# When Your View Goes Up In Flames: Effect of Wildfires on Real Estate Prices

Cloé Garnache and Todd Guilfoos*

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**Abstract**

Properties located near the wilderness often benefit from amenities such as scenic vistas and nearby recreation opportunities. However, proximity to the wilderness may also come with disamenities caused by wildfires such as view of a burn scar and risk of wildfire damage. Using a unique data set of sales transactions spanning the Los Angeles and San Diego Basins between 2000 and 2015, combined with detailed wildfire characteristics, we estimate the effect of burn scar view on real estate prices in an urban setting. Our identification strategy employs entropy balancing, a data preprocessing technique designed to eliminate model dependency based on observables, combined with a fixed effects approach to control for potential unobservables. We compare this approach with nearest neighbor matching techniques where treated properties with a burn scar view are matched with controls without a burn scar view. Furthermore, to separate the effect of burn scar view from burn scar proximity, we estimate a difference-in-differences model for different proximity thresholds to the burn scar, holding burn scar view constant. Findings show a 4.5% decrease in the price of properties with a burn scar view and a 3-4% decrease in the price of properties within proximity of a burn scar but without a view.

**JEL codes:** Q51, Q54, Q58, R31

**Keywords:** hedonic pricing model, wildfire disamenities, viewshed, risk, entropy balancing

## 1 Introduction

Over 9,000 fires blazed throughout California making 2017 the worst wildfire season on record. The year included the largest and most destructive wildland-urban fires in California's history. The Thomas fire started in December 2017 and burned a total of 280,000 acres in Ventura and Santa Barbara counties. The Tubbs fire destroyed over 5,600 structures in October 2017 in Sonoma county (California Department of Forestry and Fire Protection, 2017). Despite wildfires being a

*Corresponding author: Garnache, Dept. of Agricultural, Food, and Resource Economics, Michigan State University (garnache@msu.edu). Guilfoos: Dept. of Environmental and Natural Resource Economics, University of Rhode Island. We thank seminar participants at Montana State University, MSU AFRE, Ohio State University, and University of Colorado, Boulder for helpful comments. We thank April Ross and Sophia Tanner for valuable research assistance.

natural part of forest ecology, policy makers have two main reasons to be concerned. First, wildfires are predicted to increase in frequency and severity with climate change (Westerling et al., 2006). Second, the wildland-urban interface (WUI), which consists of properties on private land adjacent to fire-prone public land, is growing (Lueck and Yoder, 2016). According to International Association of Wildland Fire (2013), approximately 46 million homes are located on the WUI in the United States and are potentially affected by wildfire. This corresponds to an estimated \$9.2 trillion in property value at risk—using the 2017 Zillow Home Value Index for the median American home of \$200,000.

In the United States, the annual cost of federal wildfire suppression and prevention programs has often exceeded \$3 billion and cost is predicted to keep rising (Hoover et al., 2015). While the cost of government intervention to prevent or mitigate wildfire is relatively easy to monitor, the net effect of wildfires on society is clearly more difficult to assess. Wildfires may affect the provision of many non-market goods, including wilderness amenities and vistas, local air quality, water supply, recreation opportunities, and erosion and flood protection. Due to the frequency and size of wildfires, a vast number of properties may be affected by amenity losses with considerable welfare implications. Implementing socially optimal public policies that balance the cost of intervention with the avoided damages from intervention relies on improving our knowledge of the effect of wildfires on society and the pathways through which they damage these non-market goods.

Our paper uses a series of quasi experimental methods to estimate and disentangle the various effects that wildfires have on property prices. By doing so we recover the homeowner's willingness to pay for various amenities related to mitigation of wildfires, specifically through destruction of scenic views, proximity to wildfire, and changes in risk saliency. The value of these damages, in addition to property damaged, can be combined to better understand the disamenities created by wildfires.

A large body of literature has examined the impact of wildfire on property prices, however, most studies are based on cross-section analyses with omitted variable bias concerns. The vast majority of studies has focused on low-population density and forested areas such as Colorado (Loomis, 2004; Donovan et al., 2007; Huggett et al., 2008; Mueller and Loomis, 2008; Champ et al., 2009; McCoy and Walsh, 2014) and Montana (Stetler et al., 2010). Two exceptions are Mueller et al. (2009) and Mueller and Loomis (2014) who explore the effect of three wildfires that burned in Los Angeles

County over 6 years on a small geographic area containing 54,000 single family residences. They find that the second wildfire causes a larger price decrease. Loomis (2004) finds that 5 years after a fire affected a town located 2 miles away, property values are still 15% lower, suggesting lasting amenity losses and/or heightened risk perceptions. Donovan et al. (2007) analyze the effect of new risk ratings on property values in Colorado Springs and find that heightened risk perceptions post information disclosure completely offset the preexisting positive wilderness amenity values of homes in the WUI, although the effect diminishes over time.

Viewsheds provide considerable environmental amenities or disamentities. The natural landscape and its viewsheds capture significant value in properties, as shown by Benson et al. (1998), Paterson and Boyle (2002), Cavailhès et al. (2009), and Wasson et al. (2013). Cavailhès et al. (2009) find that tree lines and farmland increases property prices while view of major roads decrease them. Wasson et al. (2013) find that Alpine views increase the price of farmland considerably in Western Wyoming. Considering the lasting visible evidence of damage and destruction that wildfires leave in their wake, we feel views of burn scars may be a critical part of the disamenities related to wildfires. Few studies have investigated the role of burn scar view on property prices, precluding the ability to tease out the view effect from the proximity effect (Stetler et al., 2010; McCoy and Walsh, 2014). Stetler et al. (2010) estimate the effect of a burn scar view on a 1996 cross-section of 19,000 property sales in northwest Montana. They find that properties with a burn scar view sell for 2.5% less than homes without a view, and properties within 5km of a burn scar sell for 14% less than those 20km away. They suggest that buyers may not update their risk perceptions when burn scars are not visible from homes.

The most closely related study to ours is McCoy and Walsh (2014). They investigate how wildfire affect risk salience in the Colorado Front Range between 2002 and 2012. To tease out the three likely pathways of risk saliency, namely, burn scar proximity, burn scar view, and physical risk attributes, they define three treatment groups: 1) proximity to burn scar with no view, 2) burn scar view but not in direct proximity to the burn scar, and 3) high latent risk area based on the physical attributes of the terrain, i.e., slope, aspect, elevation and vegetation fuel type. The first two treatment groups may confound disamenity value with changes in risk perceptions, while the third measure aims at directly measuring the saliency effect through changes in risk perceptions. They find that proximity (within 2km from the burn scar) reduces home values by 7 to 8% in the first three years following a wildfire, burn scar view results in a 3 to 4% drop in the first three years, while location in a high-risk area (more than 5km from the burn scar) leads to a 6 to 9% loss in home value but only in the first year following a wildfire. McCoy and Walsh (2014) further investigate the effect of risk saliency on transaction rates using a duration model. Their results reveal that burn scar view has no significant impact on property turnover. Similarly, proximity has no impact on transaction rates in the first two years but is associated with a 21% increase in transaction rates in the third year following a wildfire. High-latent risk is associated with a 19% increase in property turnover in the first year after a wildfire.

Our paper is further related to the literature on the effect of natural disasters on risk perceptions (e.g., Hallstrom and Smith (2005); Bin and Landry (2013)). One of the fundamental problems in those studies is to disentangle changes in homewoners' risk perceptions from visual disamenity and proximity effects. Hallstrom and Smith (2005) use data for Lee County, Florida, considered a near-miss by Hurricane Andrew, to cleanly identify changes in risk perceptions in the absence of storm damage. In contrast, Kousky (2010), Atreya et al. (2013), and Bin and Landry (2013) do not know precisely which homes are damaged by the flood and are not able to tease out changes in risk perceptions from changes in amenity levels. Taking a different approach, two recent studies have developed models of the hedonic price function formation that account for flood risk beliefs updating. Bakkensen and Barrage (2017) examine the role of flood risk beliefs and coastal amenity value on residential location choices, while Gibson et al. (2017) develop a model of a hedonic price function that incorporates risk beliefs updating in response to flood risk and (insurance) price signals in New York City. Our paper also broadly relates to a fast growing literature that explores multiple pathways through which shale gas development affects property prices, including visual disamenity, proximity to the well pad, and environmental risk, in particular to drinking water supply (e.g., Muehlenbachs et al. (2015); Boslett et al. (2016)).

This paper makes three contributions to the literature. First, we assemble a uniquely large dataset of real estate transactions spanning six counties in southern California over 16 years and containing over 2 million observations, including repeat sales. Every property is geo-coded and linked to a detailed wildfire history, neighborhood characteristics, and environmental amenities. In addition, a viewshed analysis in ArcGIS enables us to precisely identify which properties have a burn scar view. It allows us to tease out the pathways, i.e., burn scar view and/or proximity, through which wildfires affect real estate prices.

Second, to estimate the effect of burn scar view on real estate prices, we compare treated properties (with a view) with similar properties (without a view), holding constant proximity to the burn scar and risk latency. One important concern is that wildfires do not happen randomly over space but, more likely, in the wilderness. As a consequence, model dependency and correlated unobservables may confound identification as properties near and/or with a view of a burn scar may differ from properties farther away and/or without a burn scar view. Our empirical strategy employs entropy balancing, a new technique from political science, that allows to completely eliminate model dependence based on observables, while controlling for unobservables with other usual statistical techniques, e.g., fixed effects. We show that entropy balancing outperforms nearest-neighbor matching techniques, as well as other traditional OLS methods with fixed effects. In addition, we use a difference-in-differences approach, holding burn scar view constant, to estimate the proximity effect (and update in risk perceptions), independent of burn scar view.

Third, it is the first large scale study in a heavily urban geographical area: the Los Angeles and San Diego basins. Properties in low-population density areas and located near the wilderness are at the greatest risk of being impacted by wildfires. Yet, by nature, wildfires affect more properties (and value) when they occur in high-population density areas, making the Los Angeles metropolitan area a particularly relevant case study for policy. Furthermore, this region of southern California, characterized by a (dry) Mediterranean climate, is dominated by fire-prone, shrub and scrub vegetation that can ablaze with every few years. Wildfires in the region are frequent, with indication of an upward trend (Miller and Safford, 2012).

Our results reveal that the value of homes with a burn scar view located within 1km of a burn scar decreases by 4.5% during (at least) the first year post-fire. This finding is consistent with that of McCoy and Walsh (2014) for the first year. In addition, proximity to a burn scar, independent of burn scar view, also affects property prices. Estimates suggest that properties within 2km of a burn scar *without view* experience a 3 to 4% drop in value. This result differs from Stetler et al. (2010) who conclude for properties in Montana that out of sight is out of mind. In addition, in contrast with studies in the Rockies, this effect is not detectable beyond the first year.

The remainder of the paper is structured as follows. The next section describes the data sources and viewshed analysis. Section 3 motivates the identification strategy. Section 4 discusses the results. The final section concludes.

## 2 Data

To capture all the properties likely affected by wildfires, we selected zip codes located within a 30km bandwidth of the national forests surrounding the Los Angeles and San Diego basins. Those zip codes span across seven counties: Santa Barbara, Los Angeles, Orange, Ventura, Riverside, San Bernardino, and San Diego.[1] Transaction records for all properties located within those zip codes sold between January 2000 and December 2015 were purchased from CoreLogic. We start with a data set of 2,187,007 unique observations of sales. Single family residences sales, excluding mobile homes, account for 1,495,849 observations. Further restricting our analysis to arms-length transactions of owner-occupied properties, our sample contains 1,215,523 properties. Observations with missing sale price, properties sold more than once within a year or sold in the same year as built are also dropped to eliminate potential house flippers and made-to-order homes (1,070,639 remaining observations). All sales prices are deflated using the CPI and natural logarithm transformations are used throughout the analysis. We then drop observations with sale prices in the bottom and top 1% and observations for properties with the top 1% of bedrooms, bathrooms, and square footage. Of the remaining 1,022,072 properties, xxx are repeat sales in our 16-year time period. Properties were then geocoded to obtain exact latitude and longitude coordinates and further refine our sample based on geospatial features.

Wildfire spatial data comes from the California Fire Resource and Assessment Program (FRAP; frap.fire.ca.gov/). The data contain wildfire perimeters, area burned, start and containment dates. Spatial data on the WUI and the Fire Hazard Severity Zone (FHSZ) also come from FRAP. The FHSZ is determined using an ember diffusion model developed at the University of California, Berkeley, based on vegetation and terrain. Location in the FHSZ has to be disclosed at the time of sale. National forests boundaries come from the National Datasets maintained by the US Forest Service (data.fs.usda.gov/). State and local parks boundaries come from the California Protected Areas Data Portal (calands.org/data). Spatial data on primary roads come from the US Data Catalog (catalog.data.gov/). We use spatial data on the 2010 census tracts boundaries and census

[1] After data cleaning and keeping transactions around the timing of wildfires, too few properties are located in Santa Barbara. Therefore, we choose to drop all of Santa Barbara county.

characteristics from the American Community Survey, including median household income, race, and ethnicity.

Linking each property to those spatial layers, we calculate distances to burn scars, nearest national forest, state or local park, and primary road in ArcGIS. In addition, slope and elevation are calculated for every property. We then restrict our analysis to the wildfires located within 4km of any property.[2] In total, our analysis includes 264 fires between 1998 and 2015, ranging between 51 to 270,686 acres, with median and mean sizes of 362 and 6,988 acres, respectively.

Properties located on national forest land, that overlap wildfire perimeters, are excluded from the analysis due to concerns of belonging to different markets (993,741 properties remaining).[3]

We define a sale as post-fire when a sale is recorded more than two months post fire. The reason is that there is a lag between the time the sale was recorded and the time the price of the property was negotiated and agreed upon by the buyer and seller (Mueller and Loomis, 2014). Similarly, pre-fire sales capture sales up to two months post fire.

Last, we restrict the analysis to properties that are located within 4km of a wildfire and sold within two years (pre or post) of a single wildfire, with no wildfire occurring in the third year prior to sale (and within 4km). These restrictions drastically cut our property sample size: 119,815 properties sold within 4km and two years of a wildfire, of these 32,489 properties sold within 4km and one year post-wildfire. The properties and wildfires are depicted in Figure 1. Our dataset includes some of the largest wildfires in California's history. The 2003 Cedar Fire (in San Diego County) is the largest fire in our dataset (270k acres; second largest in California's history after the 2017 Thomas Fire); the 2007 Witch Fire (in San Diego County) is the second largest fire in our dataset (160k acres; third largest in California's history after the 2017 Thomas Fire); while the 2009 Station Fire (in Los Angeles County) is the fourth largest fire (160k acres). It is worthwhile pointing out that the Cedar and Witch fires overlapped in space, despite being only 4 years apart, illustrating the sometimes short fire interval typical of southern California, which contrasts with that of some forested areas in the rest of the western US.

[2]We further assume that fires older than 5 years or smaller than 50 acres are not large or visible enough to be noticeable to affect aesthetic amenities and risk perceptions. McCoy and Walsh (2014) use a 500-acre minimum fire size threshold, while Stetler et al. (2010) use a 4-hectare threshold. Earlier analysis included fires as early as 1995 and within 20km of the properties. However, fires further than 4km do not appear to affect our properties.

[3]In practice, we discard properties that lie on a wildfire perimeter or within a 20m buffer outside the perimeter to ensure we exclude any property that have been structurally damaged by a wildfire.

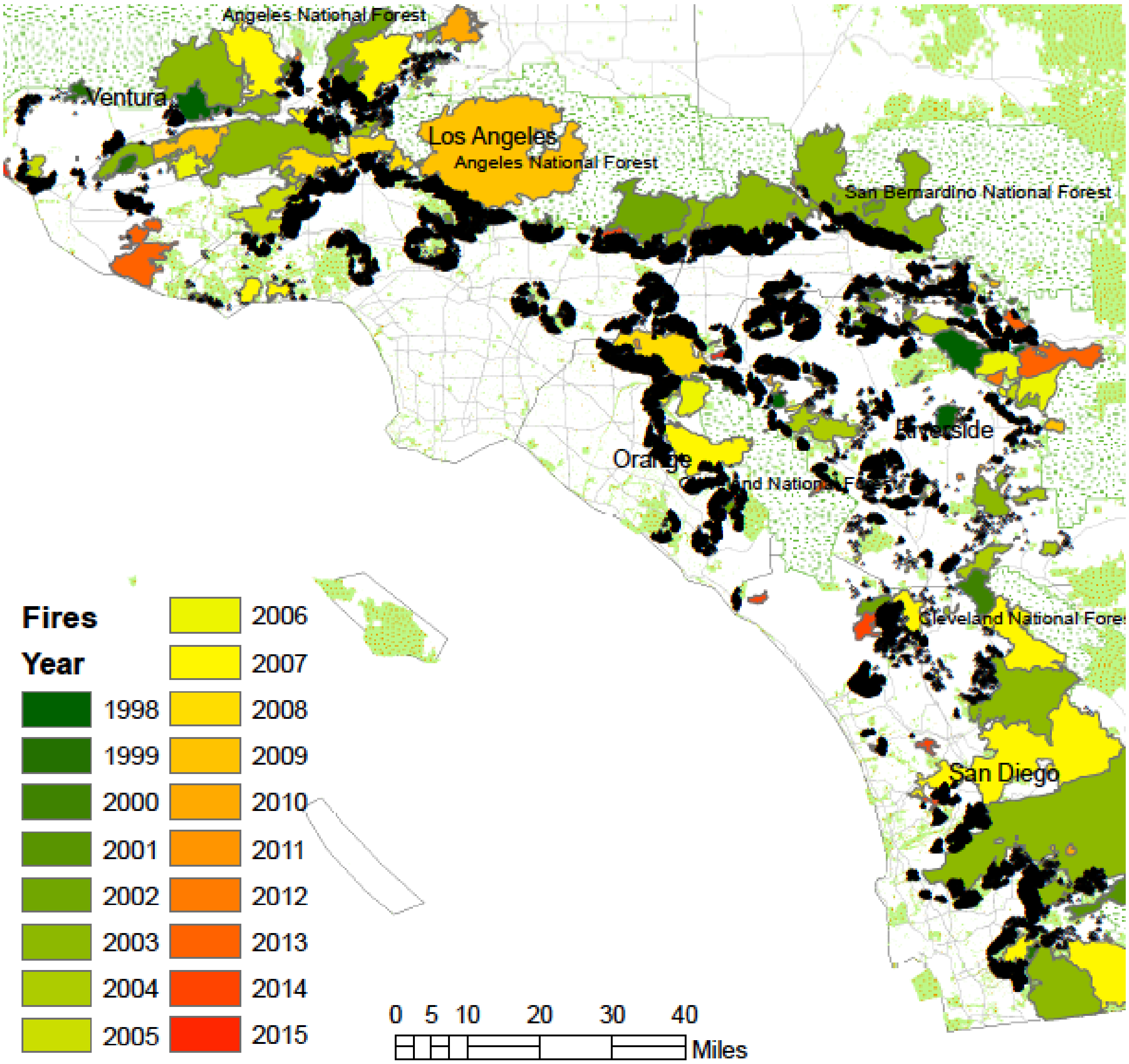



**Figure 1** Wildfire perimeters between 1998 and 2015 and properties sold within 4km and two years of a wildfire. Each property is represented by a black dot; the darker an area, the higher the density of properties. 2010 census tract boundaries are depicted in grey. National forests are depicted with green dots. State and local parks are depicted with a green background.

We run a viewshed analysis in ArcGIS for the 40,000 properties sold within a year post-fire and 4km of a burn scar.[4] Following the methodology employed in much of the literature on visual dis/amenities, e.g., wildfire (Stetler et al., 2010; McCoy and Walsh, 2014), wind turbines (Gibbons, 2015), or shale gas development (Muehlenbachs et al., 2015), we use ArcGIS's Viewshed tool with a Digital Elevation Model (DEM) of the terrain from the USGS National Elevation Dataset (with

[4]Our burn scar view estimate likely provides a lower bound of the total effect since we omit the effect on properties that sold 2 or 3 years post-fire. Future work will extend the analysis to properties that sold up to two years post-fire.

a 10m spatial resolution) to predict how far a 5-foot tall person can see in a 4km radius at the time of sale.[5] To determine whether a property has a view of a burn scar, we intersect each property's 4km viewshed with the burn scar area from the previous year's wildfire.

Table 1 provides summary statistics for our sample of properties sold within one year post-fire by distance bin to the burn scar (0-2km bin or 2-4km bin).

**Table 1** Summary characteristics for different distance bins from the burn scar

| | 0-2km distance bin | | | | 2-4km distance bin | | | |
|---|---|---|---|---|---|---|---|---|
| | All | | Burn scar view | | All | | Burn scar view | |
| | Means | (sd) | Means | (sd) | Means | (sd) | Means | (sd) |
| Sale price (k \$2015) | 581 | (292) | 575 | (291) | 517 | (266) | 488 | (253) |
| Age | 24.2 | (19.5) | 24.9 | (19.9) | 28.9 | (20.2) | 30.6 | (21.) |
| Living area (k sqft) | 2.00 | (0.81) | 1.97 | (0.81) | 1.84 | (0.74) | 1.77 | (0.70) |
| # bedrooms | 3.35 | (0.88) | 3.33 | (0.88) | 3.23 | (0.88) | 3.20 | (0.87) |
| # bathrooms | 2.65 | (0.83) | 2.63 | (0.84) | 2.47 | (0.79) | 2.39 | (0.77) |
| Swimming pool (0/1) | 0.22 | (0.42) | 0.22 | (0.41) | 0.22 | (0.41) | 0.20 | (0.40) |
| Dist. to national forest (km) | 11.5 | (8.5) | 11.4 | (8.5) | 11.6 | (8.5) | 11.0 | (8.1) |
| Dist. to park (km) | 0.5 | (0.5) | 0.5 | (0.5) | 0.5 | (0.5) | 0.5 | (0.5) |
| Dist. to primary road (km) | 1.3 | (1.2) | 1.3 | (1.2) | 1.2 | (1.0) | 1.1 | (0.9) |
| Elevation (m) | 280 | (172) | 279 | (174) | 265 | (177) | 270 | (190) |
| Slope | 4.5 | (4.7) | 4.0 | (4.3) | 3.8 | (4.3) | 2.8 | (3.3) |
| FHSZ (0/1) | 0.17 | (0.38) | 0.16 | (0.37) | 0.08 | (0.28) | 0.05 | (0.23) |
| WUI (0/1) | 0.84 | (0.36) | 0.83 | (0.37) | 0.65 | (0.48) | 0.56 | (0.50) |
| Dist. to burn scar (km) | 1.08 | (0.57) | 1.05 | (0.58) | 3.04 | (0.58) | 2.94 | (0.56) |
| Days since fire | 242 | (104) | 241 | (104) | 246 | (105) | 245 | (104) |
| Burn scar view (0/1) | 0.90 | (0.31) | 1.00 | (0.00) | 0.64 | (0.48) | 1.00 | (0.00) |
| Visible burn scar area (ha) | 101 | (136) | 113 | (139) | 28 | (56) | 44 | (65) |
| Total burn scar area (k ha) | 25 | (33) | 26 | (33) | 18 | (30) | 18 | (27) |
| Median hh. income (k \$) | 91.7 | (28.0) | 90.6 | (28.0) | 82.9 | (28.0) | 78.1 | (27.0) |
| % white | 73.51 | (13.32) | 73.22 | (13.46) | 71.55 | (14.25) | 70.85 | (13.74) |
| % hispanics | 24.10 | (17.87) | 24.74 | (18.37) | 27.77 | (18.83) | 30.57 | (19.71) |
| Number of properties | 13,686 | | 12,262 | | 20,541 | | 13,108 | |
| Number of census tracts | 588 | | 576 | | 1,015 | | 866 | |
| Number of fires | 91 | | 89 | | 114 | | 96 | |

## 3 Empirical strategy

We use the hedonic pricing method to value changes in the attributes related to wildfires as observed in housing prices (Rosen, 1974). The change in attributes that results from a wildfire affects the comparative prices of houses with these attributes and can measure the disutility of living close to

[5] Because the human eye would have trouble distinguishing burned from unburned shrubs from more than a few kilometers, the choice of the 4km threshold is not restrictive—as is revealed by the our estimates for the 4th km bin analysis. McCoy and Walsh (2014) use a 5km threshold, however, their setting consists of forested areas and burned trees visible from much farther.

a wildfire, have a view of the burn scar, or living in a high-risk area after a notable wildfire. Our objectives are two-fold. First, we estimate the average treatment effect of having a burn scar view on the sales prices of treated properties (ATT), holding constant other effects that vary with the proximity to the burn scar, including latent risk—although risk perceptions may still vary. Second, we investigate the ATT of burn scar proximity, while holding constant burn scar view.

ATT is subject to biases if the properties that received treatment are systematically different from those that did not receive treatment. For example, homes located near burn scars may be older and smaller than the average home farther away, or may be located in neighborhoods that experience different amenity levels such as better schools or access to the wilderness. Failure to control for an unobservable that is correlated with both the treatment and price will bias our estimate of burn scar view or proximity. The key issue is that we do not observe the counterfactual for treated observations, i.e., the price of a property if that same property did not have a burn scar view or were located farther away from the burn scar. We employ multiple approaches to compare treated to untreated properties while controlling for model dependence on observables and unobservables that may be correlated with both the treatment and home prices. Next, the empirical strategy lays out our approach to recover unbiased average treatment effects.

### 3.1 Effect of burn scar view

To identify the effect of burn scar views on property values, one must control for proximity effects such as lost access to the recreation opportunities, and changes in risk latency that may confound the burn scar view estimate. By construction, comparing treated properties to control properties that are located at the same distance to the burn scar will exactly control for proximity effects. Assuming that risk latency is determined by physical characteristics such as elevation, slope, distance to the wilderness, location on the WUI and FHSZ, we compare properties that share similar latent risk characteristics. In addition, we argue that we can partially control for changes in risk perceptions to the extent that the distance to the burn scar generates a comparable information signal to homeowners. Last, it is likely that insurance companies update their premiums using similar readily available information.

Our empirical model controls for distance to burn scar views in two ways. First, we run separate models for each 1km distance bin from the burn scar, i.e., 0-1 km, 1-2 km, 2-3 km, and 3-4 km,

**Table 2** Covariates balance, e.g., with an OLS model with census tract by year fixed effects, for the 0-1km bin

| | Treatment Mean (sd) | | Control Mean (sd) | |
|---|---|---|---|---|
| Age | 21.68 | (18.25) | 15.44 | (13.46) |
| Living area (k sqft) | 2.08 | (0.83) | 2.26 | (0.83) |
| # bedrooms | 3.40 | (0.86) | 3.58 | (0.94) |
| # bathrooms | 2.75 | (0.83) | 2.99 | (0.76) |
| Swimming pool (0/1) | 0.22 | (0.42) | 0.27 | (0.45) |
| FHSZ (0/1) | 0.21 | (0.41) | 0.23 | (0.42) |
| WUI (0/1) | 0.95 | (0.22) | 1.00 | (0.00) |
| Dist. to national forest (km) | 11.47 | (8.68) | 11.82 | (8.33) |
| Dist. to burn scar (km) | 0.51 | (0.28) | 0.72 | (0.21) |
| Elevation (m) | 289.55 | (169.84) | 318.14 | (148.53) |
| Slope | 4.68 | (4.67) | 10.70 | (6.51) |
| Observations | 5629 | | 346 | |

therefore allowing for heterogeneous effects of burn scar view across distance bins. Second, in our preferred specification we compare properties that are located on average at the same distance to the burn scar within each 1km bin. We further restrict the burn scar view analysis to properties that sold within one year post-fire. Because our estimate does not rely on time variation, we mostly avoid concerns about the unstability of the hedonic price function discussed in Kuminoff and Pope (2014).

To illustrate how treatment assignment may be correlated with observables (and unobservables) that may also influence property values in our data when running an OLS model, e.g., with census tract by year fixed effects, we present summary statistics for the control (no burn scar view) and treatment (burn scar view) for the first 1km bin in Table 2. Comparing means across the two groups reveals that treated properties are on average older, smaller, with fewer bedrooms and bathrooms, less likely to have a pool or be on the WUI and risk zone (FHSZ), and closer from the national forest and the burn scar. In contrast, control properties are on average at a higher elevation and with more slope.

Matching techniques can reduce model dependence by balancing covariates among control and treated groups such that assignment to treatment appears random based on observables (Abadie and Imbens, 2006, 2011). Matching prunes observations from the original data set so that the remaining data show better covariates balance. A growing number of studies have used nearest-neighbor matching (NNM) techniques to infer the average capitalized value of environmental amenities, including lake community amenities, shale gas development, and brown field remediation (Abbott and Klaiber, 2013; Muehlenbachs et al., 2015; Haninger et al., 2017). Yet, one important pitfall of matching techniques such as NNM is that they may not improve the balance of *all* covariates, and to the contrary, may worsen the balance of potential confounders. As a result, it may be difficult to determine whether matching has actually reduced model dependence and estimate bias (Diamond and Sekhon, 2013).

We employ NNM to recover the average capitalized value of burn scar views by comparing treated properties with a burn scar view to similar control properties without a burn scar view in the same 1km distance bin to the burn scar. The effect of the burn scar view treatment results from averaging across the home value differences for matched treated and control pairs. One approach to evaluate whether NNM unambiguously reduces model dependence for our data is to compare how the empirical distributions of the covariates compare across the matched control and treated groups, as discussed in Abbott and Klaiber (2013). Table 3 provides such distributions when matching on the two nearest neighbors, based on the Euclidean metric, for the first 1km bin, while requiring an exact match on fire and sale year and soft match on distance to the burn scar, and an array of property and neighborhood characteristics. While NNM has improved the balance on age, likelihood of a swimming pool, distance to the burn scar, elevation and slope, covariates balance has actually worsened for living area, number of bedrooms and bathrooms, and distance to national forest. Distance to the burn scar, which is a key variable that can potentially confound burn scar view and proximity effects, is hardly satisfactorily balanced between the matched treated and control groups.

As a result of our concerns with strong model dependence arising from using OLS or poorly performing matching estimators, we use entropy balancing, a new method developed in political science by Hainmueller (2012). Entropy balancing is a data preprocessing technique that generates a set of weights for each observation in the control group so that the distributions of the relevant covariates in the treated and weighted control groups are identical for the sample moments specified by the researcher (up to the third moment). To reduce information loss, entropy balancing solves for the set of weights that satisfies the balance conditions for the selected covariates while minimizing the departure from the uniform base weights. It is important to note that observations are neither

**Table 3** Covariates balance with NNM for the 0-1km bin

| | Treatment | | Control | |
|---|---|---|---|---|
| | Mean (sd) | | Mean (sd) | |
| Age | 19.67 | (25.95) | 15.45 | (19.31) |
| Living area (k sqft) | 2.08 | (0.72) | 2.38 | (0.73) |
| # bedrooms | 3.39 | (0.76) | 3.64 | (0.86) |
| # bathrooms | 2.78 | (0.71) | 3.09 | (0.69) |
| Swimming pool (0/1) | 0.23 | (0.18) | 0.26 | (0.19) |
| FHSZ (0/1) | 0.26 | (0.18) | 0.23 | (0.19) |
| WUI (0/1) | 0.94 | (0.06) | 1.00 | (0.00) |
| Dist. to national forest (km) | 13.18 | (61.41) | 12.27 | (79.46) |
| Dist. to burn scar (km) | 0.49 | (0.08) | 0.64 | (0.06) |
| Elevation (m) | 253.16 | (169.84) | 303.44 | (148.53) |
| Slope | 4.82 | (24.67) | 10.35 | (40.25) |
| Observations | 3449 | | 346 | |

Note: Exact matching on fire and sale year using 2 nearest neighbors based on the Euclidean metric. Soft match on census tract id, square footage, age, #bedrooms and bathrooms, pool, FHSZ, WUI, distances to nearest burn scar, forest, city, park, and primary road, elevation, slope, census tract's median household income, %white and hispanic.

matched nor pruned but simply weighted (unlike with NNM or propensity score matching techniques). Any estimation technique can then be employed using the treated and entropy weighted control groups. Table 4 illustrates the covariates balance between the treated and entropy weighted control groups. The assignment to the burn scar view treatment appears as close to possible to random based on observables.

Our preferred model specification, which uses the entropy weights that balance the set of covariates listed in Table 4 up to the second moment,[6] is presented in equation (1):

$$\ln p_{it} = \beta Treat_i + \mathbf{Z}_i'\boldsymbol{\omega}_Z + \mathbf{X}_g'\boldsymbol{\omega}_X + Census \times Year_{it} + Quarter_q + Fire_f + \epsilon_{it}. \tag{1}$$

The dependent variable represents property $i$'s sale price at time $t$ in 2014 CPI adjusted dollars. Our set of structural property-specific controls, $\mathbf{Z}_i$, include: second-order polynomials in square footage and age, indicator variables for number of bathrooms and bedrooms; a variable indicating if a property has a swimming pool, geographic characteristics including distance to the national forest, elevation, and slope; and neighborhood characteristics, $\mathbf{X}_g$, include median household income, % white and hispanic at the census tract level. Our preferred model specification further includes a

[6] We find that matching on the third moment is unnecessary in our data as the control and treated variables have a good level of balance on the third moment without additional specification.

**Table 4** Covariates balance with entropy balancing on first and second moments for the 0-1km bin

| | Treatment Mean (sd) | | Weighted control Mean (sd) | |
|---|---|---|---|---|
| Age | 21.68 | (18.25) | 21.68 | (18.25) |
| Living area (k sqft) | 2.08 | (0.83) | 2.08 | (0.83) |
| # bedrooms | 3.40 | (0.86) | 3.40 | (0.86) |
| # bathrooms | 2.75 | (0.83) | 2.75 | (0.83) |
| Swimming pool (0/1) | 0.22 | (0.42) | 0.22 | (0.42) |
| FHSZ (0/1) | 0.21 | (0.41) | 0.21 | (0.41) |
| WUI (0/1) | 0.95 | (0.22) | 0.95 | (0.22) |
| Dist. to national forest (km) | 11.47 | (8.68) | 11.47 | (8.68) |
| Dist. to burn scar (km) | 0.51 | (0.28) | 0.51 | (0.28) |
| Elevation (m) | 289.55 | (169.84) | 289.55 | (169.84) |
| Slope | 4.68 | (4.67) | 4.68 | (4.67) |
| Observations | 5629 | | 346 | |

large set of fixed effects to control for potential unobservable confounders. In particular, $Census \times Year_{it}$ denote census tract by sale year fixed effects controlling for time-varying unobservables at the local and macro levels, $Quarter_q$ denote quarter fixed effects controlling for seasonality, and $Fire_f$ represent fire fixed effects.[7] Census tract by year fixed effects control for spatial heterogeneity at a finer level of resolution, however, they also absorb a large share of the variation in home prices, which can limit our ability to precisely identify the effect of burn scar view. Standard errors are clustered at the census tract level to correct for spatial autocorrelation across census tracts.

## 3.2 Effect of burn scar proximity

To identify the effect of burn scar proximity independently of the effect of the burn scar view, we restrict the analysis to properties that do not have a burn scar view. This selection of properties provides us with a clean estimate of proximity to wildfire burn scars.

We restrict the burn scar proximity analysis to properties that sold within two years of a wildfire and define the treatment group as properties located within $K$ km of the burn scar, while the control group consists of properties located between the $K$ km threshold and 4km. Because properties in the treatment or control group may differ in terms of distance to the burn scar, homeowners' risk perceptions may vary substantial, for instance for treated homes next to the burn scar relative to

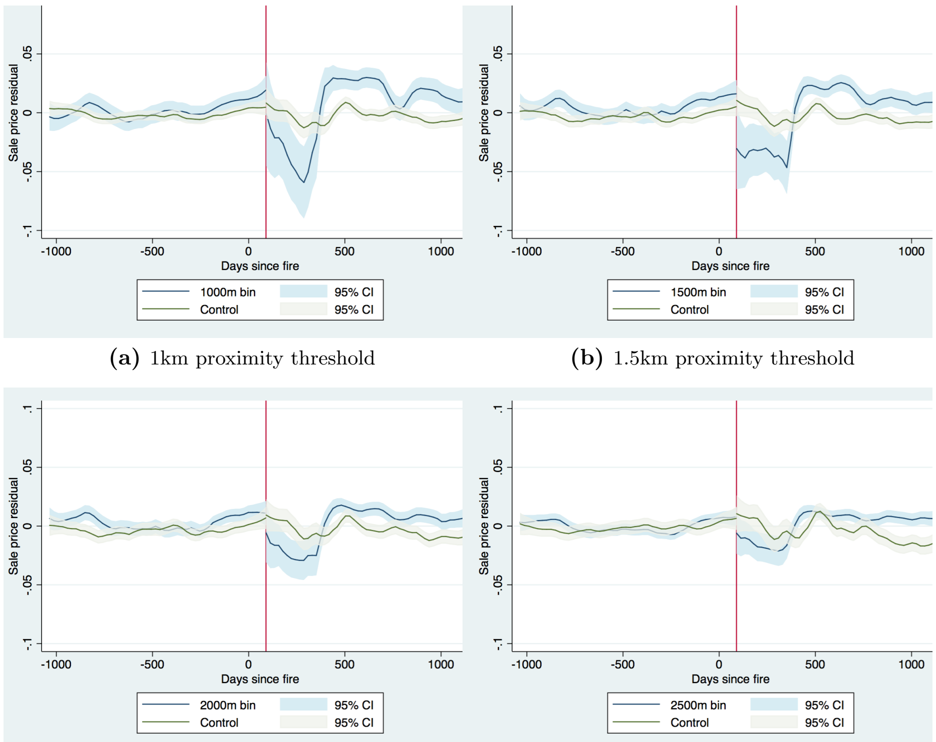
[7]Fire and sale year do not perfectly overlap since a property may sell within one year post-fire but overlap two fiscal years.

treated homes next to the threshold $K$. In the rest of the analysis, we investigate the extent of the proximity effect by examining various thresholds $K$. Table 5 describes summary statistics for treatment and control groups for two proximity thresholds, i.e., $K = 1.5$ and $K = 2.5$.

**Table 5** Summary characteristics for properties without view of a burn scar for different proximity threshold definitions

| | Proximity threshold $K = 1.5$km | | | | Proximity threshold $K = 2.5$km | | | |
|---|---|---|---|---|---|---|---|---|
| | Treatment | | Control | | Treatment | | Control | |
| | Means | (sd) | Means | (sd) | Means | (sd) | Means | (sd) |
| Sale price (k $2015) | 579 | (317) | 517 | (284) | 559 | (306) | 506 | (279) |
| Age | 23.4 | (18.9) | 27.5 | (20.5) | 24.7 | (19.6) | 28.3 | (20.6) |
| Living area (k sqft) | 2.02 | (0.80) | 1.88 | (0.75) | 1.97 | (0.78) | 1.86 | (0.74) |
| # bedrooms | 3.35 | (0.87) | 3.26 | (0.88) | 3.31 | (0.88) | 3.26 | (0.87) |
| # bathrooms | 2.67 | (0.81) | 2.51 | (0.79) | 2.61 | (0.81) | 2.48 | (0.79) |
| Swimming pool (0/1) | 0.23 | (0.42) | 0.21 | (0.41) | 0.22 | (0.42) | 0.21 | (0.41) |
| Dist. to national forest (km) | 11.2 | (8.6) | 11.7 | (8.3) | 11.3 | (8.4) | 11.8 | (8.4) |
| Dist. to park (km) | 0.5 | (0.5) | 0.5 | (0.5) | 0.5 | (0.5) | 0.5 | (0.5) |
| Dist. to primary road (km) | 1.4 | (1.2) | 1.3 | (1.1) | 1.3 | (1.1) | 1.3 | (1.0) |
| Elevation (m) | 291 | (179) | 267 | (179) | 280 | (179) | 266 | (180) |
| Slope | 4.5 | (4.6) | 3.8 | (4.3) | 4.2 | (4.5) | 3.8 | (4.3) |
| FHSZ (0/1) | 0.17 | (0.37) | 0.09 | (0.28) | 0.14 | (0.35) | 0.08 | (0.27) |
| WUI (0/1) | 0.88 | (0.33) | 0.66 | (0.48) | 0.79 | (0.41) | 0.64 | (0.48) |
| Dist. to burn scar (km) | 0.79 | (0.43) | 2.83 | (0.72) | 1.36 | (0.71) | 3.28 | (0.43) |
| Days since fire | 52 | (663) | 77 | (654) | 63 | (663) | 77 | (648) |
| Total burn scar area (k ha) | 28 | (33) | 19 | (30) | 25 | (32) | 18 | (30) |
| Fire duration (days) | 10.9 | (8.2) | 9.4 | (8.2) | 10.7 | (8.2) | 8.9 | (8.1) |
| Median hh. income (k $) | 92.5 | (28.0) | 83.8 | (27.8) | 89.7 | (28.1) | 82.3 | (27.7) |
| % white | 73.91 | (13.06) | 71.90 | (14.33) | 73.33 | (13.38) | 71.47 | (14.66) |
| % hispanics | 23.20 | (17.54) | 27.11 | (18.45) | 24.13 | (17.64) | 28.18 | (18.77) |
| Number of properties | 43,858 | | 108,423 | | 82,526 | | 69,755 | |
| Number of census tracts | 597 | | 1,236 | | 874 | | 1,127 | |

We employ a difference-in-differences (DiD) analysis to recover the causal effects of burn scar proximity if the average change in housing prices for treated properties would have been proportional to the average change in outcomes for the non-treated in the absence of treatment. For our DiD estimate to be unbiased, two assumptions need to be satisfied. First, the treatment needs to be exogenous, i.e., burn scar proximity must not coincide with any other shock differentially affecting the control and treatment groups. Because we explore the effects of multiple wildfires taking place over more than 1,500 census tracts (in 6 counties) and 15 years, we are not concerned about violating this assumption. Second, the control and treatment groups must satisfy common trends. Because we do not observe counter-factual outcomes, we cannot explicitly test this assumption. As an alternative, we examine how home prices vary in the control and treatment groups before and after a wildfire. We regress log-prices on a set of year-by-quarter fixed effects, county fixed effects, and structural control variables for four different proximity thresholds: 1km, 1.5km, 2km, and 2.5km. Figure 2 plots group-specific, kernel-weighted local polynomials fitted on the residuals of these regressions. The visual evidence provides support for the common trends assumption, in particular for proximity thresholds defined as 1km and 1.5km.




**(a)** 1km proximity threshold

**(b)** 1.5km proximity threshold

**(c)** 2km proximity threshold

**(d)** 2.5km proximity threshold

**Figure 2** Visual evidence of common trends between the treatment and control groups.
Note: For each treatment definition, e.g., 1.5km, we regress log-prices on a set of year-by-quarter and county fixed effects, and structural control variables. We fit group-specific, kernel-weighted local polynomials on the residuals of these regressions separately for the pre- and post-fire periods.

Our DiD model of the effect of burn scar proximity on property values is as follows:

$$\ln p_{it} = \alpha Post_{it} + \beta Treat_i \times Post_{it} + \gamma Treat_i + \mathbf{Z}_i' \boldsymbol{\omega}_Z + \mathbf{X}_g' \boldsymbol{\omega}_X + \epsilon_{it}. \tag{2}$$

The dependent variable represents property $i$'s sale price at time $t$ in 2014 CPI adjusted dollars. The indicator variables $Post_{it}$ and $Treat_i$ are equal to 1 if the sale occurred within one year of a wildfire and if the property is in the treatment group, respectively. Our set of structural property-specific controls, $\mathbf{Z}_i$, include: second-order polynomials in square footage and age, numbers of bathrooms and bedrooms, an indicator variable for the presence of a swimming pool; and geographic characteristics including distance to burn scar, the national forest, local or state park, and primary road, location on the WUI and FHSZ, elevation, and slope. Neighborhood characteristics, $\mathbf{X}_g$, include median household income, %white and hispanic at the census tract level.

To investigate potential persistence of the burn scar proximity effect over time, we allow for multiple post-treatment years $n$. We run model (2) replacing $Post_{it}$ by a series of dummy variables that capture the number of years since the wildfire occurred, $\sum_{n=0}^{N} Post_{nit}$, for $N \in \mathcal{N}_+$:

$$\ln p_{it} = \sum_n \alpha_n Post_{nit} + \sum_n \beta_n Treat_i \times Post_{nit} + \gamma Treat_i + \mathbf{Z}_i' \boldsymbol{\omega}_Z + \mathbf{X}_g' \boldsymbol{\omega}_X + \epsilon_{it}.$$

Our preferred model specifications further include county and quarter fixed effects, as well as year or fire fixed effects. Robust standard errors are clustered at the census tract level.

# 4 Results

This section presents and discusses the burn scar view and proximity estimates results. First, we estimate the burn scar view effect holding constant the proximity effect and risk latency by restricting the analysis to properties located in the same 1km distance bin that share similar characteristics, including risk latency. Second, we identify the effect of burn scar proximity independently of that of burn scar view by removing properties with a burn scar view.

## 4.1 Effect of burn scar view estimates

Table 6 reports the results of the entropy balancing preprocessing and estimates from model (1) over different 1km distance bins. The effect of burn scar view for each distance bin is estimated with and without Census×Year, Quarter, and Fire fixed effects. Using the entropy weights eliminates model dependence based on observables. However, one may still be concerned about unobservables correlated with both the treatment and price outcome in our model without fixed effects. Therefore, the large and significant estimate of -11.3% in the first 0-1km bin may be biased due to, say, neighborhood unobservables correlated with both the treatment and price outcome, e.g., higher crime rates or lower school quality. The preferred estimates with fixed effects show a decrease of

**Table 6** Burn scar view entropy balancing estimates by distance bin to the burn scar

| | 0-1km bin | | 1-2km bin | | 2-3km bin | | 3-4km bin | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| View | -0.113** | -0.043* | -0.026 | 0.004 | -0.069** | -0.005 | -0.059** | 0.009 |
| | (0.057) | (0.024) | (0.046) | (0.014) | (0.034) | (0.016) | (0.024) | (0.011) |
| Census×Year FE | | Yes | | Yes | | Yes | | Yes |
| Quarter FE | | Yes | | Yes | | Yes | | Yes |
| Fire FE | | Yes | | Yes | | Yes | | Yes |
| N | 5,999 | 5,999 | 7,687 | 7,687 | 9,586 | 9,586 | 10,958 | 10,958 |
| $R^2$ | 0.553 | 0.927 | 0.514 | 0.907 | 0.475 | 0.887 | 0.469 | 0.874 |

Note: Entropy balancing on the first and second moments of property square footage, age, #bedrooms and baths, pool, FHSZ, WUI, distances to nearest burn scar and forest, elevation, and slope. Regressions with the entropy balancing weights use the same set of covariates. The share of properties with burn scar views in bins 0-1, 1-2, 3-4km is 94%, 86%, 74%, and 55%, respectively. Robust standard errors clustered at the census tract level. * p<0.1, ** p<0.05, *** p<0.01.

4.3% in price for properties that have a view of the burn scar and are within 1km of the burn scar. This effect becomes insignificant at distances greater than 1km. These estimates control for proximity effect, risk latency (based on physical characteristics and location on the WUI and FHSZ), and insurance premium increases. We are thus able to isolate the burn scar view disamenity, specifically the marginal willingness to pay (MWTP) to avoid a burn scar view at time of purchase. Furthermore, because we are estimating the effect using only property sales within one year post-fire, we also eliminate concerns about any instability of the hedonic price function. Assuming a $3k per month rent for our median home of $500k, our estimate corresponds to a reduced rent of $1k per month for two years, which seems plausible. We note that a burn scar is mostly visible in the first couple of years after a fire, with the burn scar rapidly fading away as it is being replaced by new, green shrubs and grasses.[8]

To gain a better understanding of how well our entropy approach performs, we conduct a falsification test by estimating the effect of post-fire burn scar view on pre-fire sales, taking advantage of our repeat sales properties. To construct the data set for the test, we keep only properties with repeat sales and with no fire within 4km and the three years preceding the *prior sale*, i.e., prior sales were not influenced by any wildfire (approximately 12,500 properties). We assign the burn scar view and distance to burn scar associated with the most recent sale to the prior sale. We bal-

[8]Our estimate of burn scar view focuses on the effect within the first year post-fire. Further analysis will explore the effect of the burn scar view beyond the first year and examine potential persistence past this first year.

ance our placebo treatment and control groups using our entropy preprocessing procedure and then perform the regression analysis with Census×Year, Quarter, and Fire fixed effects (our preferred specification). Figure 3 illustrates the results from this falsification test. We find no significant estimate of burn scar view across all distance bins, as expected. This gives us confidence that our entropy preprocessing estimates are not subject to significant Type I error.

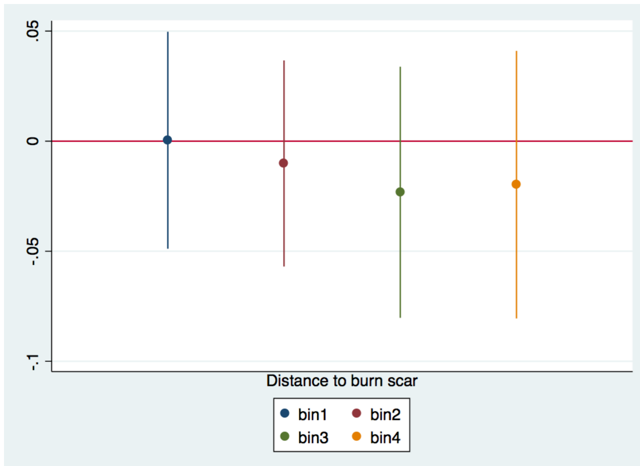



**Figure 3** Falsification test: Burn scar view entropy balancing estimates with Census×Year, Quarter, and Fire fixed effects, by distance bin to the burn scar, using post-fire characteristics (burn scar view and distance) with pre-fire sales.

We also provide NNM estimates of burn scar view in Table 7. We require matching exactly on Fire and Year and require a minimum of two nearest neighbors based on the Euclidean metric. We find significant estimates of burn scar view in the 1-2km bin and find no significance in other bins. We are concerned that these estimates are biased based on the poor balancing of covariates across treated and control groups and therefore prefer the fixed effects estimates from Table 6 using entropy balancing preprocessing of the data. In addition, the closer the property is to the burn scar, the likelier it is to have a burn scar view and, therefore, the higher the proportion of treated properties (with burn scar view) relative to controls. As a result, the probability of a successful match, i.e., a treated property matched with (at least) two controls, is lower near the burn scar, e.g., only 66.7% in bin 0-1km. This further raises concerns about the internal validity of NNM estimates for distance bins close to the burn scars.

**Table 7** Burn scar view nearest-neighbor matching estimates by distance bin to the burn scar

| | 0-1km bin | 1-2km bin | 2-3km bin | 3-4km bin |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| View | -0.006 | -0.060*** | -0.008 | -0.005 |
| | (0.023) | (0.017) | (0.017) | (0.013) |
| N | 3933 | 6489 | 8639 | 10085 |
| % of successful matches | 66.7 | 84.4 | 90.8 | 96.6 |

Note: Matches using two nearest neighbors based on the Euclidean metric with exact matching on fire and year. Soft match on census tract id, square footage, age, #bedrooms and bathrooms, pool, FHSZ, WUI, distances to nearest burn scar, forest, city, park, and primary road, elevation, slope, census tract's median household income, %white and hispanic. The share of properties with burn scar views in bins 0-1, 1-2, 3-4km is 94%, 86%, 74%, and 55%, respectively. Robust standard errors in parentheses. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

### 4.2 Effect of proximity to burn scar estimates

In Table 8, Panel A, we present the estimates of the DiD estimates for proximity to wildfire burn scar. We find a decrease of 4.6% in price for properties within 1.5km of the burn scar that sold within one year post-fire, and without a burn scar view. We find the effects are attenuated and not detectable when using a proximity threshold of 2.5km or more, suggesting a 1.5 to 2km limit up to where proximity generates a disamenity. In this analysis we compare treated and control properties that are close together (both within 4km of the burn scar), and therefore can control for time-varying unobservables that may confound and bias outcomes in a cross-sectional analysis. We rely on a common trends assumption, as discussed previously in section 3.2 for valid identification. To examine the persistence of the proximity effect over time, our analysis includes multiple years post-wildfire. Table 8, Panel B, depicts results for treatment across two years post-wildfire; estimates for a 3-year post-fire analysis are qualitatively similar. Our burn scar proximity estimates, with various sets of spatial and temporal fixed effects, show a -4.4% price change within one year of the wildfire and within 1.5km of the burn scar. We again find no support for the effect of proximity beyond 2.5km, or lasting more than one year. The absence of persistence beyond one year is likely partially due to the fast regrowth of vegetation. Indeed, despite our analysis excluding properties with burn scar views, the rapid greening of burn scars seems to contribute to the short-lasting negative proximity effect.

The identification of the MWTP to avoid the disamenities of the wildfire relies on the assumption that the hedonic price function is stable over time (Kuminoff and Pope, 2014). Otherwise, our

**Table 8** Proximity to burn scar difference-in-differences estimates

| | Proximity threshold | | | | | |
|---|---|---|---|---|---|---|
| | $K$=1.5 | | $K$=2 | | $K$=2.5 | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Panel A: One year post-fire | | | | | |
| $Treat_K \times Post$ | -0.046*** | -0.068** | -0.034** | -0.048* | -0.019 | -0.034 |
| | (0.017) | (0.029) | (0.015) | (0.027) | (0.012) | (0.022) |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | Yes | | Yes | |
| Fire FE | | Yes | | Yes | | Yes |
| Observations | 90,144 | 90,144 | 90,144 | 90,144 | 90,144 | 90,144 |
| $R^2$ | 0.847 | 0.820 | 0.847 | 0.820 | 0.847 | 0.820 |
| | Panel B: Two years post-fire | | | | | |
| $Treat_K \times Post_1$ | -0.044** | -0.044* | -0.031** | -0.032 | -0.017 | -0.023 |
| | (0.017) | (0.024) | (0.014) | (0.021) | (0.011) | (0.018) |
| $Treat_K \times Post_2$ | 0.014 | 0.008 | 0.009 | -0.007 | 0.009 | -0.011 |
| | (0.011) | (0.022) | (0.009) | (0.020) | (0.009) | (0.020) |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | Yes | | Yes | |
| Fire FE | | Yes | | Yes | | Yes |
| Observations | 121,062 | 121,062 | 121,062 | 121,062 | 121,062 | 121,062 |
| $R^2$ | 0.843 | 0.747 | 0.843 | 0.747 | 0.843 | 0.747 |

Note: Controls include property square footage, square footage$^2$, age, age$^2$, #bedrooms and bathrooms, pool, FHSZ, WUI, distances to nearest burn scar, forest, park, and primary road, elevation, slope, census tract's median household income, %white and hispanic. Robust standard errors clustered at the census tract level. * p<0.1, ** p<0.05, *** p<0.01.

estimate would provide an upper bound estimate of the surplus change associated with a degradation of an environmental amenity (Banzhaf, 2015). We argue that wildfires are exogenous, for example in contrast to brownfield sites remediation, therefore, the effect we recover is expected to be the MWTP and not an upper bound capitalization effect estimate. Specifically, our estimate represents the MWTP to avoid the loss of amenities associated with proximity to the wildfire. Our identification strategy excludes the effect of burn scar view from this estimate, however we note that risk latency, risk perceptions, and expectations of higher insurance premium may conflate and be a part of the capitalized effect of the disamenities of proximity to a burn scar. Since insurance is not mandatory, at least in the absence of a mortgage, we may be recovering the full risk of being close to a wildfire or the capitalization of the insurance premium increases that are expected, or a mixture of both effects.

One potential concern with our estimates is that they could include a housing market supply side effect. This may confound our identification of MWTP for disamenities if the wildfire destroys a large enough number of homes to affect market supply, rather than solely affecting the demand for housing attributes. However, it would seem likely that any supply side effect would be longer lasting than one year to tear down and rebuild a neighborhood and bring back the supply of housing to pre-fire levels. Therefore, we suspect that we are identifying the demand effects in this analysis and not a response to supply shocks to the housing market.

# 5 Conclusion

Results reveal that properties with a burn scar view located in direct proximity to a burn scar (within 1km) experience a 4.3% price drop relative to similar properties without a burn scar view. In contrast, properties located near a burn scar (within 2km) but *without* a burn scar view face a 3% to 4% price loss relative to properties farther away. Our estimates of disamenity associated with proximity effects are smaller than those found in Mueller and Loomis (2014) and Loomis (2004). This is at least partially due to the fact that we identify the effect of proximity net of the burn scar view effect. Our estimate of the negative effect of burn scar view is consistent with that in McCoy and Walsh (2014) and Stetler et al. (2010). These findings suggest a heterogeneous effect on houses with and without views of the burn scar. Assuming additivity, the combination of both effects would indicate a price decrease of 7% to 8% for houses with a burn scar view and in close proximity to the burn scar.

We use a novel identification strategy that deals with poor balancing of covariates between control and treatment groups. This method, entropy balancing processing, is new, as far as we are aware, to the environmental economics literature. This method in conjunction with our regression identification strategy provides a way to estimate the specific disamenity of burn scar views when matching techniques do not sufficiently resolve covariate balancing issues. It is of particular importance in the presence of limited sample sizes and is salient to the state of the literature as matching has been used heavily in the hedonic pricing literature as it provides distinct advantages over other statistical techniques.

Our estimates come from a uniquely large data set for the Los Angeles and San Diego basins in southern California. This is advantageous and important for identification and policy as this region offers a prime empirical application to quantify wildfire disamenities in a large metropole area subject to frequent wildfires. As the increase in the severity and frequency of wildfires continues, there is much interest in how to weigh the costs and benefits of wildfire prevention and mitigation strategies in the WUI. Our estimates of the disamenities of wildfires, via reduced MWTP for key property attributes (views and proximity), suggest significant costs of wildfires—in addition to that of damaged properties and businesses. Such estimates are critical to conduct a cost-benefit analysis of government fire protection programs.

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