finally, information on fire beliefs provides a better understanding of how housing prices capitalize fire risk which informs whether people choose to rebuild in the burned areas. These insights will further add to the understanding of what drives neighborhood changes after natural disasters.

References

[1] John T. Abatzoglou and A. Park Williams. "Impact of Anthropogenic Climate Change on Wildfire across Western US Forests". In: *Proceedings of the National Academy of Sciences* 113.42 (Oct. 2016), pp. 11770–11775. DOI: 10.1073/pnas.1607171113. (Visited on 11/24/2025).

[2] Luqman Adeniyi. *Temporary Housing After a Wildfire: What's Allowed on Your Property?* https://www.latimes.com/wildfire-recovery/construction/story/temporary-housing-wildfire-property-rules. June 2025. (Visited on 10/06/2026).

[3] David Albouy et al. "Climate Amenities, Climate Change, and American Quality of Life". In: *Journal of the Association of Environmental and Resource Economists* 3.1 (Mar. 2016), pp. 205–246. ISSN: 2333-5955, 2333-5963. DOI: 10.1086/684573. (Visited on 08/29/2025).

[4] ATTOM Data. *Assessor History*. DOI: 10.82551/2VE9-NE65. (Visited on 12/19/2025).

[5] ATTOM Data. *Recorder*. DOI: 10.82551/HTE0-K798. (Visited on 12/19/2025).

[6] ATTOM Data. *Tax Assessor*. DOI: 10.82551/395J-S146. (Visited on 12/19/2025).

[7] H. Spencer Banzhaf. "Difference-in-Differences Hedonics". In: *Journal of Political Economy* 129.8 (Aug. 2021), pp. 2385–2414. ISSN: 0022-3808. DOI: 10.1086/714442. (Visited on 11/24/2025).

[8] Patrick Baylis and Judson Boomhower. "The Economic Incidence of Wildfire Suppression in the United States". In: *American Economic Journal: Applied Economics* 15.1 (Jan. 2023), pp. 442–473. ISSN: 1945-7782. DOI: 10.1257/app.20200662. (Visited on 11/25/2025).

[9] Patrick Baylis and Judson Boomhower. "Mandated versus Voluntary Adaptation to Natural Disasters: The Case of US Wildfires". In: *Journal of Political Economy* (Jan.

2026), pp. 000–000. ISSN: 0022-3808, 1537-534X. DOI: 10.1086/739331. (Visited on 02/25/2026).

[10] Kelly C. Bishop et al. "Best Practices for Using Hedonic Property Value Models to Measure Willingness to Pay for Environmental Quality". In: *Review of Environmental Economics and Policy* 14.2 (June 2020), pp. 260–281. ISSN: 1750-6816. DOI: 10.1093/reep/reaa001. (Visited on 11/24/2025).

[11] Laura Bliss. "Nearly Five Years After Fires, Recovery in Paradise Holds Lessons for Lahaina". In: *Bloomberg.com* (Aug. 2023). (Visited on 03/15/2026).

[12] Judson Boomhower, Meredith Fowlie, and Andrew J. Plantinga. "Wildfire Insurance, Information, and Self-Protection". In: *AEA Papers and Proceedings* 113 (May 2023), pp. 310–315. ISSN: 2574-0768. DOI: 10.1257/pandp.20231104. (Visited on 11/25/2025).

[13] Brantly Callaway and Pedro H. C. Sant'Anna. "Difference-in-Differences with Multiple Time Periods". In: *Journal of Econometrics*. Themed Issue: Treatment Effect 1 225.2 (Dec. 2021), pp. 200–230. ISSN: 0304-4076. DOI: 10.1016/j.jeconom.2020.12.001. (Visited on 03/23/2026).

[14] Anita Chabria and Jessica Garrison. *Five Years after the Camp Fire, Paradise Survivors See a Hard Future for Maui*. https://www.latimes.com/california/story/2023-08-20/five-years-after-the-camp-fire-paradise-survivors-see-hard-future-for-maui. Aug. 2023. (Visited on 03/15/2026).

[15] Hongwei Dong. "Climate Change and Real Estate Markets: An Empirical Study of the Impacts of Wildfires on Home Values in California". In: *Landscape and Urban Planning* 247 (July 2024), p. 105062. ISSN: 0169-2046. DOI: 10.1016/j.landurbplan.2024.105062. (Visited on 07/22/2025).

[16] CAL FIRE. *Our Organization*. https://www.fire.ca.gov/about/our-organization. (Visited on 12/08/2025).

[17] CAL FIRE. *Statistics*. https://www.fire.ca.gov/our-impact/statistics. (Visited on 11/25/2025).

[18] Jacob Gellman, Margaret Walls, and Matthew Wibbenmeyer. "Welfare Losses from Wildfire Smoke: Evidence from Daily Outdoor Recreation Data". In: *Journal of Environmental Economics and Management* 132 (June 2025), p. 103166. ISSN: 0095-0696. DOI: 10.1016/j.jeem.2025.103166. (Visited on 03/04/2026).

[19] Kevin Haninger, Lala Ma, and Christopher Timmins. "The Value of Brownfield Remediation". In: *Journal of the Association of Environmental and Resource Economists* 4.1 (Mar. 2017), pp. 197–241. ISSN: 2333-5955. DOI: 10.1086/689743. (Visited on 11/24/2025).

[20] Yurou He, Ariel Ortiz-Bobea, and Jiong Wu. "Creative Destruction or Lasting Decline: Evidence from Post-Disaster Recovery". In: (2026).

[21] Hannah Hennighausen and Alexander James. "Catastrophic Fires, Human Displacement, and Real Estate Prices in California". In: *Journal of Housing Economics* 66 (Dec. 2024), p. 102023. ISSN: 1051-1377. DOI: 10.1016/j.jhe.2024.102023. (Visited on 03/12/2026).

[22] Zeying Huang and Mark Skidmore. "The Impact of Wildfires and Wildfire-Induced Air Pollution on House Prices in the United States". In: *Land Economics* 100.1 (Feb. 2024), pp. 22–50. ISSN: 0023-7639, 1543-8325. DOI: 10.3368/le.100.1.102322-0093R. (Visited on 06/15/2026).

[23] Paulo Issler et al. "Neighborhood Externalities and Coordinated Rebuilding after Wildfires: Evidence from California". In: (2026).

[24] Matthew W. Jones et al. "Wildfires in 2025". In: *Nature Reviews Earth & Environment* 7.6 (June 2026), pp. 334–336. ISSN: 2662-138X. DOI: 10.1038/s43017-026-00793-z. (Visited on 09/01/2026).

[25] Stephanie Kestelman. "Environmental Externalities of Urban Growth: Evidence from the California Wildfires". In: *SSRN Electronic Journal* (2023). ISSN: 1556-5068. DOI: 10.2139/ssrn.4629558. (Visited on 04/15/2026).

[26] H. Allen Klaiber and V. Kerry Smith. "Quasi Experiments, Hedonic Models, and Estimating Trade-Offs for Local Amenities". In: *Land Economics* 89.3 (Aug. 2013), pp. 413–431. ISSN: 0023-7639, 1543-8325. DOI: 10.3368/le.89.3.413. (Visited on 08/17/2026).

[27] Nicolai V. Kuminoff, Christopher F. Parmeter, and Jaren C. Pope. "Which Hedonic Models Can We Trust to Recover the Marginal Willingness to Pay for Environmental Amenities?" In: *Journal of Environmental Economics and Management* 60.3 (Nov. 2010), pp. 145–160. ISSN: 0095-0696. DOI: 10.1016/j.jeem.2010.06.001. (Visited on 11/24/2025).

[28] Nicolai V. Kuminoff and Jaren C. Pope. "Do "Capitalization Effects" for Public Goods Reveal the Public's Willingness to Pay?" In: *International Economic Review* 55.4 (2014), pp. 1227–1250. ISSN: 1468-2354. DOI: 10.1111/iere.12088. (Visited on 11/24/2025).

[29] Goeun Lee and Timothy K. M. Beatty. "Wildfires and Agricultural Worker Movement". In: *Journal of the Association of Environmental and Resource Economists* 12.6 (Nov. 2025), pp. 1459–1492. ISSN: 2333-5955, 2333-5963. DOI: 10.1086/733350. (Visited on 11/11/2025).

[30] Seunghoon Lee, Xibo Wan, and Siqi Zheng. "Beyond Asset Losses: Estimating the Economic Cost of Floods". In: (2026).

[31] Zhiyun Li and William Yu. *Economic Impact of the Los Angeles Wildfires*. https://www.anderson.ucla anderson-forecast/economic-impact-los-angeles-wildfires. Jan. 2025. (Visited on 03/12/2026).

[32] Yanjun (Penny) Liao and Carolyn Kousky. "The Fiscal Impacts of Wildfires on California Municipalities". In: *Journal of the Association of Environmental and Resource Economists* 9.3 (May 2022), pp. 455–493. ISSN: 2333-5955, 2333-5963. DOI: 10.1086/717492. (Visited on 11/14/2024).

[33] Steven G. Malliaris et al. *Wildfires and the Resilience of Commercial Activity*. SSRN Scholarly Paper. Rochester, NY, Feb. 2026. Social Science Research Network: 6220858. (Visited on 03/01/2026).

[34] Lucija Muehlenbachs, Elisheba Spiller, and Christopher Timmins. "The Housing Market Impacts of Shale Gas Development". In: *American Economic Review* 105.12 (Dec. 2015), pp. 3633–3659. ISSN: 0002-8282. DOI: 10.1257/aer.20140079. (Visited on 11/24/2025).

[35] Julie Mueller, John Loomis, and Armando González-Cabán. "Do Repeated Wildfires Change Homebuyers' Demand for Homes in High-Risk Areas? A Hedonic Analysis of the Short and Long-Term Effects of Repeated Wildfires on House Prices in Southern California". In: *The Journal of Real Estate Finance and Economics* 38.2 (Feb. 2009), pp. 155–172. ISSN: 0895-5638, 1573-045X. DOI: 10.1007/s11146-007-9083-1. (Visited on 10/10/2025).

[36] Sherwin Rosen. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition". In: *Journal of Political Economy* 82.1 (1974), pp. 34–55. ISSN: 0022-3808. JSTOR: 1830899. (Visited on 11/25/2025).

[37] Longzhong Shi et al. "Assessing the Impact of Wildfires on Property Values in Wildland-Urban Intermix and Interface in Colorado: A Hedonic Approach". In: *Journal of Environmental Management* 319 (Oct. 2022), p. 115672. ISSN: 03014797. DOI: 10.1016/j.jenvman.2022.115672. (Visited on 05/30/2026).

[38] Paige St. John. *From Watts to L.A. Wildfires: The Rise of California's Troubled FAIR Plan*. https://www.latimes.com/business/story/2026-09-20/from-watts-to-la-wildfires-rise-of-californias-troubled-fair-plan. Sept. 2026. (Visited on 09/21/2026).

[39] Frederik Strabo, Calvin Bryan, and Matthew N. Reimer. "Wildfire Damages and the Cost-Effective Role of Forest Fuel Treatments". In: *Science* 392.6798 (May 2026), pp. 629–635. DOI: 10.1126/science.aea6463. (Visited on 08/17/2026).

[40] Frederik Strabo and Matthew N Reimer. "Before the Burn: The Economic Benefits of Fuel-Reduction Treatments in Wildfire-Prone Forests". In: *The Economic Journal* (Mar. 2026), ueag037. ISSN: 0013-0133. DOI: 10.1093/ej/ueag037. (Visited on 08/17/2026).

[41] US Forest Service Research and Development. *Wildland-Urban Interface Growth in the U.S. — US Forest Service Research and Development*. https://research.fs.usda.gov/nrs/projects/wuig Text. July 2023. (Visited on 11/25/2025).

[42] Coady Wing, Seth Freedman, and Alex Hollingsworth. *Stacked Difference-in-Differences*. Tech. rep. w32054. Cambridge, MA: National Bureau of Economic Research, Jan. 2024, w32054. DOI: 10.3386/w32054. (Visited on 03/23/2026).

[43] Jiarui Zhang, Daniel J. Phaneuf, and Blake A. Schaeffer. "Property Values and Cyanobacterial Algal Blooms: Evidence from Satellite Monitoring of Inland Lakes". In: *Ecological Economics* 199 (Sept. 2022), p. 107481. ISSN: 09218009. DOI: 10.1016/j.ecolecon.2022.107481. (Visited on 08/25/2025).

Appendix A. Tables

Variable	Coefficient
Yearly Time Trend	-0.680
Assessed change from year 0 to 1	-3.389
Year Built	0.000
Year Built Effective	-0.000
Minimum Area	-0.000
Maximum Area	-0.000
Minimum Bath Count	0.002
Bath Count Change	-0.249
Maximum Bedroom Count	0.053
Bedroom Count Change	0.124
Minimum Pool	0.001
Pool Change	-0.000
Minimum Stories	-0.069
Maximum Stories	-0.096
Intercept	10.053
Number of properties	15,766

Table A1: LASSO predictor variables with non-zero coefficients. This table provides the variables in the LASSO cross-validation that have non-zero coefficients. The data comes from ATTOM's Assessor data. The outcome variable is an indicator variable of whether a property was damaged or not and comes from CAL FIRE's DINS data.

	In Fire		Out of Fire	
	Mean	St. Dev.	Mean	St. Dev.
Sale Price	474,458.88	381,444.79	454,239.47	301,789.03
Log Sale Price	12.81	0.73	12.85	0.59
Bath Count	2.43	0.81	2.30	0.75
Bedroom Count	3.07	0.87	3.11	0.92
Age	30.06	18.32	32.82	21.07
Year Built	1982.28	17.75	1978.73	20.70
Number of Sales	1.85	0.68	1.95	0.75
Single Family	0.82	0.39	0.76	0.42
Multifamily	0.00	0.06	0.00	0.06
Condo/Townhouse	0.10	0.30	0.22	0.41
Other Housing	0.08	0.27	0.02	0.12
Number of Properties	3116		266,010	
Number of Transactions	4977		804,872	

Table A2: Summary statistics for pre-fire transactions split between in the fire perimeter and out of the fire perimeter. This table provides summary statistics of transactions within versus outside the fire from 2004 to 2024. These are statistics of the pre-fire data to see how similar the two groups are before treatment. Transaction prices have been normalized to 2010 dollars. In Fire is a dummy indicating if a property is within a fire perimeter or not. Single Family, Multifamily, Condo/Townhouse, and Other Housing are dummy variables indicating the type of property. The multifamily category consists of buildings like apartments, duplexes, and triplexes. The Other Housing category consists of buildings like mobile homes and manufactured homes.

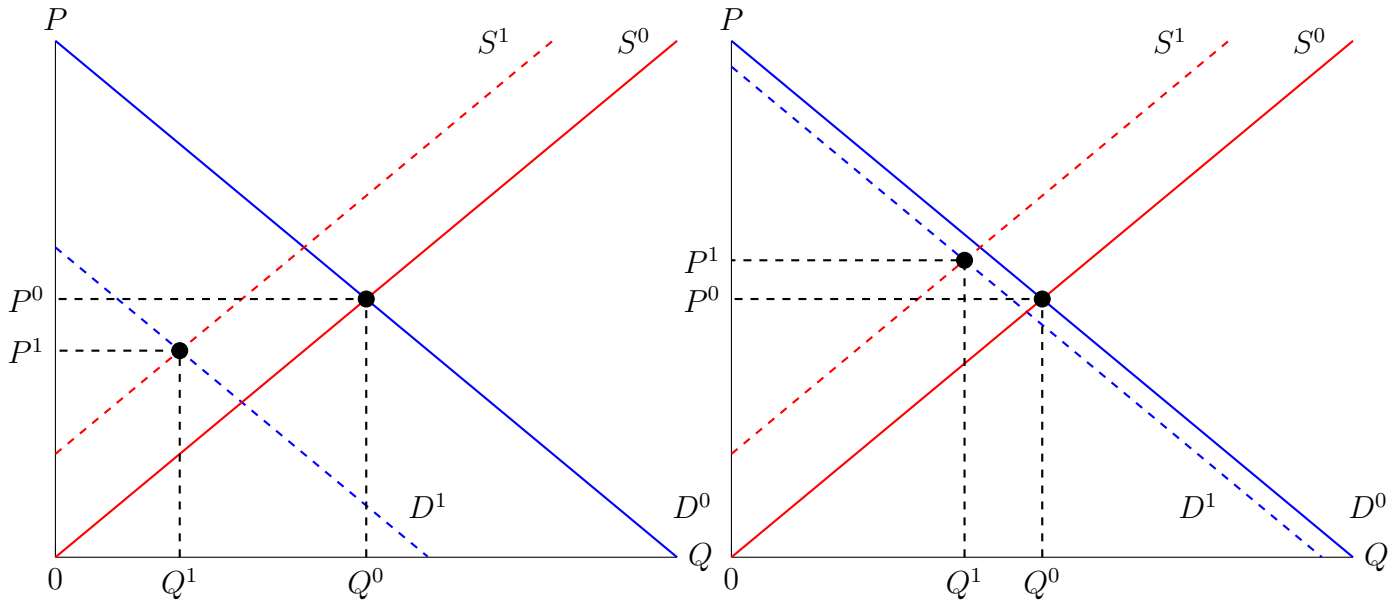
fire name and year	n dam	n undam	total	pre-fire price dam	pre-fire price undam	amenity costs	housing quality costs	total costs
camp 2018	19558.00	4066	23624	193733.60	229666.05	1461306797.65	2091410701.14	3552717498.79
glass 2020	1810.00	2957	4767	742492.48	917435.51	1255209365.33	741789319.48	1996998684.81
tubbs 2017	5949.00	74	6023	535423.05	448425.09	995813583.09	1758129957.56	2753943540.65
woolsey 2018	2007.00	0	2007	1301297.65	1073110.15	808090495.16	1441564113.72	2249654608.87
atlas 2017	903.00	469	1372	1247851.28	914470.02	481349756.65	621957235.14	1103306991.79
mountain 2024	369.00	1471	1840	784883.54	860629.80	481322625.79	159860635.13	641183260.92
caldor 2021	1086.00	3358	4444	209123.08	252924.56	333058948.17	125355019.80	458413967.97
nuns 2017	1527.00	27	1554	682358.24	790251.40	328996214.59	575123904.04	904120118.63
thomas 2017	1346.00	19	1365	757348.07	676429.27	319387401.53	562665808.35	882053209.88
creek 2020	929.00	2323	3252	296126.75	185764.48	218640030.53	151845980.00	370486010.52
park 2024	770.00	1332	2102	319457.35	311849.88	204634085.62	135773042.75	340407128.36
franklin 2024	48.00	690	738	1372447.97	791547.17	189373570.71	36361941.97	225735512.67
carr 2018	1890.00	0	1890	277044.69	283709.73	162012163.21	289015799.42	451027962.63
valley 2015	2046.00	0	2046	230874.11	219109.78	146156064.70	260729880.05	406885944.75
bond 2020	52.00	519	571	530800.00	445664.83	80107059.23	15235061.10	95342120.33
creek 2017	203.00	0	203	1142732.11	441549.57	71775536.98	128041400.03	199816937.01
river 2021	177.00	311	488	630731.20	386603.83	71744160.94	61620827.20	133364988.13
fawn 2021	211.00	519	730	109999.57	270350.86	50595534.44	12811010.09	63406544.53
valley 2020	75.00	371	446	340762.10	318448.07	44462815.31	14106604.43	58569419.74
fairview 2022	45.00	321	366	588754.06	338484.70	41816152.11	14623669.91	56439822.02
airport 2024	194.00	185	379	484651.12	211796.31	41215001.08	51896837.33	93111838.41
lilac 2017	221.00	0	221	414516.29	289087.07	28344569.24	50564279.72	78908848.96
saddleridge 2019	115.00	7	122	703444.47	728417.72	26607824.93	44651659.61	71259484.54
borel 2024	252.00	255	507	176409.64	124534.50	23580696.83	24537640.16	48118336.99
cascade 2017	274.00	0	274	250082.02	270848.27	21201618.64	37821868.67	59023487.31
bobcat 2020	216.00	12	228	292018.55	246587.33	20431983.24	34815620.23	55247603.46
mill 2022	144.00	165	309	190569.80	212418.37	19335438.12	15146995.79	34482433.91
tick 2019	75.00	0	75	529827.93	436422.68	12295100.71	21933404.81	34228505.51
west 2018	62.00	2	64	467309.00	431047.69	9231360.50	15992110.40	25223470.90
cocos 2014	49.00	0	49	590071.39	504265.87	8946159.13	15959180.36	24905339.49
holy 2018	42.00	1	43	561793.54	366053.60	7413919.22	13023747.79	20437667.01
river 2018	46.00	0	46	315284.29	342653.81	4487414.03	8005161.64	12492575.67
wall 2017	101.00	0	101	109009.60	163216.88	3406607.38	6077095.30	9483702.68
clayton 2016	327.00	0	327	151729.47			27385938.54	27385938.54
lobo 2017	51.00	0	51	469292.77			13210643.93	13210643.93
ranch 2018	273.00	0	273	221580.84			33389106.39	33389106.39
thompson 2024	34.00	151	185	473426.11			8884665.22	8884665.22
zogg 2020	231.00	334	565	287032.86			36597679.09	36597679.09

Table A3: Costs for each fire in the DINS data. This table provides costs for each fire in the DINS data cost calculation in Table 2. Data comes from CAL FIRE's DINS data. To obtain the amenity costs, pre-fire median transaction prices for damaged and undamaged properties are multiplied with their respective counts and then by the upper bound of the amenity effect 12 months after the fire (31%). To obtain the housing quality costs, pre-fire median transaction prices for damaged properties are multiplied by the number of damaged properties and by the housing quality effect 12 months after the fire (55%). Median transaction prices are in 2010 dollars. The estimates come from Figure 8.

fire name and year	n dam	n undam	total	pre-fire price dam	pre-fire price undam	amenity costs	housing quality costs	total costs
woolsey 2018	18039	10303	28342	1301297.65	1073110.15	10684079594.65	12956838588.61	23640918183.26
thomas 2017	9665	666	10331	757348.07	676429.27	2404208585.80	4040241484.18	6444450069.99
glass 2020	981	5559	6540	742492.48	917435.51	1803374847.79	402041614.59	2205416462.38
camp 2018	24567	3846	28413	193733.60	229666.05	1745929502.70	2627041962.11	4372971464.81
tubbs 2017	9559	293	9852	535423.05	448425.09	1624253120.86	2825006600.15	4449259721.01
czulightningcomplex 2020	1941	5020	6961	526946.90	439628.74	999317675.79	564549899.79	1563867575.58
atlas 2017	2100	302	2402	1247851.28	914470.02	896258213.45	1446412174.73	2342670388.18
saddleridge 2019	124	3693	3817	703444.47	728417.72	859319505.72	48146137.32	907465643.04
creek 2017	2077	109	2186	1142732.11	441549.57	749264971.15	1310059053.51	2059324024.67
hennessey 2020	1100	4524	5624	549682.11	348281.10	674601115.71	333744586.16	1008345701.87
nuns 2017	2904	243	3147	682358.24	790251.40	672535923.10	1093752336.17	1766288259.27
canyonii 2017	1858	89	1947	900566.59	1464289.56	558046082.47	923573541.88	1481619624.35
carr 2018	4897	319	5216	277044.69	283709.73	447777135.97	748841465.49	1196618601.46
caldor 2021	1287	4314	5601	209123.08	252924.56	420879001.83	148556087.00	569435088.83
creek 2020	956	4588	5544	296126.75	185764.48	351300679.73	156259157.02	507559836.75
rice 2007	1953	23	1976	479222.04	931820.63	296215556.69	516593538.36	812809095.05
tick 2019	88	2060	2148	529827.93	436422.68	292596391.49	25735194.98	318331586.47
latuna 2017	1104	71	1175	683914.93	767825.82	250486195.19	416755270.93	667241466.13
northcomplex 2020	2575	1412	3987	151408.76	174257.73	196763681.45	215197978.92	411961660.37
holy 2018	1076	13	1089	561793.54	366053.60	188508302.77	333656014.77	522164317.53
lilac 2017	878	204	1082	414516.29	289087.07	130855881.32	200884333.01	331740214.34
bond 2020	10	798	808	530800.00	445664.83	111681505.16	2929819.44	114611324.61
bobcat 2020	186	1109	1295	292018.55	246587.33	101419039.43	29980117.42	131399156.85
river 2021	175	258	433	630731.20	386603.83	65014014.70	60924546.66	125938561.36
cascade 2017	724	40	764	250082.02	270848.27	59373934.41	99938076.34	159312010.75
west 2018	177	242	419	467309.00	431047.69	57868314.54	45654895.81	103523210.35
mill 2022	197	434	631	190569.80	212418.37	40140473.64	20721931.74	60862405.38
valley 2020	30	361	391	340762.10	318448.07	38732899.56	5642641.77	44375541.33
fawn 2021	138	309	447	109999.57	270350.86	30544561.76	8378764.89	38923326.65
fairview 2022	16	209	225	588754.06	338484.70	24803440.89	5199527.08	30002967.97
river 2018	183	23	206	315284.29	342653.81	20290584.67	31846621.30	52137205.97
wall 2017	177	27	204	109009.60	163216.88	7333525.52	10649959.09	17983484.61
oak 2017	9	12	21	889391.24	400919.08	3965274.29	4418199.31	8383473.60
angora 2007	675	15	690	550243.51			205006977.36	205006977.36
buckweed 2007	4184	41	4225	536412.95			1238799078.04	1238799078.04
canyoni 2017	242	8	250	570378.40			76188317.13	76188317.13
clayton 2016	630	9	639	151729.47			52761899.95	52761899.95
corral 2007	499	10	509	1365295.47			376042681.02	376042681.02
crown 2010	946	0	946	404986.00			211466262.13	211466262.13
esperanza 2006	406	23	429	142723.07			31983806.86	31983806.86
fortynine 2009	96	0	96	450142.04			23852326.92	23852326.92
foxborough 2008	57	0	57	1076610.42			33872197.94	33872197.94
freeway 2008	2631	9	2640	632072.66			917905126.08	917905126.08
harris2 2007	1405	101	1506	472682.56			366569097.74	366569097.74
jesusita 2009	209	2	211	1368537.10			157874797.15	157874797.15
lobo 2017	88	3	91	469292.77			22794836.58	22794836.58
martinranch 2007	70	0	70	565937.78			21866369.10	21866369.10
mill 2013	89	2	91	492105.29			24174527.02	24174527.02
mountain 2013	42	0	42	238500.00			5529013.09	5529013.09
pedley 2010	552	0	552	383803.52			116938623.36	116938623.36
powerhouse 2013	510	5	515	147282.36			41460147.58	41460147.58
pressley 2017	94	8	102	348271.53			18069900.99	18069900.99
ranch 2007	407	2	409	1421730.64			319390266.09	319390266.09
ranch 2018	763	29	792	221580.84			93318271.71	93318271.71
rosa 2007	15	2	17	1015614.66			8408725.31	8408725.31
sand 2016	365	9	374	986650.64			198777035.35	198777035.35
santaanita 2008	158	1	159	1220217.55			106415355.22	106415355.22
sayre 2008	2388	1	2389	678976.41			894950374.00	894950374.00
sesnon 2008	5072	70	5142	629688.18			1762847440.21	1762847440.21
shekell 2006	1222	62	1284	570424.81			384750821.40	384750821.40
slide 2007	3640	58	3698	210382.34			422688665.41	422688665.41
station 2009	3584	16	3600	1084566.31			2145527352.96	2145527352.96
summit 2013	159	1	160	748204.77			65664031.65	65664031.65
zogg 2020	137	155	292	287032.86			21705117.03	21705117.03

Table A4: Costs for each fire in the predicted damage data. This table provides costs for each fire in the DINS data cost calculation in Table 2. Data comes from the predicted damage data which is a combination of CAL FIRE's DINS data, Baylis and Boomhower (2026), and LASSO. To obtain the amenity costs, pre-fire median transaction prices for damaged and undamaged properties are multiplied with their respective counts and then by the upper bound of the amenity effect 12 months after the fire (31%). To obtain the housing quality costs, pre-fire median transaction prices for damaged properties are multiplied by the number of damaged properties and by the housing quality effect 12 months after the fire (55%). Median transaction prices are in 2010 dollars. The estimates come from Figure 8.

Appendix B. Figures



(a) Price decreases

(b) Price increases

Figure 6: Possible price changes after a wildfire

Figure A1: Possible price effects of wildfire exposure. Illustrated are the potential impacts wildfire exposure can have on housing transaction prices. In (a) the price decreases from P^0 to P^1 because the shift in demand is larger than the shift in supply. On the other hand, in (b) the price increases because the shift in demand is smaller than the shift in supply.

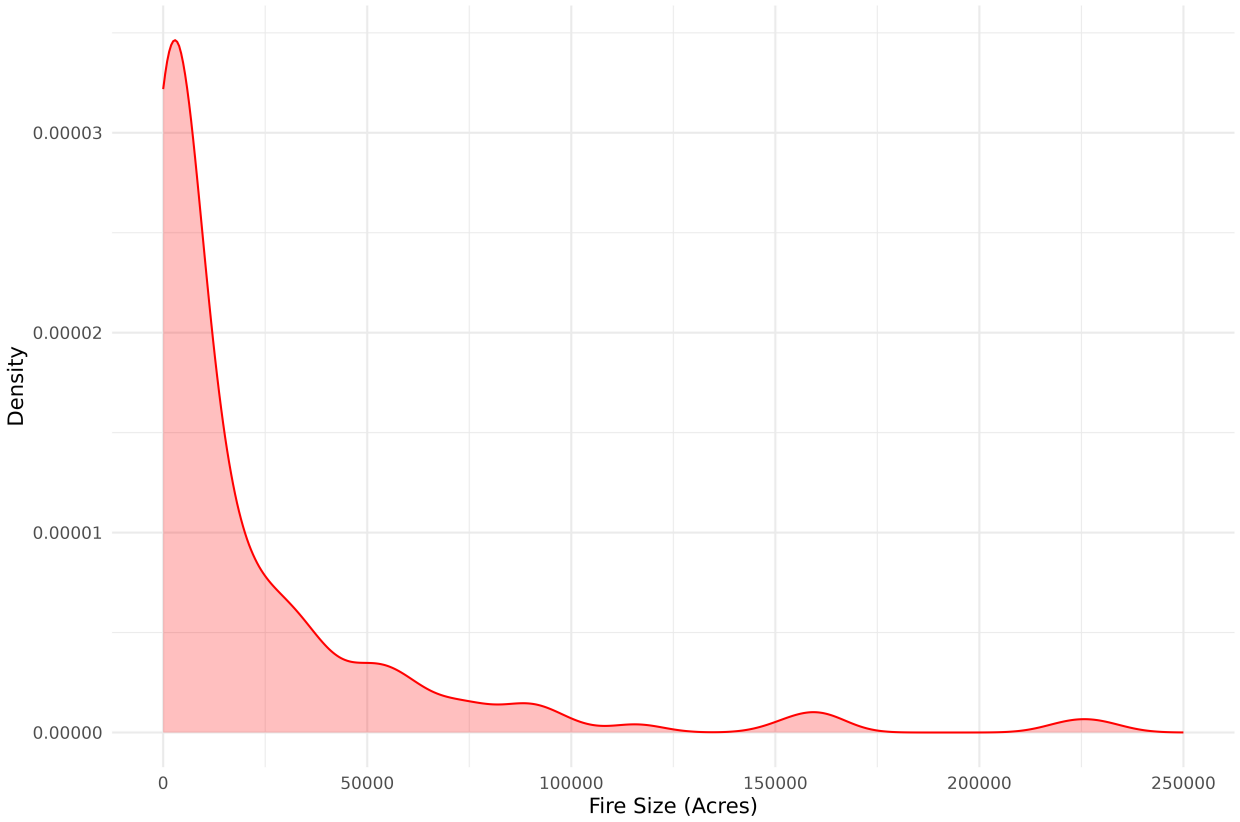
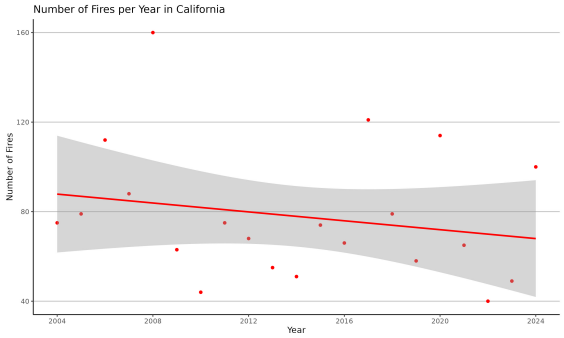
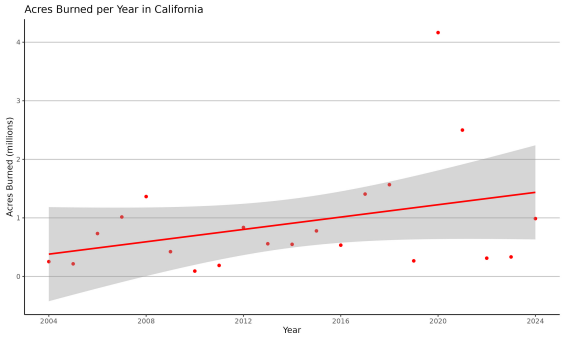


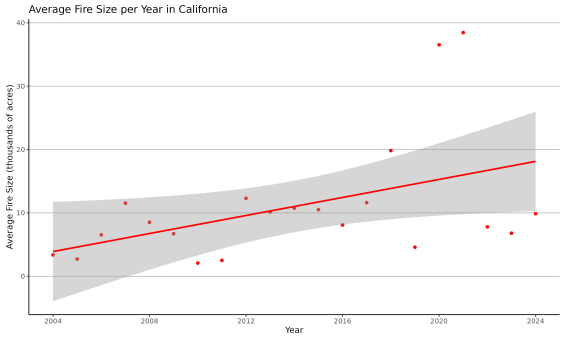
Figure A2: Distribution of fire size. All fires in the CAL Fire perimeter data is used.



(a) Fires per year



(b) Total acres burned



(c) Average fire size (acres)

Figure A3: Fire trends by year. All fires in the CAL Fire perimeter data is used.

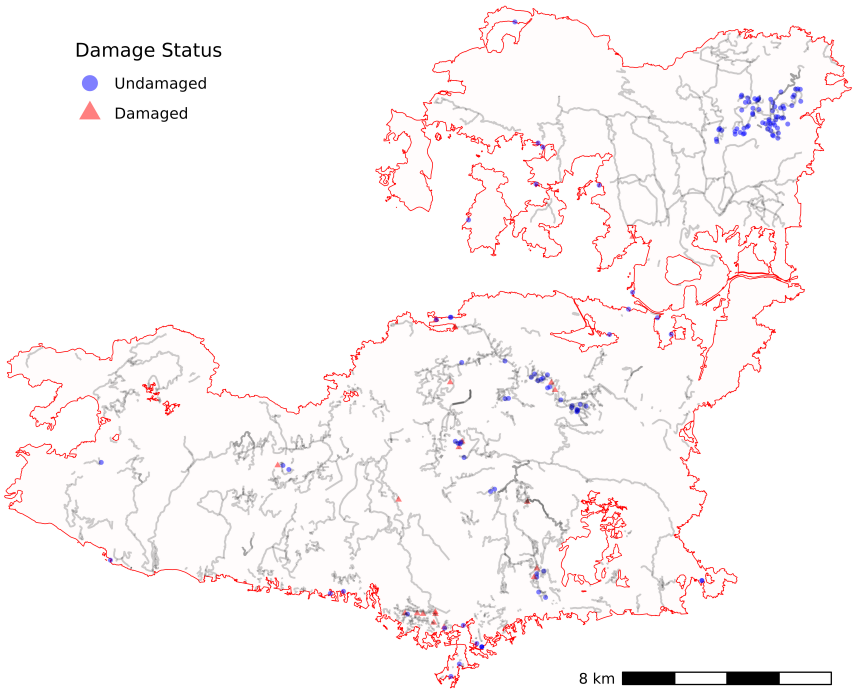


Figure A4: Map of damaged and undamaged properties in the Woolsey Fire (November 2018). Damaged and undamaged properties are plotted for the November 2018 Woolsey Fire in Los Angeles and Ventura Counties.

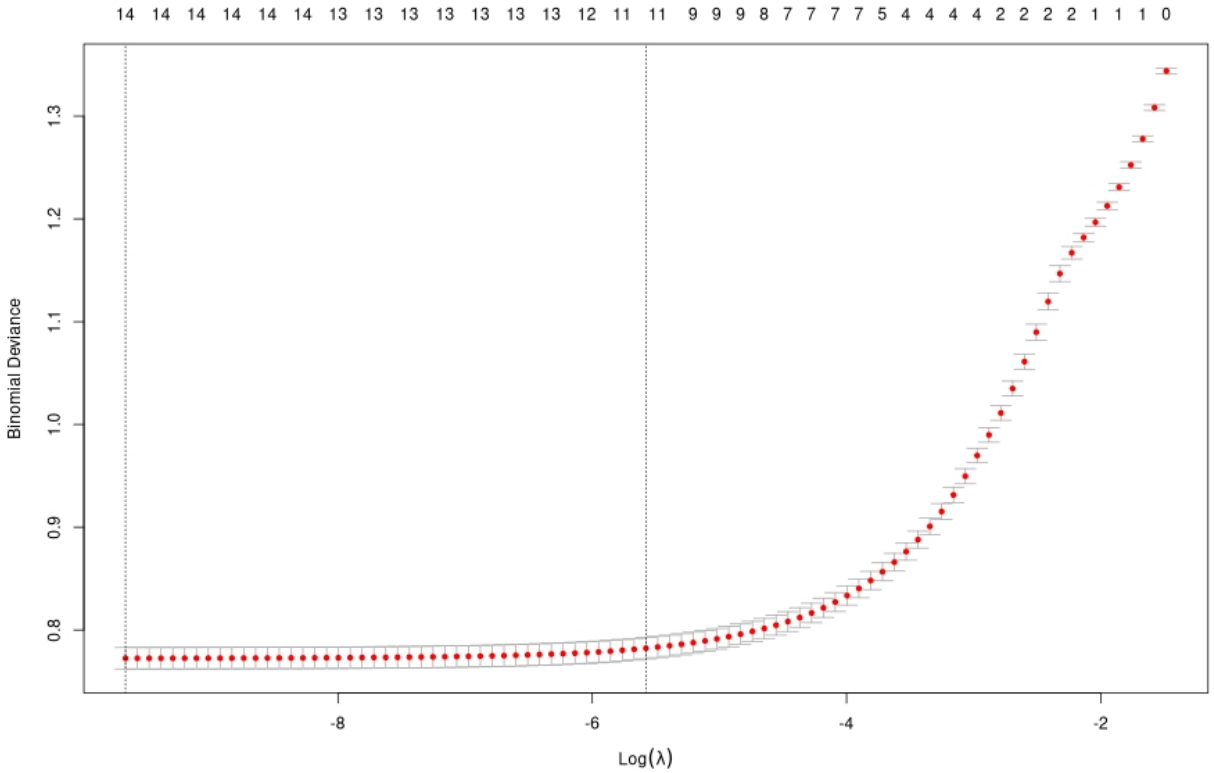


Figure A5: Cross-validation plot for LASSO methodology. The cross-validation curve and standard deviation bars are presented. The lambda that results in the minimum mean cross-validated error (0.00006306975) and that which provides the most regularized model such that the cross-validated error is within one standard error of the minimum (0.003780932) are denoted. The number of selected variables is denoted by the numbers on the top of the plot.

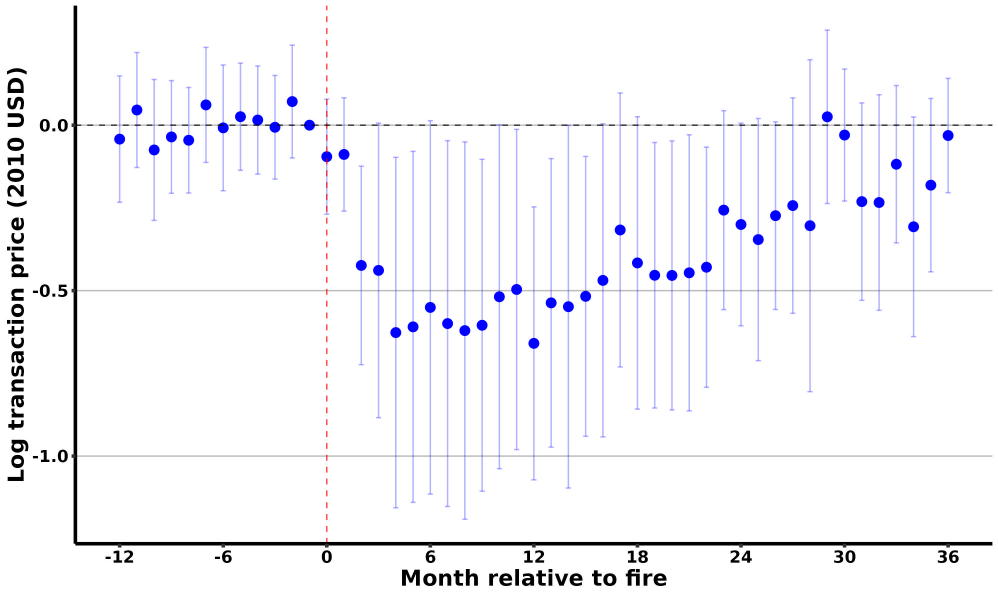


Figure A6: The effect of being in the fire perimeter on log transaction prices with controls within 1 km. This figure plots point estimates and 95% confidence intervals for the event study. Now the control group is properties within 1 km of the fire. Fires between 2005 and 2021 are used. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

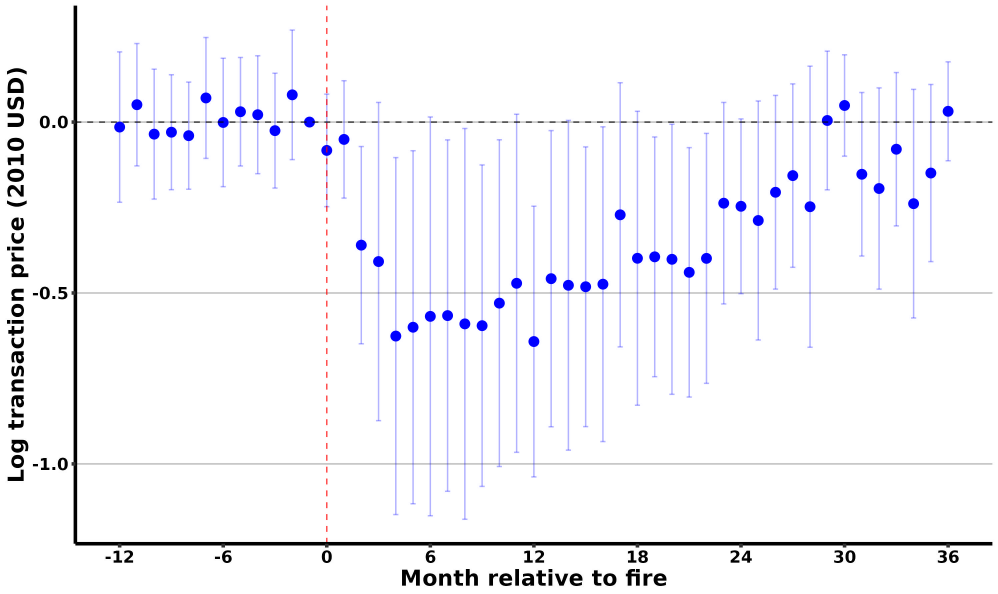


Figure A7: The effect of being in the fire perimeter on log transaction prices with controls within 5 km. This figure plots point estimates and 95% confidence intervals for the event study. Now the control group is properties within 5 km of the fire. Fires between 2005 and 2021 are used. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

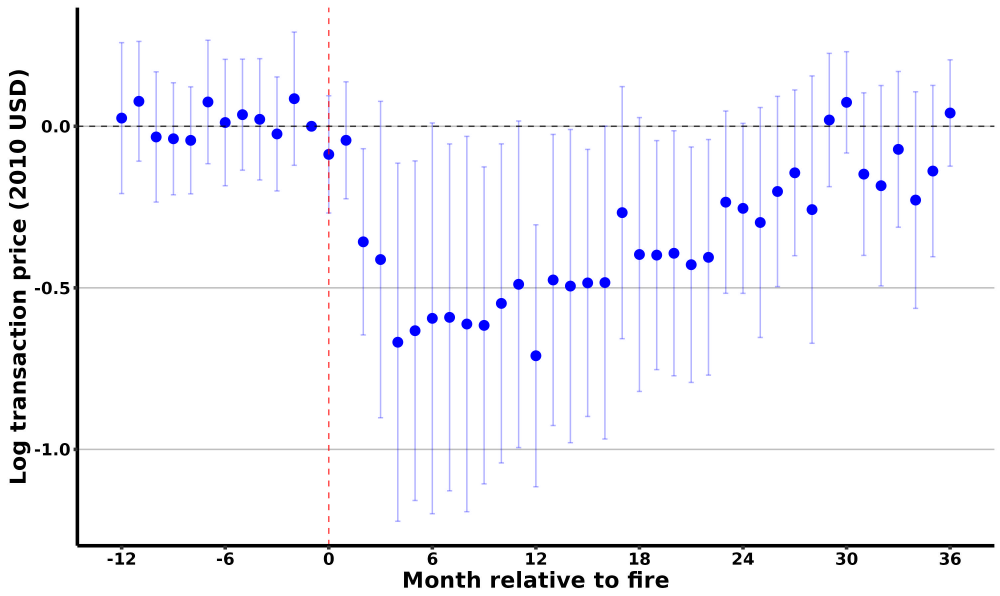


Figure A8: The effect of being in the fire perimeter on log transaction prices with controls within 10 km. This figure plots point estimates and 95% confidence intervals for the event study. Now the control group is properties within 10 km of the fire. Fires between 2005 and 2021 are used. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

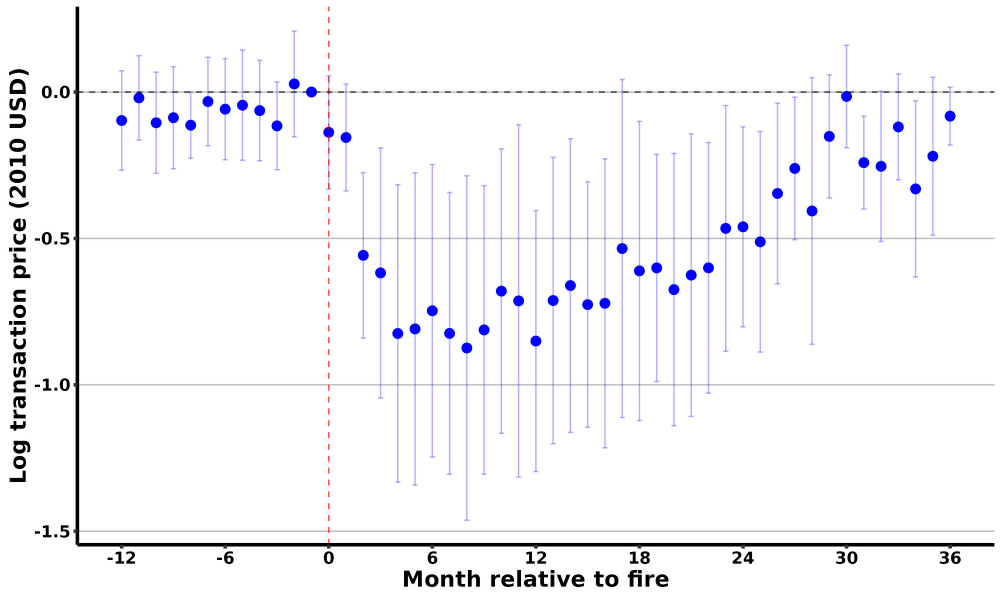


Figure A9: The effect of being in the fire perimeter on log transaction prices with controls between 1 and 2 km. This figure plots point estimates and 95% confidence intervals for the event study. Now the control group is properties between 1 and 2 km of the fire. Fires between 2005 and 2021 are used. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

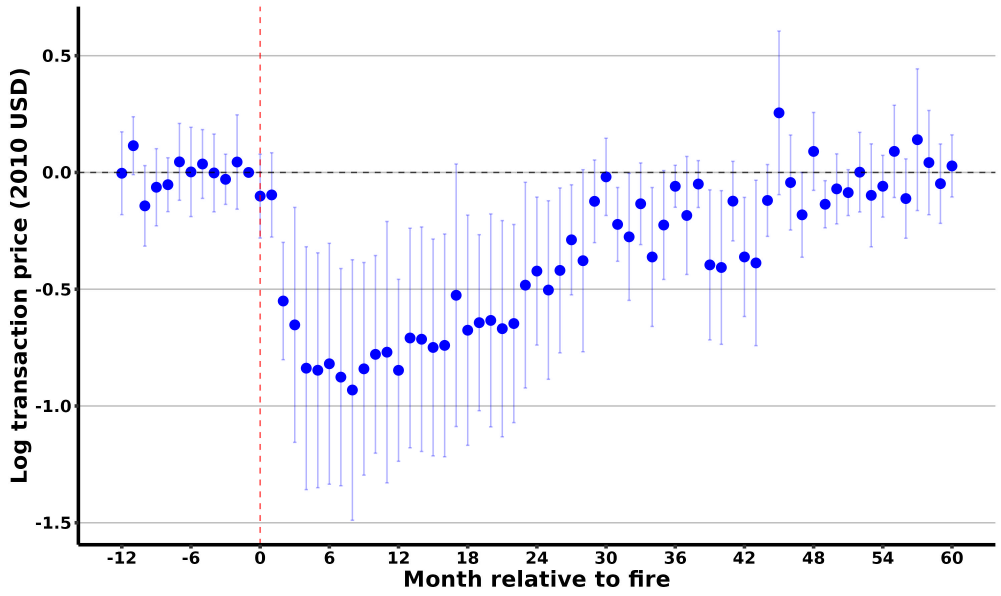


Figure A10: The effect of being in the fire perimeter on log transaction prices extended post-period. This figure plots point estimates and 95% confidence intervals for the event study. 12 months are used for the pre-period, and 60 months are used for the post-period. Fires that take place before 2005 and after 2019 are dropped to allow for fires where the whole pre-period and post-periods can be observed. Treated units are transactions within the fire perimeter that took place at any point between 2005 and 2019 except for transactions in event time -1. Control units are transactions between 1 and 10 km from the fire perimeter or those within the perimeter that took place in event time -1. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

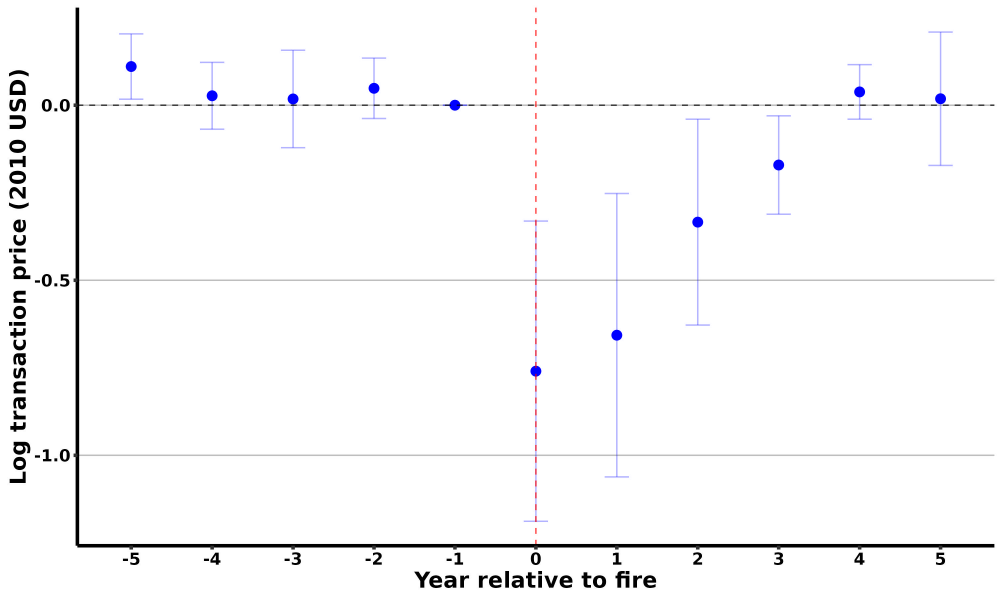


Figure A11: The effect of being in the fire perimeter on log transaction prices at the annual level. This figure plots point estimates and 95% confidence intervals for the event study. 5 years are used for the pre-period and post-period. Fires that take place before 2009 and after 2019 are dropped to allow for fires where the whole pre-period and post-period can be observed. The control group is properties between 1 and10 km from the fire. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

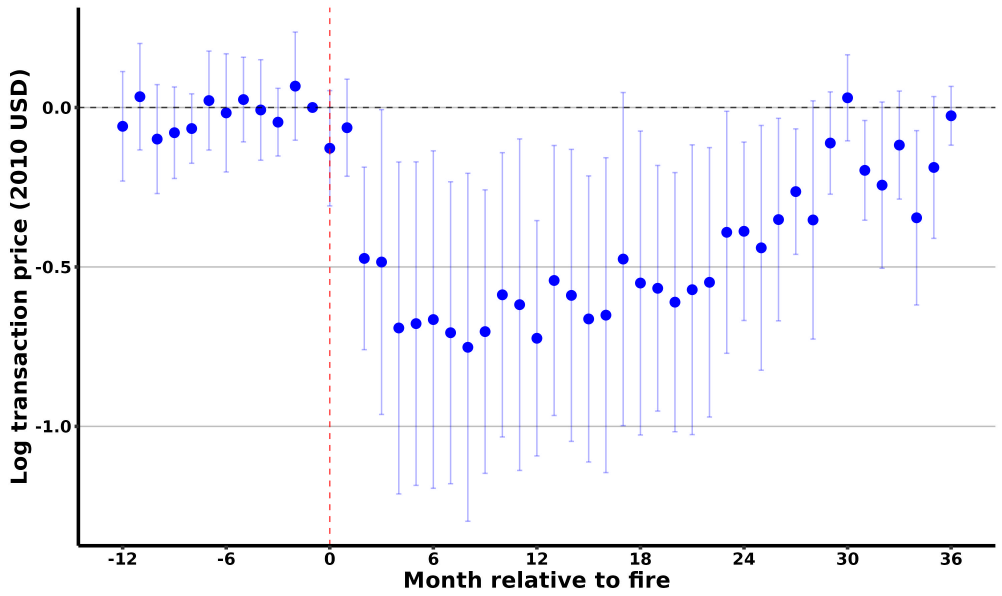


Figure A12: The effect of being in the fire perimeter on log transaction prices with cross-sectional data. This figure plots point estimates and 95% confidence intervals for the event study using cross-sectional data (properties that transacted at least once). 12 months are used for the pre-period, and 36 months are used for the post-period. Fires that take place between 2005 and 2021 are used. Control units are transactions between 1 and 10 km from the fire. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

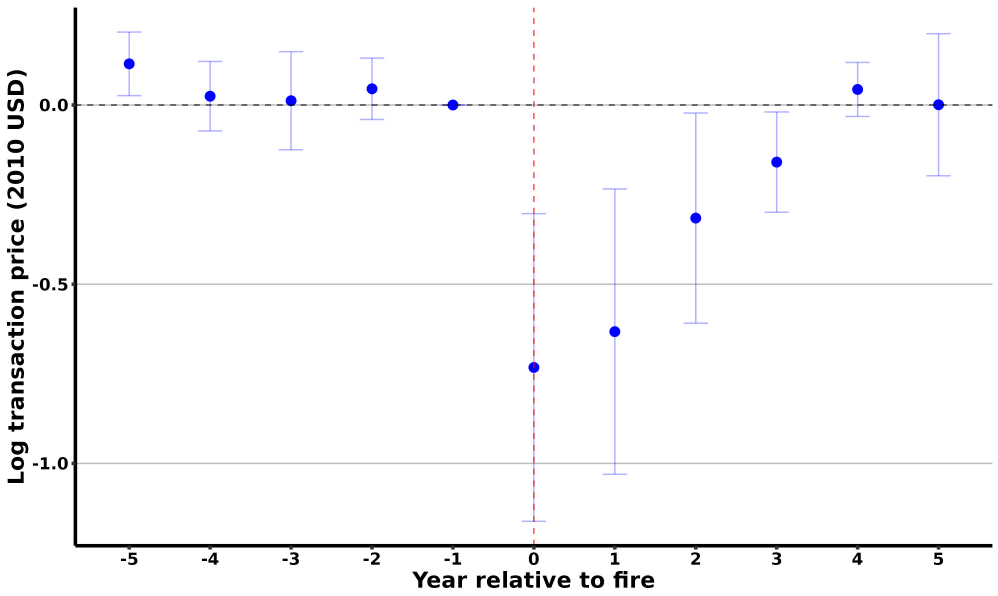


Figure A13: The effect of being in the fire perimeter on log transaction prices at the annual level with cross-sectional data. This figure plots point estimates and 95% confidence intervals for the event study using cross-sectional data (properties that transacted at least once). 5 years are used for the pre-period and post-period. Fires that take place before 2009 and after 2019 are dropped to allow for fires where the whole pre-period and post-period can be observed. The control group is properties between 1 and10 km from the fire. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

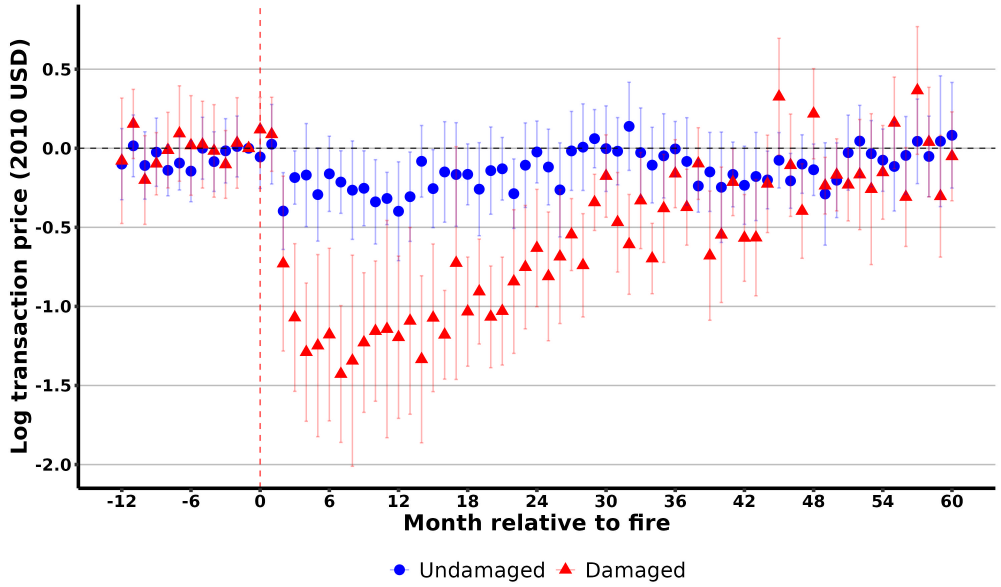


Figure A14: The effect of being in the fire perimeter on log transaction prices split by damage status. This figure plots point estimates and 95% confidence intervals for the event study split by whether the property was damaged or not. 12 months are used for the pre-period, and 60 months are used for the post-period. Fires that take place before 2005 and after 2019 are dropped to allow for fires where the whole pre-period and post-period can be observed. Treated units are transactions within the fire perimeter that took place at any point between 2005 and 2019 except for transactions in event time -1. Control units are transactions between 1 and 10 km from the fire perimeter or those within the perimeter that took place in event time -1. Fixed effects for property, month of year, and census tract-year are interacted with a fire indicator. Standard errors are clustered at the fire level.

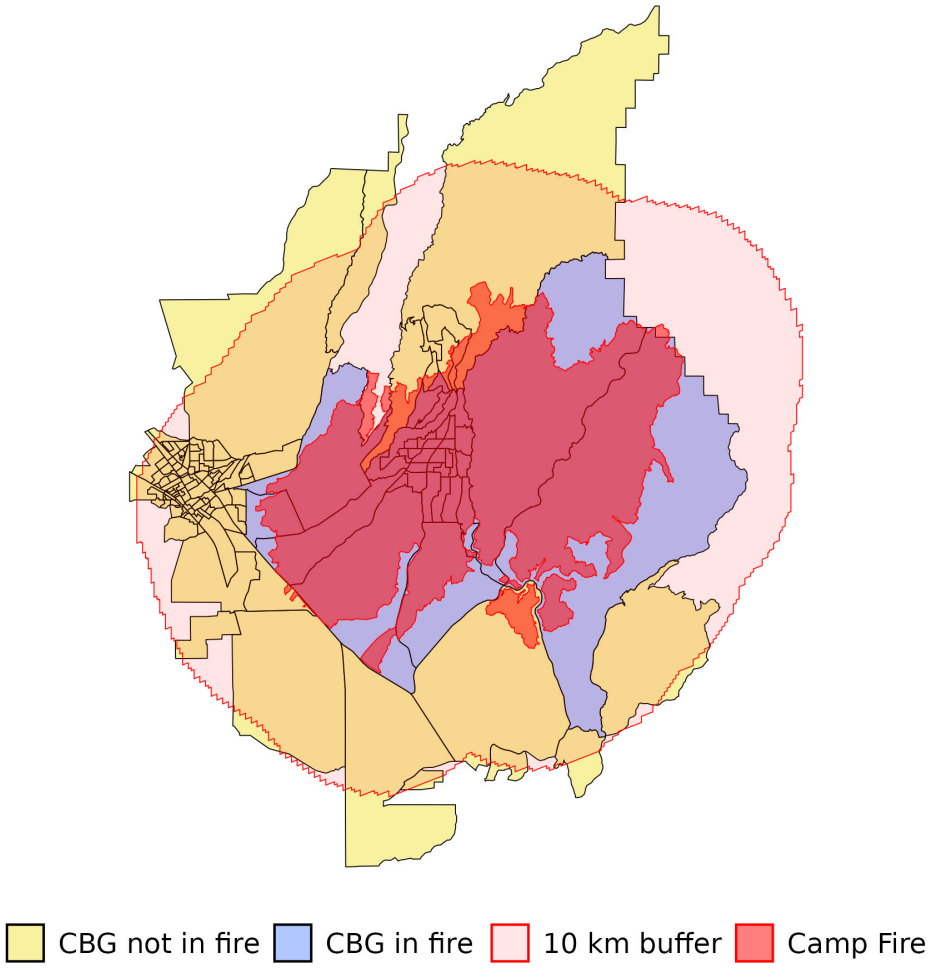


Figure A15: Census block group treated and control units. This map plots census block groups (CBGs) for the 2018 Camp Fire by whether they are treated or control units. The Camp Fire perimeter and 10 km buffer are plotted in red. Treated CBGs are those whose centroids are within the fire perimeter and are denoted in blue. Control CBGs are those whose centroids are within 10 km of the fire perimeter but not within the fire and are denoted in blue.

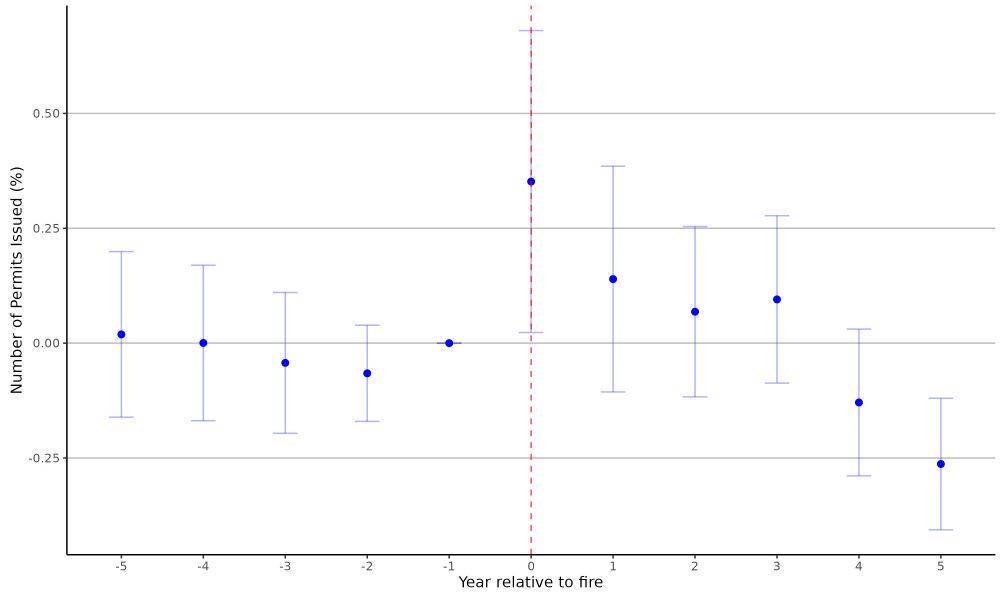


Figure A16: The effect of fire exposure on number of permits issued in a CBG. This figure plots point estimates and 95% confidence intervals for the event study estimated with a Poisson regression. Fires that take place before 2009 and after 2019 are dropped. The reference period is the preceding year. The control group is CBGs outside the fire perimeter but within 10 km. Fixed effects for CBG and permit issuance year are interacted with a fire indicator. Standard errors are clustered at the fire level.