A City on Fire?
Effect of Salience on Risk Perceptions

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Abstract

Using a unique dataset containing over 2 million real estate sales transactions for the Los Angeles and San Diego Basins, we investigate how different forms of salience affect homeowners' natural disaster risk perceptions. We find that prices of homes newly assigned to the risk zone drop by 10.3% to 11.1% relative to homes just outside the new designation, controlling for changes in home prices before and after designation. While the risk zone assignment is discontinuous, arguably, the underlying risk is continuous, suggesting the new designation triggers greater risk salience, rather than greater risk. We then turn to another form of salience by investigating how exposure to natural disaster damages affects home prices. We find that prices of homes with a view of the damages are 4.2% to 5.0% lower that similar homes with no view. This effect is strongly significant only for the first year post-wildfire and is therefore less likely to be fully attributable to the loss of visual amenities.

JEL codes: Q51, Q54, Q58, R31

Keywords: risk salience, risk perceptions, natural disasters, wildfires, hedonic pricing model, repeat sales

1 Introduction

Understanding what factors drive households' risk perceptions is a fundamental economic question. Early insights from psychology suggest that salience could play a critical role (Tversky and Kahneman, 1974).[1] More recently, Bordalo et al. (2012) formalize a model of choice over lotteries with salient payoffs, where true probabilities are replaced by decision weights. Their model can explain many deviations from rational expectations, including risk-seeking behavior and preference reversals. In practice, how much does salience affect households' risk taking decisions?

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[1] We use the term salience as defined by: "the phenomenon that when one's attention is differentially directed to one portion of the environment rather than others, the information contained in that portion will receive disproportionate weighting in subsequent judgments" (Taylor and Thompson, 1982).

For most households, buying a home represents their most important financial decision. Thus, forming unbiased risk perceptions about real estate is paramount to many households' finances. For example, risk perceptions have been shown to drive migration and development patterns in disaster-prone areas (Boustan et al., 2012), insurance uptake (Gallagher, 2014), and private defensive behavior (Shafran, 2008). Yet, choosing a risky location, as in Bakkensen and Barrage (2017) and Baylis and Boomhower (2018), could be evidence that households selectively pay attention to salient risk and ignore less salient information. The private and social costs of miscalculating these risks could be extremely high in some regions (Bogardi and Warner, 2009). Moreover, the literature has used residential property sales to estimate households' time preferences (Giglio et al., 2014), preferences for school quality (Black, 1999), and the effect of environmental health risks (Davis, 2004; Chay and Greenstone, 2005; Greenstone and Gallagher, 2008; Muehlenbachs et al., 2015). To examine the effect of salience on households' environmental risk perceptions, our paper focuses on the effect of wildfire risk salience on Southern California real estate prices.[2]

We assemble a uniquely large dataset of over 2 million real estate transactions that spans seven southern California counties over 16 years. Using a series of quasi-experimental methods, we examine which forms of risk salience are effective in triggering a behavioral response, specifically, a new risk zone designation and exposure to damages from natural disasters. First, we investigate the effect of new risk zone designation. We compare prices of homes newly assigned to the risk zone relative to homes just outside the new designation, controlling for changes in home prices before and after designation with property fixed effects. While the risk zone designation is discontinuous, arguably, the underlying risk is continuous. Conditional on changes in insurance premiums being "not too" discontinuous across the risk zone, our estimate picks up the effect of the new designation on risk salience. Relaxing that assumption, our estimate captures the combination of a differential change in insurance premiums and the salience effect. Second, we then turn to the effect of burn scar views, which is unlikely to be associated with changes in insurance premiums, on home prices. To this end, we conduct a viewshed analysis using three-dimensional maps to precisely identify which properties have a view of a burn scar. We then compare the prices of homes with a view of a burn scar with those of homes in the same distance bin from the burn scar but with no view, taking into account changes in home prices before and after the wildfire with property fixed effects. Conditional on changes in risk and insurance premiums not varying systematically across homes with a burn scar view and homes without a view but in the same distance bin from the wildfire, our estimate captures a combination of visual disamenities and risk salience.

We find that prices of homes newly assigned to the risk zone drop by 10.3% to 11.1% relative to homes just outside the new designation. Because of the discontinuity of the risk designation, these estimates likely indicate that the new designation triggers greater risk salience, rather than

[2]We are not able to distinguish between changes in risk preferences and changes in risk perceptions. Throughout the paper, we will refer to risk perceptions but acknowledge that risk preferences may also be changing.

greater risk. A placebo test in which the 'treatment' group consists of homes on the risk zone both before and after the new designation shows no effect. We find that a burn scar view located within 2km lowers home values by 4.2% to 5.0%, while a burn scar view located between 3km and 4km reduces home values by 1.9% to 3.2%. This effect is strongly significant only for the first year post-fire. Because of the magnitude of the effect and its short-term nature, it is unlikely to be fully attributable to the loss of visual amenities, suggesting exposure to visual damages affects risk salience.

Our findings have important policy implications because risk salience may bias homeowners' risk perceptions. This matters in its own right given the considerable asset value of the California real estate market. In addition, understanding the effect of salience on risk perceptions may help policy-makers understand how salience affects household financial decision-making in general, and how to better convey risk to homeowners in disaster-prone areas in particular. The latter is a pressing issue as impacts from climate change will include more frequent and severe natural disasters and the economic costs of natural disasters are predicted to rise as new development expands in disaster-prone areas (Rappaport and Sachs, 2003; Kahn, 2005).[3] In particular, both the wildland-urban interface has been developing rapidly (Radeloff et al., 2018)[4] and wildland-urban fires are predicted to continue to increase in frequency and severity with climate change (Westerling et al., 2006; Schoennagel et al., 2017).[5]

A large number of studies focuses on homeowners' risk perceptions, but do not study the role of salience.[6] A small number of studies look at the salience effect of a recent natural disaster on the prices of homes farther away and, in theory, unaffected by the disaster—thus, absent direct damages (Hallstrom and Smith, 2005; Bin and Landry, 2013; McCoy and Walsh, 2018). In the case of managers, who arguably have received a higher level of financial education that most households, Dessaint and Matray (2017) find they overreact to recent hurricanes by holding excessive cash—despite true risk remaining unchanged. However, one key issue in this literature is that often micro-level data on changes in insurance take-up and premiums are not available, confounding

[3]For example, the number of billion-dollar disasters has been growing rapidly, with cumulative costs in the United States exceeding $300 billion in 2017 (NOAA, 2018).

[4]According to the International Association of Wildland Fire (2013), there are approximately 46 million homes in the United States on the wildland-urban interface, defined as properties adjacent to fire-prone public land. These homes correspond 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). Of the approximately 13.6 million homes in California, 3.6 million are located in the wildland-urban interface (Martinuzzi et al., 2015).

[5]Large wildfires in the western United States have increased by around 500% over the last 30-40 years (Resources Radio Podcast broadcast on Dec. 4th, 2018 with Dr. Wibbenmeyer from Resources for the Future). Recent years have witnessed some of the worst wildland-urban fires in California's history, with the 2018 Camp Fire holding the record for the most destructive fire with over 15,000 lost structures (and estimated insured losses of $7.5 to $10 billion (RMS)). In addition, the annual cost of US federal wildfire suppression and prevention programs is now exceeding $3 billion—and is predicted to keep rising (Hoover et al., 2015).

[6]For example, Bakkensen and Barrage (2017) show that coastal homeowners select into risky locations for the coastal amenities, but also have lower risk beliefs. Baylis and Boomhower (2018) show how government fire suppression programs subsidize development in high fire risk areas, while Peralta and Scott (2018) show how the availability of subsidized flood insurance enables households to move to more risky locations, leading to moral hazard.

risk salience and changes in insurance. For example, Gallagher (2014) finds that flood events lead to temporary increases in insurance take-up, suggesting recent natural disasters make risk more salient and households respond (at least partially) by insuring more. A few studies have looked at the salience effect of damages from natural disasters (McCoy and Walsh, 2018; McCoy and Zhao, 2018). One concern is that these homes also experience lower amenity values due to the damages. By contrast, the main treatment in the present paper is a policy intervention (a new risk zone designation), rather than a recent natural disaster.[7] This matters as it can inform policy-makers' choice and design of instrument to better convey risk to homeowners, in particular in disaster-prone areas.

This paper makes three contributions to the literature. First, we show that salience likely affects (and possibly biases) households' risk perceptions about real estate investment, as suggested by the effects of a new risk zone designation and exposure to damages of natural disasters on home prices. Although we cannot rule out that the new designation estimate includes differential changes in insurance premiums (relative to control properties on the other side of the new risk zone), our estimate of exposure to natural disaster damages does not (the caveat is that it likely includes temporary visual disamenities). Taken together, these two estimates suggest that households may respond to multiple types of salience. Second, it is the first large-scale study of wildfire risk salience for the Los Angeles and San Diego regions. This metropolitan area is a particularly relevant case study because of the high number of homes at risk and high value of these homes. Wildfires in the region are highly frequent and destructive (with an upward trend). Such data position us well to investigate the effect of salience on households' risk perceptions. Third, our paper contributes to the quasi-experimental literature on eliciting unbiased households' preferences for environmental risk and local amenities (e.g., Black (1999); Chay and Greenstone (2005); Greenstone and Gallagher (2008); Muehlenbachs et al. (2015)). Our identification strategy combining difference-in-differences with repeat sales and stringent sample definitions on each side of the risk zone allows us to control for both time-invariant and time-varying unobservables that may bias many cross-sectional or difference-in-differences analyses.

The remainder of the paper is structured as follows. The next section describes the data sources. 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 wildfire risk, we selected zip codes located within a 30km bandwidth of the national forests surrounding the Los Angeles and San Diego basins. Those

[7] The study most similar to ours is Gibson et al. (2018) who find that updated floodplain maps in 2013, one year after Hurricane Sandy, lower home values by about 5% in New York City. Their study differs in that the salience effect of the new flood maps cannot be easily disentangled from that of Sandy.

zip codes span across seven counties: Santa Barbara, Los Angeles, Orange, Ventura, Riverside, San Bernardino, and San Diego. Transaction records for all properties located within those zip codes sold between January 2000 and December 2015 were purchased from CoreLogic.[8] We start with a dataset of 2,187,007 unique properties. Single family residence sales (excluding mobile homes) and arms-length transactions of owner-occupied properties account for 1,215,523 observations. Properties with missing sale price as well as those sold more than once within the same 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). We deflate all prices using the Consumer Price Index from the U.S. Bureau of Labor Statistics. We then further drop observations with sale prices in the bottom and top 1%, and properties with the top 1% of bedrooms, bathrooms, and square footage. Of the remaining 1,022,072 properties, 439,796 are repeat sales in our 16-year time period. To construct our repeat sales dataset, we keep properties that sold twice between 2000 and 2015 (in practice, we do not observe more than two sales since CoreLogic only contains information up to the prior sale). To eliminate potential outliers and reduce the likelihood that a property experienced significant renovation or unusual damages in-between sales, we drop properties whose price change across transactions is in the top and bottom 1% and whose transactions took place more than 10 years apart. To minimize the probability of house flippers, we further drop properties that sold less than 2 years apart.

Risk zones and insurance data

The California Fire Resource and Assessment Program (FRAP; frap.fire.ca.gov) provide spatial data on wildfires, wildfire risk zones, and the wildland-urban interface (WUI). The California Department of Forestry and Fire Protection (CAL FIRE) produces maps of significant fire hazard, called Fire Hazard Severity Zones (FHSZ), which we will refer to generically as "risk zones" hereinafter. These maps are generated using an ember diffusion model developed at the University of California, Berkeley, that takes into account the physical attributes of the area, including vegetation type, topography, local climate and wind directions. The maps focus on hazards and do not account for private risk mitigating actions on a given property, e.g., fuel reduction and defensible space. As a result, homeowners do not have the ability to influence their assignment to the risk zone.[9] By law, sellers have to disclose the property's risk zone status to the buyer at the time of sale. While early maps for the state responsibility area were in place since 2000, new maps (relying on better science and, in general, expanding the risk zone) were adopted in November 2007. In addition, following the 1992 Bates bill 337, CAL FIRE worked with over 200 local governments to develop fire hazard severity zones in local responsibility areas. Such maps were recommended for adoption starting in

[8] Because there is a lag between the time the sale is recorded in the CoreLogic data and the time the price of the property is negotiated and agreed upon by the buyer and seller, we make the assumption that the price is agreed upon 2 months before it is recorded. Results are qualitatively similar when using a 3-month lag.

[9] Risk zones are managed by the state (state responsibility area) or local governments (local responsibility area).

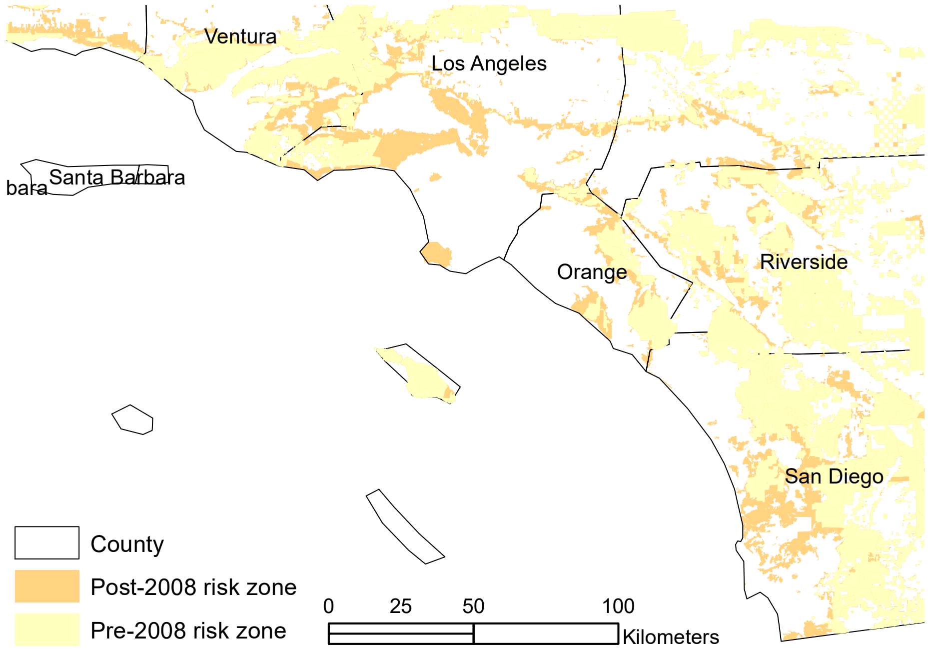


Figure 1 California wildfire risk zone, including the new risk zone expansion.

July 2008. Yet, because CAL FIRE has no regulatory authority to enforce map adoption in local responsibility areas, local governments may have adopted such risk zones until as late as 2011 or never at all. Because we do not know which local responsibility areas adopted the new maps (and when), we discard sales on the new 'recommended' risk zones in local responsibility areas. The old and new risk zones for our entire study area are depicted in Figure 1.

One important question is whether home insurance premiums vary in response to the new risk designation. Because fire damages are covered as part of regular home insurance policies, answering this question would require access to individual homes' insurance policies, which we do not have. Indeed, home insurance policies are customized to each property based on building materials, age, size, and natural disaster risk, among others. Because natural disaster risk represents a major part of insurance companies' business, in particular in California, insurance companies are relying on very sophisticated models taking into account 100s of factors and spatial layers, which are arguably much finer (and continuous) than CALFIRE's somewhat simple hazard zone designation, and in addition account for homeowners risk mitigation actions.[10] To further prevent premium increases, the California Department of Insurance and CALFIRE signed a Memorandum of Understanding on October 2007 (fire.ca.gov; insurance.ca.gov). In addition, a story in the Orange County Registar (March 5, 2012) by Mark Bouchy documented that an insurance agent that provides information to insurance underwriters does not use these hazard maps despite being publicly available.

[10]Risk Management Solutions is one example of businesses generating fine resolution, spatial risk layers for insurance companies.

Table 1 Wildfire characteristics in our sample

Year	Number of fires	Mean fire size (acres)	Min fire size (acres)	Max fire size (acres)	Total area burned (acres)
1998	15	3,727	95	28,136	55,908
1999	11	2,016	107	7,846	22,174
2000	10	1,468	52	11,734	14,679
2001	10	2,325	182	10,438	23,246
2002	19	5,212	65	38,119	99,022
2003	22	33,146	51	270,686	729,204
2004	15	3,305	53	16,447	49,577
2005	11	3,493	65	23,396	38,428
2006	14	6,142	64	40,177	85,990
2007	31	15,192	87	162,070	470,952
2008	13	5,699	65	30,305	74,084
2009	19	10,550	55	160,833	200,459
2010	13	1,264	64	12,582	16,432
2011	8	152	51	411	1,214
2012	9	674	54	2,637	6,063
2013	13	3,904	59	24,060	50,758
2014	11	2,678	78	15,186	29,456
2015	7	459	56	1,287	3,211
1998-2015	251	5,634	51	270,686	1,970,857

Wildfire characteristics and local amenities

The wildfire data contain information on perimeters, area burned, and start and containment dates. We discard fires smaller than 50 acres because they are likely not large enough to affect local amenities or risk perceptions. Thus, our analysis includes 251 fires between 1998 and 2015. Burn scars range between 51 to 270,686 acres (with median and mean sizes of 695 and 5,634 acres, respectively; Table 1). Our analysis includes some of the largest wildfires in California's history. For example, the 2003 Cedar Fire (271k acres, i.e., the largest fire in our dataset; San Diego County) is the third largest in California's history after the 2018 Mendocino Complex Fire and the 2017 Thomas Fire; followed by the 2007 Witch Fire (162k acres; San Diego County); and the 2009 Station Fire (161k acres; Los Angeles County). It is noteworthy that the Cedar and Witch fires partially overlapped (by over 40,000 acres) despite being only 4 years apart. It illustrates the short fire interval existing in southern California, which contrasts with that of most forested areas in the rest of the western United States.

National forests spatial layers come from the National Datasets maintained by the US Forest Service (data.fs.usda.gov). State and local parks layers 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). The 2010 census tract boundaries and census characteristics come from the American Community Survey and include median household income, race, and ethnicity—which we use in Appendix D to examine changes in neighborhood composition.

All properties are geo-coded to obtain exact latitude and longitude coordinates and link them

Table 2 Summary characteristics for the full sample (with pooled sales) and repeat sales sample

	Full sales sample		Repeat sales sample	
	Means (sd)		Means (sd)	
Sale price (k$2015)	514.92	(568.75)	504.91	(306.24)
Age	38.65	(23.98)	36.40	(25.01)
Living area (k sqft)	1.84	(0.72)	1.88	(0.75)
# bedrooms	3.32	(0.82)	3.35	(0.82)
# bathrooms	2.34	(0.82)	2.39	(0.82)
Swimming pool (0/1)	0.20	(0.40)	0.19	(0.40)
Dist. green space (km)	0.56	(0.49)	0.57	(0.51)
Elevation (m)	241.10	(194.64)	261.67	(197.65)
Slope	2.92	(4.23)	2.89	(4.19)
FHSZ (0/1)	0.07	(0.26)	0.08	(0.27)
WUI (0/1)	0.47	(0.50)	0.50	(0.50)
Dist. main road (km)	1.42	(1.17)	1.46	(1.20)
Median hh. income (k$)	75.89	(28.02)	75.50	(27.54)
% white	65.47	(18.10)	65.41	(17.45)
% hispanic	38.29	(24.44)	39.07	(23.89)
Years between sales	(5.34)	(3.15)	4.57	(2.31)
# of sales	1,455,186		770,874	
# of census tracts	4,084		4,009	

to aforementioned spatial data. In ArcGIS, we calculate slope and elevation as well as distances to the neareast risk zone boundary, neareast burn scars, nearest national forest, nearest state or local park, and nearest primary road. Summary statistics for the full and repeat sales samples are comparable. They are presented in Table 2.[11]

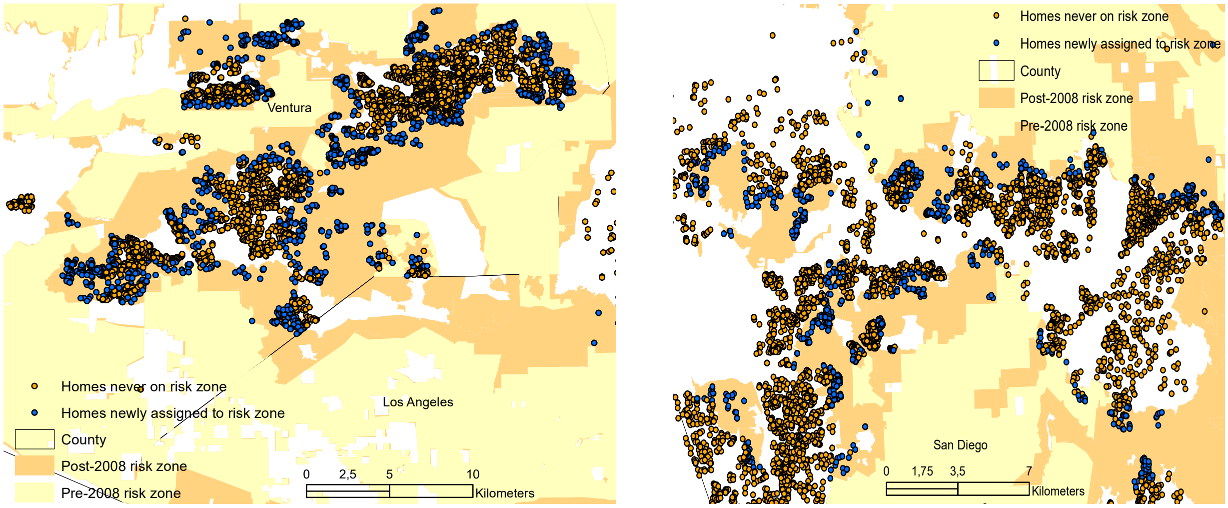
2.1 Sample selection for the effect of the new risk designation on salience

To isolate the effect of the new risk designation on risk salience, we focus on homes that do not experience any wildfire before the time of sale. Thus, we select for this analysis properties with no fire in the five years prior to the time of sale and within 30km.[12]

To investigate the effect of the change in the risk zone (absent any wildfire), we focus on repeat sales properties near the new risk zone boundary (either inside or outside) that sold both before and after the new risk designation. (Summary statistics for the property samples used for this analysis are shown in Table A1.) Figure 2 shows the spatial distribution of two subsamples of properties in Ventura and San Diego Counties newly assigned to the risk zone and neighboring properties never on the risk zone.

[11]Properties located on national forest land are excluded from the analysis due to concerns of belonging to different markets. We further discard properties that lie on a wildfire perimeter or within a 50m buffer outside the perimeter to ensure we exclude properties potentially exposed to structural damage by the fire. Note that (at least until recently) wildfires in California were not associated with large numbers of homes destroyed. For example, between 2000 and 2015, 16,761 structures (including both residential and commercial) were lost in the state of California (California Department of Forestry and Fire Protection, 2018).

[12]Multiple wildfires ablaze in Southern California every year. Imposing a 30km cutoff ensures that no wildfire occur in nearby communities.



(a) (b)

Figure 2 Properties always off the risk zone and properties newly assigned to the risk zone. Examples in a) Ventura County and b) San Diego County.

2.2 Sample selection for the effect of the burn scar view on salience

To focus our analysis on the effect of a single wildfire event on sales one or two years post-fire, we drop properties that experience a second fire in the five years prior to the sale.

Because the human eye would have trouble distinguishing burned from unburned shrubs (the dominant vegetation type in the region) from more than a few kilometers away, we restrict the analysis to repeat sales properties for which one of the sales occurred within 4km of a burn scar.[13] Due to the fast regeneration of shrubs, we further focus our analysis on the first and second years post-fire. (Summary statistics for the property samples for this analysis are shown in Table A2, with properties depicted in Figure 3.) The closer to the burn scar perimeter, the likelier it is that a property has a burn scar view, as is illustrated by the larger number of treated properties (with view) relative to the controls (without view) in the 0-2km bin than in the 3-4km bin.

Following the methodology employed in the literature on visual (dis)amenities, e.g., wildfire (McCoy and Walsh, 2018) 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 a 10m spatial resolution) to predict how far a 5-foot tall person can see from the property in a 4km radius. We then intersect each property's 4km-radius viewshed with burn scar footprints from the prior two years. Because the Digital Elevation Model only takes into account the bare earth, considerable measurement error may be associated with our burn scar view variable. To resolve part of this imprecision, we collected Light Detection and Ranging (LiDAR) data to construct a Digital Surface Model (DSM) that captures structures on the earth such as

[13] McCoy and Walsh (2018) find that a 5km threshold is appropriate in their Colorado setting with forests and burned trees visible from farther away than shrubs.

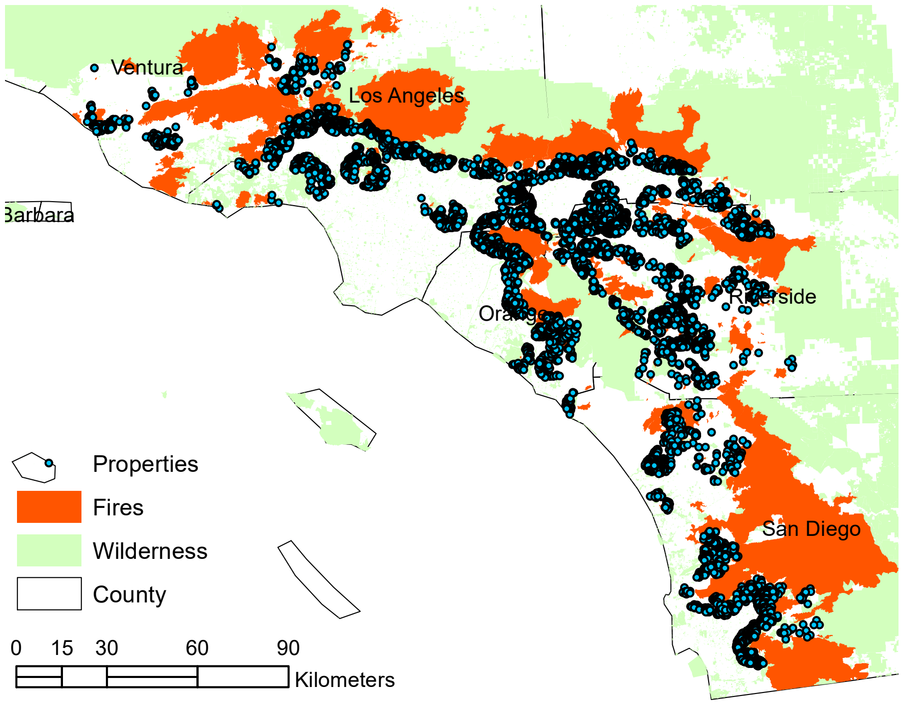


Figure 3 Wildfire perimeters between 1998 and 2015 and repeat sales properties sold within 4km of burn scar and during the first two years post-fire.

buildings and trees. One limitation of this approach is that LiDAR data are only available for three counties—San Diego, San Bernardino, and Riverside counties.[14]

Figure 4 demonstrates the distribution of properties that are treated with a view of burn scars compared to the properties without a view for four fires in our sample (top and middle panels use the standard DEM, while the bottom panels rely on the LiDAR DSM). As expected, as properties are closer to the burn scar it becomes more likely that properties also have a view of the burn scar. Homes with a view of the burn scar tend to be clustered together, which highlights the need to control for spatial variables that are correlated with the burn scar that are time invariant, such as distance to amenities, via property fixed effects.

3 Empirical strategy

We use the hedonic pricing method to value the effect of rezoning and wildfires on the changes in housing attributes (Rosen, 1974). The change in attributes that results from rezoning or a wildfire affects the comparative prices of houses with these attributes and can measure the disutility of having increased risk of a wildfire. The average treatment effect on the treated (ATT) is subject to biases if the properties that receive treatment are systematically different from those that do

[14]We are not aware of other valuation studies using finer-resolution, LiDAR data to explore the effect of measurement error in the visual amenity variable.

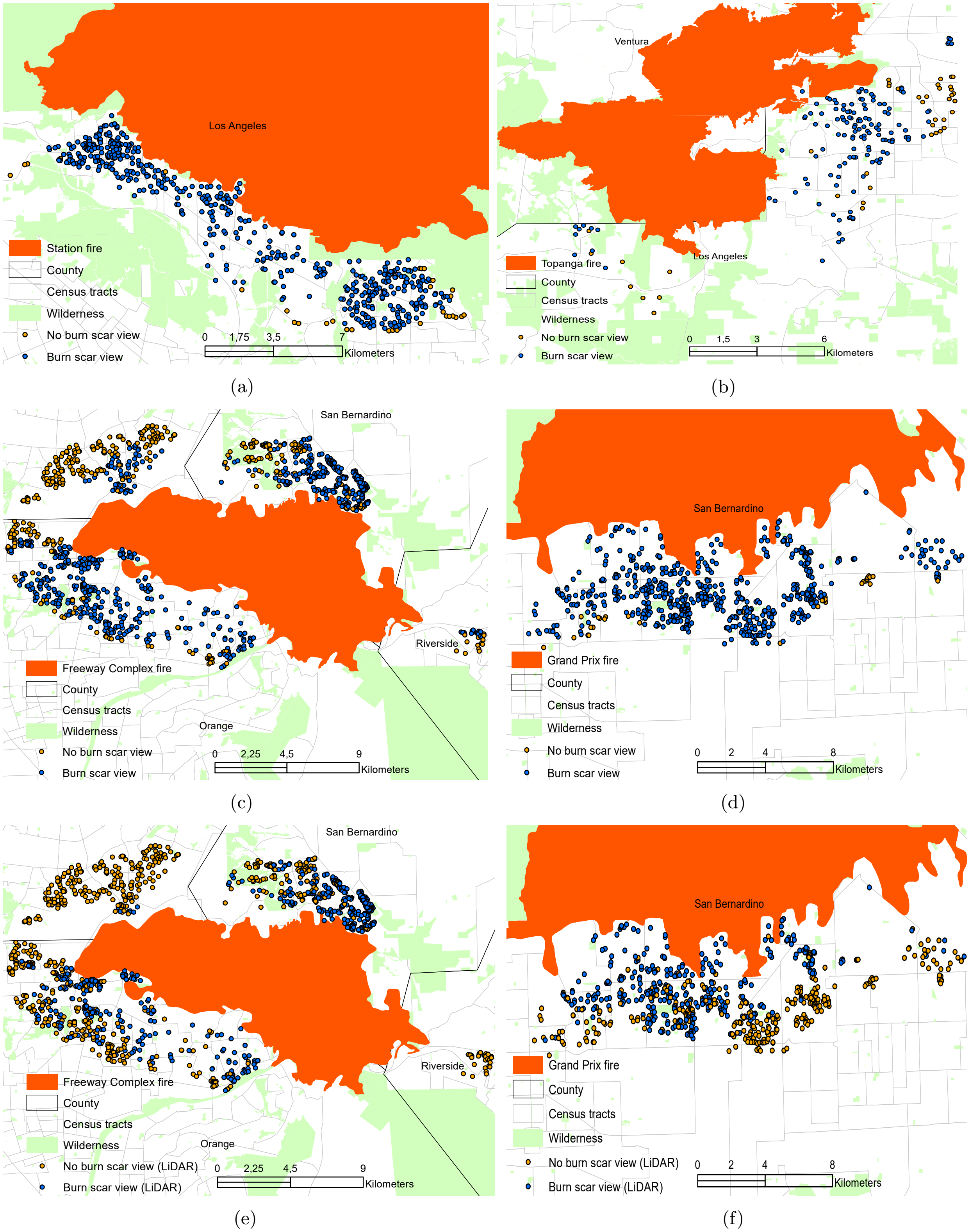


Figure 4 Properties with or without burn scar view sold within 4km and two years post-fire for: a) the 2009 Station Fire in Los Angeles County, b) the 2005 Topanga Fire in Ventura County, c) the 2008 Freeway Complex Fire in Orange County, and d) the 2003 Grand Prix Fire in Los Angeles County. LiDAR data are used to construct the viewshed for: e) the 2008 Freeway Complex Fire and f) the Grand Prix Fire.

not. For example, homes located near burn scars may experience different amenity levels, e.g., school quality or access to the wilderness. Failure to control for an unobservable that is correlated with both the treatment and home price will lead to biased estimates. The fundamental issue is that we do not observe the counterfactual for treated observations, e.g., the price of a property if that same property did not have a burn scar view. Throughout the paper, we take advantage of our large dataset to restrict the analysis to repeat sales properties and control for house and neighborhood time-invariant unobservables that may confound identification. In addition, stringent sample restrictions allow us to compare treated properties to similar, neighboring control properties to minimize concerns about varying unobservable trends. Next, the empirical strategy lays out our approach to recover unbiased ATT of the new risk zone designation or wildfire treatments on home prices.

3.1 Effect of the new risk designation on salience

We take advantage of an update in the risk zone to compare the value of properties newly assigned to the risk zone relative to their neighbors that did not experience a change in risk status.[15] We focus the analysis on the repeat sales properties that change risk zone assignment across the two sales, i.e., that become assigned to the risk zone in the most recent sale, so as to control for time-invariant unobservables that may be correlated with home prices via property fixed effect. To reduce concerns of unobservable trends varying over space, we restrict our analysis to homes in the 0m to 500m bin and 500m to 1km bin on each side of the risk zone boundary.

Our quasi-experimental design consists of a difference-in-differences approach, while controlling for changes in home prices before and after the designation with property fixed effects, as shown in regression (1).

$$\ln p_{it} = \beta \Delta RiskZone_{it} + \gamma PostRezoning_{it} + \delta \Delta RiskZone_{it} \times PostRezoning_{it} + \lambda_i + \mu_{it} + \epsilon_{it}. \quad (1)$$

In this equation the dependent variable is the natural log of property i's sale price at time t. $\Delta RiskZone_{it}$ denotes the treatment group, $PostRezoning_{it}$ is post treatment. The parameter of interest is δ. We show evidence of the common trends in pre-rezoning prices in Figure 5. λ_i are property fixed effects, and μ_{it} are spatial and temporal fixed effects and/or trends. Because our approach relies on time variation, it is critical to control for the potential heterogeneity in temporal shocks across the region. For example, macro-level housing shocks could drive price changes and confound the effect of wildfires.[16] Thus, we rely on time varying fixed effects to

[15]Because we do not know precisely when or whether the 200+ local governments adopted risk zoning for the local responsibility areas, we restrict the study to risk zones in the state responsibility area, which were updated on November 2007.

[16]We are not concerned about housing booms because housing supply is inelastic in the region due to the presence of steep-sloped terrain (Green et al., 2005; Saiz, 2010). Saiz (2010) reports MSA-level elasticities for Los Angeles-Long Beach, Riverside-San Bernardino, and San Diego are 0.63, 0.67, and 0.94, respectively.

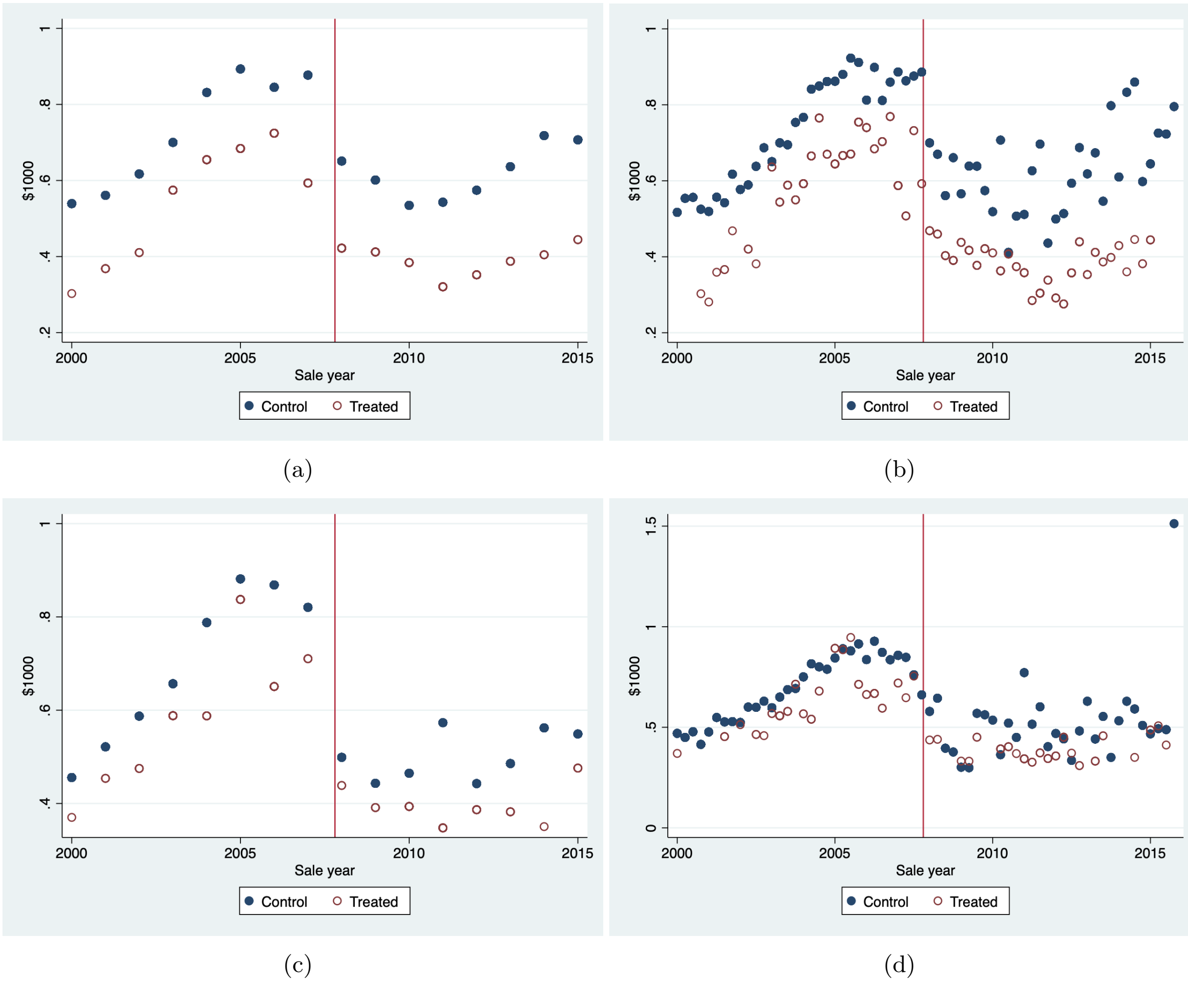


Figure 5 Visual evidence supporting the common trends assumption. The left panels show average yearly home prices, and rights panels average quarterly prices for the repeat sales properties newly assigned to the risk zone (treated group) and those that always remained outside the risk zone (control group). The top panels include properties in the 0-500m from the risk zone boundary, while the bottom panels include properties in the 500m-1km from the boundary.

control for unobservables at the local and macro level, including either year-by-quarter fixed effects combined with quadratic county trends or county-by-year-by-quarter fixed effects, which are more flexible (but also soak up more of the variation).[17]

While the risk zone designation is discontinuous, arguably, the underlying risk is continuous. Thus, conditional on changes in insurance premiums being "not too" discontinuous across the risk zone, our estimate picks up the effect of the new designation on risk salience. Relaxing that assumption, our estimate captures the combination of a differential change in insurance premiums and the salience effect.

[17]Due to the large number of census tracts, we cannot afford to control for temporal shocks that vary at the census tract level by year.

3.2 Effect of the burn scar view on salience

Second, we measure the effect of the view of a burn scar on property values. To identify the effect of burn scar views on property values, one must control for other amenity effects, e.g., proximity effects such as lost access to recreation sites, that may confound the view effect. By construction, comparing treated properties to control properties that are located in the same distance bin from the burn scar will pin down most of the proximity effects.[18] Running separate models for different distance bins from the burn scar allows us to capture the heterogeneous effect of the burn scar view over space. The thinner the bin, the more heterogeneity we allow, but the fewer the number of observations and the potentially less precise our estimates. (We test multiple bin widths and show results for the 2km-bin width in Section 4 and relegate results for the 1km-bin width to Appendix B.)

Using the repeat sales model we estimate equation (2) where careful selection of our sample of property sales determines β_j, the estimated ATT effect of burn scar view across the first and second years post-fire $j = \{1, 2\}$.

$$\ln p_{it} = \sum_j (\beta_j View_{jit} + \gamma_j View_{jit} \times Large_{jit}) + \lambda_i + \mu_{it} + \epsilon_{it}. \tag{2}$$

In this equation the dependent variable is the natural log of property i's sale price at time t. λ_i are property specific fixed effects, μ_{it} are temporal and spatial fixed effects and/or trends as in regression (1), i.e., year-by-quarter fixed effects and quadratic county trends, or county-by-year and quarter fixed effects. To investigate potential treatment heterogeneity in the burn scar view intensity, we consider the effect of large burn scar views (above 10 acres) on property values, i.e., γ_j. The hypothesis is that properties with large burn scar views may be impacted more severely than properties from which the visible burn scar is small.

Importantly, by using properties without a view of the burn scar as controls we can estimate the effect of burn scar view within the same distance bin. Conditional on the trends for prices for homes with and without a burn scar view being identical, our estimate provides an unconfounded estimate of the effect of view on the price of a property.[19] Because changes in insurance premiums should not vary systematically across homes with a burn scar view and homes without a view in the same distance bin from the wildfire, our estimate captures a combination of visual disamenities and risk salience.

[18] Despite not having insurance data, it is likely that insurance premium updating in the aftermath of a wildfire is largely determined by the proximity to the fire along with other property and neighborhood characteristics that are controlled for in our repeat sales approach.

[19] In practice, we discard a small number of properties that experience fires across the two sales so that it is straightforward to assign the property to a single distance bin within 0 and 4km.

Effect of proximity to burn scar on salience

To further test whether salience through other effects of wildfire than the view of the damages, we look at the effect of the distance to the burn scar on home prices. To this end, we focus our analysis on repeat sales properties for which one of the sales is affected by 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. Our empirical model (3) allows for heterogeneity of the proximity effect K across the first and second years post-fire $j = \{1, 2\}$, while controlling for properties that have a burn scar view $View_{jit}$.

$$\ln p_{it} = \sum_j (\beta_j K_{jit} + \gamma_j View_{jit} + \delta_j K_{jit} \times View_{jit}) + \lambda_i + \mu_{it} + \epsilon_{it}. \tag{3}$$

The parameters β_j reflect the ATT effect of proximity over time. We control for property and neighborhood time-invariant unobservables λ_i, and local and macro shocks μ_{it} through year-by-quarter fixed effects and quadratic county trends, or county-by-year and quarter fixed effects. Section 4 shows results for K ranging from 1km to 3km. As a robustness check, Appendix C depicts results running separate regressions for properties that have a burn scar view and those that do not. This selection of properties provides another way to estimate the effect of proximity to wildfire burn scars, holding constant burn scar view.

4 Results

This section presents and discusses the estimates of multiple forms of risk salience on home prices. First, we estimate the effect of the new risk zone designation. Second, we estimate the effect of burn scar view. Last, we estimate the effect of a wildfire in a different community on high-risk properties that do not experience direct disamenities from the wildfire.

4.1 Effect of the new risk designation on salience

We find evidence that the new risk zone designation significantly affects the value of homes (Table 3). Our preferred sample definitions restrict the analysis to properties as close to possible to the risk zone boundary (0-500m; columns (1) and (2)) to alleviate concerns of unobservable trends varying over space across the treated and control properties. The effect of being newly assigned to the fire risk zone reduces property values by 10.3% to 11.1% in the 0-500m bin and by 10.8% to 11.9% in the 500m-1km bin. This effect combines homeowners' updated risk perceptions and, possibly, insurance premium increases if those vary differently for homes on the new risk zone relative to nearby homes that remained just outside the risk zone. Yet, conditional on changes in insurance premiums being "not too" discontinuous across the risk zone, our estimate would mostly pick up

Table 3 Effect of new risk zoning on risk perceptions' updating

	Sample restrictions around the risk zone			
	0-500m		500m-1km	
	(1)	(2)	(3)	(4)
ΔRiskZone×PostRezoning	-0.103***	-0.111***	-0.108**	-0.119**
	(0.0301)	(0.0343)	(0.0538)	(0.0589)
Quadratic county trends	Yes		Yes	
Year×Quarter	Yes		Yes	
County×Year×Quarter		Yes		Yes
N	2992	2992	3010	3010
R^2_{adj}	0.819	0.845	0.864	0.873

Note: Each specification includes Property fixed effects. Robust clustered standard errors at the census-tract level in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table 4 Placebo test - Effect of new risk zoning on risk perceptions' updating when treatments are always on the risk zone

	Sample restrictions around the risk zone			
	0-500m		500m-1km	
	(1)	(2)	(3)	(4)
ΔRiskZone×PostRezoning	0.0139	0.0119	-0.0687	-0.0464
	(0.0416)	(0.0514)	(0.0555)	(0.0724)
Quadratic county trends	Yes		Yes	
Year×Quarter	Yes		Yes	
County×Year×Quarter		Yes		Yes
N	3792	3792	3030	3030
R^2_{adj}	0.793	0.805	0.869	0.879

Note: Each specification includes Property fixed effects. Robust clustered standard errors at the census-tract level in parentheses. * p<0.1, ** p<0.05, *** p<0.01

the effect of the new designation on risk salience (see discussion on insurance rates in Section 2). Because we are focusing on within-property variation for properties that sold once prior and once past the 2007 rezoning (including immediately and multiple years post 2007—until as late as 2015), our estimates capture the average of the short and medium term effects of the new designation, suggesting the salience effect of the designation may be persistent over time rather than temporary.

A placebo test using properties always on the risk zone as 'treatment' compared to properties always off the risk zone (control) shows no effect of the new risk zone designation (Table 4). This placebo test rules out that we are capturing a local effect affecting other homes in the area. This is important given that the rezoning coincides with the beginning of the financial crisis.

4.2 Effect of the burn scar view on salience

Table 5 suggests that having a view of a burn scar decreases home prices from 4.2% to 5.0% for properties within 2km of a burn scar in the first year post-fire.[20] The effect is in general attenuated

[20]One potential concern with our estimates of view of a burn scar is that they could include a housing market supply side effect. If wildfires destroy a large enough number of homes, thus reducing market supply and increasing housing prices, our results likely underestimate the actual demand effect. Alternatively, if wildfires lead to more households leaving the neighborhood and, thus, more homes on the market, it may dampen home prices and bias

the farther a property is from the burn perimeter, with home values reduced by 1.9% to 3.2% between 3km and 4km. The subscripts 1 and 2 on coefficients in Table 5 refer to the year post-fire for which a coefficient is reported (e.g., View_1 indicates the coefficient for a property with a burn scar view sold in the first year post-fire). We do not find evidence of heterogeneity based on the size of the burned viewshed (γ_j). In general, properties selling during the second year post-fire show no or weak burn scar view effects. In Table 5, under the specification with year-by-quarter fixed effects and county-level quadratic trends, having a burn scar view causes a decrease in property prices of 4.2% in the first 0-2km bin and 1.9% in the 3-4km bin in the first year post-fire. The second year post-fire is only statistically significant for properties in the 3-4km bin. When allowing for the more flexible county-by-year-by-quarter fixed effects, the effect of the burn scar view is slightly higher in the 0-2km bin (-5.0%) and remains more persistent in the 3-4km bin (-3.2%) in the first year post-fire. A smaller effect further persists in the second year post-fire in the 3-4km bin (-2.6%). Overall, our estimates of the negative effect of burn scar view are consistent with those found in McCoy and Walsh (2018) (-6.6%), although they only look at the effect between 2km and 5km. Another distinction is that we find that burn scar view effects are highly robust for the first year only.

To put our estimates in perspective, assume a home can be rented out annually for 2% of its purchase value. A home with a burn scar view within 2km would then lose an equivalent of 2.5 years of rent (a 5% drop in value) relative to its neighbor without a burn scar view. Because of the magnitude of the effect and its short-term nature, it is difficult to imagine that it is fully attributable to the loss of visual amenities. Our estimates thus suggest that views of natural disaster damages likely affect risk salience, although the effect is temporary (and is mostly not detectable past the first year post-fire).

The results are robust to an array of specifications and sample definitions, including omitting sales during the first quarter post-fire and changing the definition of the burn scar view above a minimum size threshold, e.g., 0.1 or 0.5 acre. In Appendix B, we further refine the widths of the distance bins to increase the accuracy with which we control for proximity to elicit the effect of burn scar view. Results in Table B1 are qualitatively similar. However, our estimates of a burn scar view may be attenuated by measurement error since the Digital Elevation Model assumes that views are not blocked by physical structures on the earth, such as buildings and trees. To identify how much this is an issue we run a separate Digital Surface Model viewshed analysis for three counties using LiDAR satellite data accounting for all physical structures on the ground; thereby assigning properties with less error to the treatment or control groups (Figure 4; bottom panels). The tradeoff is that LiDAR data are not available for all our study counties and therefore we face

upward our marginal willingness-to-pay for disamenities. However, it would seem likely that any supply side effect last for longer than one year. In addition, we do not find consistent evidence of changes in neighborhood composition (Appendix D). Therefore, we suspect that we are identifying the demand effects in this analysis and not a response to supply shocks to the housing market.

Table 5 Burn scar view estimates for the 0-2 and 3-4km bins

	0-2km bin		3-4km bin	
	(1)	(2)	(3)	(4)
View_1	-0.0419***	-0.0504***	-0.0194**	-0.0323***
	(0.0145)	(0.0131)	(0.0085)	(0.0079)
View_2	-0.0203	-0.0216	-0.0167**	-0.0259***
	(0.0145)	(0.0132)	(0.0075)	(0.0069)
$\text{View}_1 \times \text{Large}_1$	0.0066	0.0070	-0.0084	-0.0083
	(0.0184)	(0.0174)	(0.0141)	(0.0140)
$\text{View}_2 \times \text{Large}_2$	0.0023	-0.0090	0.0098	0.0043
	(0.0177)	(0.0162)	(0.0138)	(0.0124)
Quadratic county trends	Yes		Yes	
Year×Quarter	Yes		Yes	
County×Year×Quarter		Yes		Yes
N	10573	10573	24770	24770
R^2_{adj}	0.843	0.862	0.868	0.880

Note: Each specification includes Property fixed effects. Robust standard errors clustered at the census-tract level in parentheses. * p<0.1, ** p<0.05, *** p<0.01

a reduction in the sample size and reduced power for an increase in accuracy of assignment to treatment. Results in Table 6 suggest a similar burn scar view effect in the first year post-fire, ranging from -2.6% to -3.3%. These results are not statistically different than the results in Table 5 at the 10% level and suggest that our main findings are robust to the definition of burn scar view by LiDAR.

Effect of proximity to burn scar on salience

To test whether the salience of natural disaster damages mostly occur through the view (rather than proximity to the damages), we present the repeat sales estimates for properties within K-km to the burn scar relative to those further away in Table 7. We also interact the proximity measure with the binary indicator for a view of the burn scar. We find insignificance of proximity to a burn scar when controlling for view of a burn scar, suggesting that salience and risk updating comes through the visual reminder of risk rather than proximity. The subscripts 1 and 2 on coefficients in Table 7 refer to the year post-fire for which a coefficient is reported (e.g., K_1 indicates the coefficient for properties within K-km of the burn scar sold in the first year post-fire). Table 7 (all columns) shows no effect of proximity with estimates that are both statistically and economically insignificant. Though the results show a robust price decrease of 2.4% to 3.8% for properties with a burn scar view and within 3km that sold during the first year after a fire. These results also attenuate some in the second year post-fire with price decreases of 1.2% to 3.0%. These results qualitatively support our previous burn scar view results and proximity to a burn scar is robustly not significant.

Table 6 Burn scar view estimates for the 0-2 and 3-4km bins using LiDAR data

	0-2km bin		3-4km bin	
	(1)	(2)	(3)	(4)
View_1	-0.0263*	-0.0325**	-0.0267**	-0.0269**
	(0.0152)	(0.0139)	(0.0123)	(0.0117)
View_2	-0.0043	0.0100	-0.0222**	-0.0181*
	(0.0169)	(0.0146)	(0.0108)	(0.0109)
$\text{View}_1 \times \text{Large}_1$	-0.0062	0.0018	-0.0106	-0.0097
	(0.0206)	(0.0163)	(0.0196)	(0.0189)
$\text{View}_2 \times \text{Large}_2$	-0.0039	-0.0117	-0.0103	-0.0063
	(0.0172)	(0.0145)	(0.0188)	(0.0180)
Quadratic county trends	Yes		Yes	
Year×Quarter	Yes		Yes	
County×Year×Quarter		Yes		Yes
N	5658	5658	9248	9248
R^2_{adj}	0.882	0.896	0.873	0.884

Note: Each specification includes Property fixed effects. Robust clustered standard errors at the census-tract level in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table 7 Proximity effect estimates within threshold K-km of the burn scar

	$K = 1$		$K = 2$		$K = 3$	
	(1)	(2)	(3)	(4)	(5)	(6)
K_1	-0.0019	-0.0118	-0.0029	-0.0042	0.0110	0.0112
	(0.0190)	(0.0187)	(0.0125)	(0.0114)	(0.0108)	(0.0091)
K_2	0.0091	0.0173	0.0142	0.0137	0.0101	0.0110
	(0.0247)	(0.0246)	(0.0129)	(0.0118)	(0.0098)	(0.0088)
View_1	-0.0238***	-0.0359***	-0.0235***	-0.0361***	-0.0298***	-0.0382***
	(0.0071)	(0.0066)	(0.0076)	(0.0072)	(0.0091)	(0.0087)
View_2	-0.0127*	-0.0262***	-0.0171**	-0.0302***	-0.0158*	-0.0300***
	(0.0067)	(0.0063)	(0.0071)	(0.0066)	(0.0091)	(0.0085)
$\text{K}_1 \times \text{View}_1$	0.0072	0.0090	0.0059	0.0044	0.0030	-0.0040
	(0.0239)	(0.0236)	(0.0168)	(0.0159)	(0.0151)	(0.0137)
$\text{K}_2 \times \text{View}_2$	-0.0003	-0.0076	0.0025	0.0028	0.0005	0.0015
	(0.0260)	(0.0253)	(0.0158)	(0.0142)	(0.0129)	(0.0120)
Quadr county trends	Yes		Yes		Yes	
Year×Quarter	Yes		Yes		Yes	
County×Year, Quarter		Yes		Yes		Yes
N	35343	35343	35343	35343	35343	35343
R^2_{adj}	0.859	0.859	0.860	0.859	0.860	0.859

Note: Each specification includes Property fixed effects. Robust clustered standard errors at the census-tract level in parentheses. * p<0.1, ** p<0.05, *** p<0.01

4.3 Neighborhood composition

A potential concern with identifying the value of disamenities using temporal variation in prices, as we do with repeat sales, is the instability of the hedonic price function (Kuminoff and Pope, 2014). For example, if neighborhoods change in response to fire events, our disamenity estimate would simply capture a capitalization effect rather than the marginal willingness-to-pay, or change in surplus, associated with a change in environmental quality. However, since wildfires appear to happen randomly over space and time across the wildland-urban interface surrounding the LA and San Diego basins, we do not expect risk zone changes or a single wildfire event to result in large neighborhood changes. One way in which we may identify more systemically such shifts in the equilibrium of the hedonic price function is through inspection of the demographics of the buyers over time in our study area. Following Bayer et al. (2016), we use data from the Home Mortgage Disclosure Act (HMDA) to capture the buyers mortgage application information. The HMDA data provide income, gender, race, and ethnicity of the applicant, as well as the loan amount and year, lender name, and census tract of the property. In Appendix D, we use these data to test whether the distributions of income, race, and ethnicity change after risk rezoning and wildfire events. Overall, we do not find evidence that neighborhood composition is affected by changes in risk zone assignment, view of burn scar, proximity to burn scar, or wildfire events.

5 Conclusions

This paper provides evidence suggesting that households' risk perceptions respond to risk salience. To show that, we use Southern Californian real estate as a laboratory. Our main measure of risk salience, a wildfire risk zone designation, indicates that the effect of salience can persist over time. This is in contrast with our second measure of salience—the view of natural disaster damages. Our estimate is only strongly significant during the first year post-disaster, suggesting households' memory of the disaster fades away quickly. Proximity to natural disaster damages do not appear to affect salience once we control for views of damages, suggesting views are the main mechanism through which exposure to natural disaster damages occur. Hence, evidence suggests that different types of cues trigger differentially strong and long-lasting risk salience effects.

Evidence of salience effects may imply that households' risk perceptions are biased as they focus their attention (momentarily or persistently) on some risks but not others (Bordalo et al., 2012). It may be because they lack accurate information about risk, which would call for private and/or government interventions such as information campaign and/or regulations. However, it may also be because of inattention or bounded rationality, calling for less but better designed and targeted information. Understanding the effect of salience therefore matters because it could explain why households make inadequate investment decisions and locate in disaster-prone areas as documented in Bakkensen and Barrage (2017).

Lastly, risk zone designation treatment is of direct relevance to policy-makers since risk zoning is a common management tool to inform local residents of underlying natural disaster risks.

Our study is subject to several caveats. Our risk zone designation measure may include differential insurance premium updates than homes just on the other side of the new risk zone. As such, our first set of estimates may confound the effect of salience with that of insurance premium updates. Having access to individual home insurance policies over time would allow to tease out the salience effect from the insurance premium updates. Similarly, our second measure of salience, likely confounds salience and visual disamenities. Survey data could shed light on the relative importance of salience versus visual disamenities. Yet, because the concerns differ across our two settings, taken together the two sets of results make it likely that there is a salience effect.

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A Additional figure and summary statistics

Table A1 Summary characteristics of the repeat sales properties that sold post updating of the risk zone map for different distance bins from the risk zone boundary (properties are referred to "newly on" or "always off" the risk zone)

	0-500m				500m-1km			
	Newly on		Always off		Newly on		Always off	
	Means (sd)		Means (sd)		Means (sd)		Means (sd)	
Sale price (k$2015)	510.58	(201.34)	782.88	(326.65)	388.46	(92.99)	720.16	(297.64)
Age	24.51	(14.39)	21.19	(14.99)	17.64	(8.57)	24.79	(18.83)
Living area (k sqft)	2.10	(0.51)	2.28	(0.79)	2.35	(0.50)	2.08	(0.75)
# bedrooms	3.39	(0.66)	3.57	(0.76)	3.58	(0.57)	3.52	(0.75)
# bathrooms	2.43	(0.67)	2.86	(0.81)	2.69	(0.63)	2.65	(0.80)
Swimming pool (0/1)	0.22	(0.41)	0.24	(0.43)	0.20	(0.40)	0.21	(0.41)
Dist. green space (km)	0.78	(0.41)	0.51	(0.45)	0.71	(0.60)	0.42	(0.35)
Elevation (m)	446.41	(60.98)	229.72	(106.59)	495.64	(65.20)	203.32	(88.30)
Slope	5.16	(3.32)	5.54	(4.35)	5.56	(2.87)	3.97	(3.67)
FHSZ (0/1)	0.50	(0.50)	0.00	(0.00)	1.00	(0.00)	0.00	(0.00)
WUI (0/1)	1.00	(0.00)	0.99	(0.12)	1.00	(0.00)	0.82	(0.39)
Dist. main road (km)	3.75	(1.51)	1.76	(1.34)	3.94	(2.10)	1.28	(1.08)
Median hh. income (k$)	96.36	(13.30)	97.36	(26.59)	94.04	(12.16)	89.43	(28.03)
% white	93.85	(3.34)	78.60	(15.83)	94.65	(3.76)	77.08	(13.78)
% hispanic	11.02	(5.07)	18.99	(13.57)	12.51	(6.13)	25.17	(18.15)
Years between sales	5.93	(1.99)	3.50	(1.90)	7.38	(1.79)	3.23	(1.75)
# of unique properties	306		1266		55		3868	

Table A2 Summary characteristics of the repeat sales properties that sold during the first two years post-fire for different distance bins from the burn scar

	0-2km distance bin				2-4km distance bin			
	No view		Burn scar view		No view		Burn scar view	
	Means (sd)		Means (sd)		Means (sd)		Means (sd)	
Sale price (k$2015)	504.88	(278.67)	515.54	(278.96)	457.71	(263.23)	433.70	(228.00)
Age	26.20	(20.61)	27.79	(21.81)	25.08	(20.28)	29.32	(23.19)
Living area (k sqft)	2.17	(0.86)	2.01	(0.77)	2.15	(0.80)	1.95	(0.72)
# bedrooms	3.55	(0.84)	3.45	(0.79)	3.55	(0.81)	3.42	(0.80)
# bathrooms	2.70	(0.86)	2.59	(0.81)	2.67	(0.78)	2.47	(0.77)
Swimming pool (0/1)	0.25	(0.43)	0.19	(0.39)	0.21	(0.41)	0.18	(0.38)
Dist. green space (km)	0.54	(0.50)	0.47	(0.44)	0.60	(0.60)	0.56	(0.51)
Elevation (m)	258.79	(167.40)	274.60	(174.72)	288.60	(160.83)	307.59	(186.96)
Slope	5.88	(5.79)	3.51	(3.90)	4.05	(4.59)	2.36	(3.11)
FHSZ (0/1)	0.23	(0.42)	0.17	(0.37)	0.16	(0.37)	0.05	(0.21)
WUI (0/1)	0.81	(0.39)	0.80	(0.40)	0.72	(0.45)	0.51	(0.50)
Dist. main road (km)	1.76	(1.17)	1.38	(1.19)	1.50	(1.28)	1.27	(1.06)
Dist. burn scar (km)	1.36	(0.46)	1.12	(0.56)	3.28	(0.54)	2.97	(0.55)
Days since fire	421.31	(199.00)	424.96	(205.77)	444.52	(203.55)	436.93	(208.58)
Median hh. income (k$)	85.59	(28.84)	84.36	(25.30)	83.43	(25.69)	76.30	(24.20)
% white	72.66	(14.39)	68.45	(13.56)	69.09	(15.40)	68.14	(13.69)
% hispanic	31.30	(18.47)	32.68	(22.27)	31.65	(17.78)	36.81	(21.12)
Years between sales	4.86	(2.16)	4.86	(2.13)	4.82	(2.21)	4.79	(2.17)
# of unique properties	1087		4199		6117		6261	
# of census tracts	184		442		705		702	
# of fires	80		107		157		129	

B Additional burn scar view results

Table B1 Burn scar view estimates for each 1km bin

	0-1km bin		1-2km bin		2-3km bin		3-4km bin	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$View_1$	-0.0313	-0.0501**	-0.0522***	-0.0634***	-0.0280**	-0.0484***	-0.0197**	-0.0316***
	(0.0245)	(0.0216)	(0.0159)	(0.0159)	(0.0131)	(0.0137)	(0.0097)	(0.0095)
$View_2$	-0.0092	-0.0151	-0.0286*	-0.0289*	-0.0334***	-0.0454***	-0.0105	-0.0265***
	(0.0225)	(0.0203)	(0.0165)	(0.0165)	(0.0111)	(0.0106)	(0.0097)	(0.0094)
$View_1 \times Large_1$	0.0027	0.0164	0.0125	0.0123	0.0021	0.0056	-0.0443**	-0.0349*
	(0.0262)	(0.0237)	(0.0212)	(0.0218)	(0.0177)	(0.0190)	(0.0202)	(0.0205)
$View_2 \times Large_2$	0.0049	-0.0111	0.0043	-0.0059	0.0142	0.0102	0.00450	0.0091
	(0.0268)	(0.0206)	(0.0194)	(0.0195)	(0.0170)	(0.0156)	(0.0176)	(0.0184)
Qd cty tr	Yes		Yes		Yes		Yes	
Year×Qtr	Yes		Yes		Yes		Yes	
Cty×Yr, Qtr		Yes		Yes		Yes		Yes
N	4048	4048	6525	6525	9928	9928	14842	14842
R^2_{adj}	0.857	0.868	0.839	0.843	0.859	0.858	0.875	0.871

Note: Each specification includes Property fixed effects. Robust standard errors clustered at the census-tract level in parentheses. * p<0.1, ** p<0.05, *** p<0.01

C Additional proximity effect results

Table C1 Proximity effect estimates within threshold K-km of the burn scar and *without* a view

	$K=1$		$K=2$		$K=3$	
	(1)	(2)	(3)	(4)	(5)	(6)
K_1	-0.000266	-0.0122	0.000969	-0.00623	0.0155	0.00645
	(0.0198)	(0.0199)	(0.0120)	(0.0104)	(0.0101)	(0.00841)
K_2	0.00389	-0.00291	0.0136	0.0134	0.00948	0.00995
	(0.0238)	(0.0183)	(0.0126)	(0.0106)	(0.00950)	(0.00767)
Quadr county trends	Yes		Yes		Yes	
Year×Qtr	Yes		Yes		Yes	
County×Year×Qtr		Yes		Yes		Yes
N	14413	14413	14413	14413	14413	14413
R^2_{adj}	0.859	0.877	0.859	0.877	0.859	0.877

Note: Each specification includes Property fixed effects. Robust clustered standard errors at the census-tract level in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table C2 Proximity effect estimates within threshold K-km of the burn scar for properties *with* a view

	$K=1$		$K=2$		$K=3$	
	(1)	(2)	(3)	(4)	(5)	(6)
K_1	-0.00241	-0.00420	-0.00398	-0.00524	-0.00439	-0.0113
	(0.0153)	(0.0141)	(0.0105)	(0.00961)	(0.00871)	(0.00828)
K_2	0.0105	0.00756	0.0162	0.0156	0.00588	0.00481
	(0.0151)	(0.0133)	(0.0100)	(0.00961)	(0.00836)	(0.00839)
Quadr county trends	Yes		Yes		Yes	
Year×Qtr	Yes		Yes		Yes	
County×Year×Qtr		Yes		Yes		Yes
N	14413	14413	14413	14413	14413	14413
R^2_{adj}	0.859	0.877	0.859	0.877	0.859	0.877

Note: Each specification includes Property fixed effects. Robust clustered standard errors at the census-tract level in parentheses. * p<0.1, ** p<0.05, *** p<0.01

D Composition of buyers in the market

Using data from the Home Mortgage Disclosure Act (HMDA), we test whether the distributions of income, race, and ethnicity change after a wildfire. We adopt a difference-in-differences framework for sales within two years pre- and post-fire to identify if treated properties are experiencing shifting demographics at the neighborhood level relative to control properties.[21]

For the effect on the 2007 rezoning on risk perceptions, we start with the properties whose sale was not affected by wildfires and within 750m of the risk zone boundary. After cleaning the data, matching as above and dropping duplicates, we obtain a 50.2% matching success rate. Table D1 shows no evidence of changes in neighborhood composition before and after the rezoning. [22]

Table D1 Composition of buyers inside and outside the risk zone after the 2007 rezoning

	Within 250m		Within 500m		Within 750m	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Income						
Risk zone×PostRezoning	-26.81	-1.664	-26.80	-17.96	-15.52	-10.90
	(37.06)	(41.08)	(33.91)	(29.95)	(31.56)	(28.31)
N	3919	3919	5865	5865	7309	7309
R^2_{adj}	0.0249	0.0506	0.0264	0.0489	0.0316	0.0425
Panel B: White						
Risk zone×PostRezoning	0.0252	0.0501	0.0215	-0.0299	0.0256	-0.00828
	(0.0654)	(0.0842)	(0.0523)	(0.0664)	(0.0502)	(0.0609)
N	3919	3919	5865	5865	7309	7309
R^2_{adj}	0.00346	0.00524	0.00385	0.00230	0.00489	0.00519
Panel C: Hispanic						
Risk zone×PostRezoning	-0.0547	-0.0284	-0.0194	-0.0592	-0.0165	-0.0463
	(0.0696)	(0.0627)	(0.0514)	(0.0481)	(0.0540)	(0.0492)
N	3919	3919	5865	5865	7309	7309
R^2_{adj}	0.00760	0.0165	0.0113	0.0230	0.0134	0.0210
Quadr county trends	Yes		Yes		Yes	
Year×Qtr	Yes		Yes		Yes	
County×Year×Qtr		Yes		Yes		Yes

Note: Each specification includes Census tract fixed effects. Robust standard errors clustered at census tract level. * p<0.1, ** p<0.05, *** p<0.01.

For the burn scar view and proximity treatments, we start with the properties that sold within two years pre- and post-fire within 4km of a burn scar (119,815 observations). We drop observations with no mortgage year, no loan amount, no lendername, or indications that the lender was a private lender (108,932 remaining observations). Matching on mortgage year, lender name, loan amount and type, county, and census tract, leads to 64,230 matches. Keeping properties with unique matches, we end up with 57,699 properties, or a 53% matching success rate.[23] Table D2 shows that the distributions of income, race, and ethnicity do not significantly change across properties with or without a view of the burn scar during the first two years after a wildfire. Overall, results for the proximity to a burn scar, presented in Table D3, show little effect of wildfire proximity on demographics, with the exception of small decreases in white (-2.5% to -2.6%) and hispanic (-1.7% to -1.9%) within 2km. Yet, these results are only significant for the within 2km threshold

[21] In all cases, results are qualitatively similar for analyses run separately for the first or second year post-fire.

[22] The results are robust to restricting the analysis to 1, 2, 3, or 4 year(s) around the 2007 rezoning.

[23] Our HMDA-CoreLogic matching success rate compares favorably with those of Bayer et al. (2016) and Haninger et al. (2017).

Table D2 Composition of buyers in the burn scar view and no-view markets

	0-2km bin		3-4km bin	
	(1)	(2)	(3)	(4)
Panel A: Income				
View×PostFire	-2.975	-2.576	0.235	0.742
	(3.723)	(3.629)	(1.565)	(1.620)
N	19093	19093	38596	38596
R^2_{adj}	0.0306	0.0298	0.0356	0.0381
Panel B: White				
View×PostFire	0.0166	0.0155	0.0205*	0.0172
	(0.0184)	(0.0192)	(0.0106)	(0.0107)
N	19097	19097	38602	38602
R^2_{adj}	0.00713	0.00973	0.0188	0.0200
Panel C: Hispanic				
View×PostFire	0.00548	-0.000777	0.00838	0.00461
	(0.0136)	(0.0138)	(0.00923)	(0.00925)
N	19097	19097	38602	38602
R^2_{adj}	0.0342	0.0394	0.0513	0.0534
Quadr county trends	Yes		Yes	
Year×Qtr	Yes		Yes	
County×Year×Qtr		Yes		Yes

Note: Each specification includes Census tract fixed effects. Robust standard errors clustered at census tract level. * p<0.1, ** p<0.05, *** p<0.01.

and not for the within 1km and 3km thresholds, raising questions about their robustness. Taken together, Tables D2 and D3 provide evidence that our repeat sales model may not be subject to significant shifts in the equilibrium hedonic price function due to sorting and changes in preferences as detectable through demographics. Thus, we can have greater confidence in the point estimates reported in Tables 5 and 7 representing willingness to pay.

Table D3 Composition of buyers near and away from the burn scar

	$K=1$		$K=2$		$K=3$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Income						
$K\times$PostFire	1.444	0.961	2.723*	2.278	3.658**	3.325**
	(2.421)	(2.317)	(1.551)	(1.555)	(1.523)	(1.547)
N	57689	57689	57689	57689	57689	57689
R^2_{adj}	0.0363	0.0374	0.0361	0.0372	0.0362	0.0373
Panel B: White						
$K\times$PostFire	-0.0233*	-0.0181	-0.0259***	-0.0250***	-0.0133	-0.0148*
	(0.0126)	(0.0121)	(0.00904)	(0.00897)	(0.00871)	(0.00869)
N	57699	57699	57699	57699	57699	57699
R^2_{adj}	0.0153	0.0169	0.0154	0.0170	0.0153	0.0169
Panel C: Hispanic						
$K\times$PostFire	-0.0186*	-0.0138	-0.0187**	-0.0174**	0.00112	0.00168
	(0.00995)	(0.0100)	(0.00740)	(0.00752)	(0.00733)	(0.00732)
N	57699	57699	57699	57699	57699	57699
R^2_{adj}	0.0494	0.0523	0.0494	0.0524	0.0494	0.0524
Quadr county trends	Yes		Yes		Yes	
Year$\times$Qtr	Yes		Yes		Yes	
County$\times$Year$\times$Qtr		Yes		Yes		Yes

Note: Each specification includes Census tract fixed effects. Robust standard errors clustered at census tract level. * p<0.1, ** p<0.05, *** p<0.01.