The Effect of Salience on Risk Perceptions and Asset Prices

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Abstract

The paper investigates how different forms of salience affect homeowners' natural-disaster risk perceptions. Using a unique repeat-sales dataset of real estate transactions in Southern California, we find that prices of homes newly assigned to a wildfire risk zone drop by 10.5% to 11.2% relative to homes just outside the new designation. While the risk zone assignment is discontinuous, the underlying risk is arguably continuous, suggesting the new designation triggers greater risk salience rather than greater risk. We then investigate the effect of a different form of salience, namely how visual cues of natural-disaster damages affect home prices. We find that prices of homes with a view of wildfire 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-fire, and is therefore unlikely to be fully attributable to the visual disamenities, which recover progressively.

JEL codes: D83, Q54, Q58, R31, R52
Keywords: salience, risk perceptions, natural disasters, hedonic pricing model, repeat sales

1 Introduction

Understanding which factors drive households' risk perceptions is a fundamental economic question. Early insights from psychology suggest that the salience of risk could play a critical role (Tversky and Kahneman, 1974).[1] Economists have developed theoretical models that propose multiple mechanisms through which salience may affect choices (Chetty et al., 2009; Bordalo et al., 2013; Gabaix, 2014). 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 capture many deviations from

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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). Moreover, recent findings from neuroscience and social psychology highlight the role of anticipatory emotions and factors such as vividness, immediacy, and background mood, in the decision process (Loewenstein et al., 2001). This emerging hypothesis of risk-as-feelings proposes that feelings, in conjunction with cognitive evaluation, drive behavior.

expected utility theory, including frequent risk-seeking behavior and preference reversals. A question that has remained open is whether salience affects household decision-making in quantitatively important ways.

This paper shows that risk salience may affect important households' decisions for their largest financial asset. Indeed, for many households buying a home represents their most important financial decision. To examine the effect of risk salience on households' home purchasing decisions, we focus on the effect of environmental risk salience on real estate prices.[2] Specifically, we assemble a unique dataset of real estate sales transactions for over 2 million homes that spans seven Southern California counties over 16 years. We use quasi-experimental methods to examine which forms of risk salience trigger a behavioral response.

First, the paper investigates the effect of a new risk zone designation implemented in 2007. We find that prices of homes newly assigned to the risk zone drop by 10.5% to 11.2% relative to homes just outside the new designation, controlling for property fixed effects. While the new risk designation is discontinuous, arguably, the underlying risk is continuous. Therefore, the estimates likely reflect the effect of risk salience on home prices. This interpretation relies on the assumption that changes in insurance premiums are "not too" discontinuous across the risk zone. This assumption is supported by the fine-resolution and sophisticated models of risk forecasting used by insurance companies, enabling them to tailor premiums based on home-level and neighborhood characteristics, and private defensive actions.[3] Furthermore, a placebo test in which the 'treatment' group consists of homes in the risk zone both before and after the new designation shows no effect. Since the treatment occurs just before the 2008-2009 housing crisis, the placebo test reduces the likelihood of a false positive due to macroeconomic factors.

Second, the paper investigates the effect of a different form of salience on home prices, namely the effect of visual cues of burn scars. To this end, we construct 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 the same distance from the burn scar but with no view, controlling for property fixed effects. Changes in risk and insurance premiums are unlikely to vary systematically across homes with or without a burn scar view (and in the same distance bin from the wildfire). The estimates thus capture a combination of risk salience and visual disamenities. We elicit their relative importance by allowing for the visual disamenity to recover over time and for large visible burn scars to differentially affect home prices. 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

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

[3]In addition, the California Department of Insurance and insurance companies signed a memorandum of understanding that rates would not be affected after the implementation of the new risk designation. Furthermore, the new risk designation does not appear to influence lending practices (see further discussion in Section 3.1).

year post-fire and there is no differential effect across large or small visible burn scars. Because of the magnitude of the effect, its short-term nature, and the absence of a differential effect for large visible burn scars, the estimates are unlikely to be fully attributable to the loss of visual amenities. It suggests that risk salience generated by the visual cues of recent natural disaster damages affects home prices.

Using the terminology from Loewenstein et al. (2001), the two mechanisms that can explain the forms of salience underlying our findings are the "insensitivity to probability variations" with households not correctly processing the risk gradient in the case of the new risk designation treatment, and the "vividness" of risk that the visual cues of a recent burn scar may trigger, with households experiencing a visceral, gut feeling of dread when looking at the burn scar with charred vegetation and barren ground in the case of the second treatment.[4]

Our findings have important policy implications because risk salience can bias homeowners' risk perceptions and investments. This matters in its own right given the over $4 trillion asset value of the Southern California real estate market.[5] Salience could bias risk perceptions and aggregate housing market outcomes and influence the location of housing development. In addition, understanding the effect of salience on risk perceptions, e.g., through policy regulation, can help policy-makers understand households' financial decision-making in general. Better conveying risk to homeowners in disaster-prone areas, through policy regulation in particular, 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; Westerling et al., 2006).[6] For example, the 2018 Camp Fire now holds the record for the most destructive fire in California's history with over 15,000 structures lost and estimated total losses of $11 to $13 billion.[7] Indeed, large wildfires in the western United States have increased by around 500% over the last 30-40 years, with climate change being one of the drivers.[8] In addition, the wildland-urban interface has been developing rapidly, with an estimated 46 million homes and $9.2 trillion in property value currently at risk in the United States (International Association of Wildland Fire, 2013; Radeloff et al., 2018).[9]

This paper makes several contributions to the literature. First, it contributes to the literature on choice theory. Empirical studies find that the salience of prices affects behavior in a variety

[4] For example, in the context of insensitivity to probability variations, some households may rely on a threshold model such that if the perceived probability of a disaster (p) is less than a threshold level (p^*), they may choose not to worry about the consequences of such disaster, e.g., due to a limited amount of time or capacity available to worry about small probability events (Kunreuther, 1996).

[5] The size of the Southern California housing market is calculated using the median home price of $536,000 in June 2018 and the number of households from the American Community Survey 2013-2017 Census estimates.

[6] 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).

[7] www.businessinsurance.com

[8] Resources Radio Podcast broadcast on Dec. 4th, 2018 with Dr. Wibbenmeyer from Resources for the Future.

[9] The property value at risk is calculated using the 2017 Zillow Home Value Index for the median American home of $200,000.

of settings, such as excise and sales tax for beer, toll fees when transponders are prevalent, and automated electricity bill payments (Chetty et al., 2009; Finkelstein, 2009; Sexton, 2015) — see DellaVigna (2009) for a review. We complement this literature both by demonstrating that salience may also affect households' risk perceptions and by showing that salience effects may be present even when making major financial decisions.[10] Second, our analysis of salience on households' risk perceptions complements a behavioral finance literature that shows how recency of experience affects risk-taking behavior (Malmendier and Nagel, 2011; Balasubramaniam, 2018).[11] Third, the paper relates to the environmental economics literature analyzing the effect of natural disasters on homeowners' risk perceptions as capitalized into housing prices. Our paper uniquely examines the effect of a policy regulation on households' risk perceptions.[12] The second treatment presented in the study, i.e., the effect of visual cues from wildfire damages, builds on recent studies examining the risk salience effect of exposure to damages from natural disasters (McCoy and Walsh, 2018; McCoy and Zhao, 2018). One concern in this literature is that the change in salience is correlated with the change in amenity values. Our first treatment suffers from having insurance as a potential confounder, and the second suffers from having disamenities as a confounder. But taken together, our two treatments are less likely to systematically suffer from these confounders at the same time, which strengthens the salience interpretation we offer. Last, our paper complements the quasi-experimental literature that exploits real estate prices to estimate households' time preferences (Giglio et al., 2014), preferences for school quality (Black, 1999), and preferences for environmental risk (Davis, 2004; Chay and Greenstone, 2005; Greenstone and Gallagher, 2008; Muehlenbachs et al., 2015). Our identification strategy combining difference-in-differences with property fixed effects and stringent spatial sample definitions allows us to control for an array of 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.

[10]Our study is not able to distinguish between theories of bounded rationality versus decision weights associated with salient payoffs. In the context of less than fully attentive households, salience may help draw attention to prices that were previously not salient and incude optimal decisions (Chetty et al., 2009; Gabaix, 2014). In contrast, under the decision-weight theory, salient payoffs lead to distortions of decision weights such that households overweight the upside of a risky choice when it is salient (risk-seeking behavior), and overweight the downside when it is salient (risk-averse behavior) (Bordalo et al., 2012).

[11]Our paper also complements survey evidence on households' real estate price expectations (Kuchler and Zafar, 2018). In the context of firms, Dessaint and Matray (2017) find empirical evidence that managers overreact to recent hurricanes by holding excessive cash — despite the risk distribution remaining unchanged.

[12]A concurrent study examines the joint effects of Hurricane Sandy and flood maps updates on home prices in New York City (Gibson et al., 2018). Their study differs in that the effect of the multiple rounds of flood map updates cannot be disentangled from that of Sandy.

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 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.[13] 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 are also dropped to eliminate potential house flippers (1,070,639 remaining observations).[14] 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%. Of the remaining 1,011,006 properties, 444,180 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% (431,000 remaining repeat-sales properties).

Risk zones and insurance data

The California Fire Resource and Assessment Program (FRAP; frap.fire.ca.gov) provides spatial data on wildfires and the wildland-urban interface (WUI). The CAL FIRE agency produces maps of significant fire hazard, called Fire Hazard Severity Zones (FHSZ), which we will refer to as "risk zones" hereinafter. These maps are created using an ember diffusion model developed at the University of California Berkeley Center for Fire Research and Outreach. The model takes into account the physical attributes of the area, including vegetation type, topography, local climate and wind directions to predict expected burn probabilities. The maps focus on hazards and do not account for private risk mitigating actions on a given property, e.g., building materials or defensible space. As a result, homeowners do not have the ability to influence their assignment to the risk zone. Risk zones are managed by the state (state responsibility area) or local governments (local responsibility area).[15] By law, sellers have to disclose the property's risk zone status to the buyer at

[13]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.

[14]We discard house that are flipped because they are often renovated before going back on the market.

[15]Local responsibility areas generally include cities and cultivated agriculture lands. Local responsibility area fire protection is typically provided by city fire departments, fire protection districts or counties. State responsibility area is a legal term defining the area where the state has financial responsibility for wildfire protection.

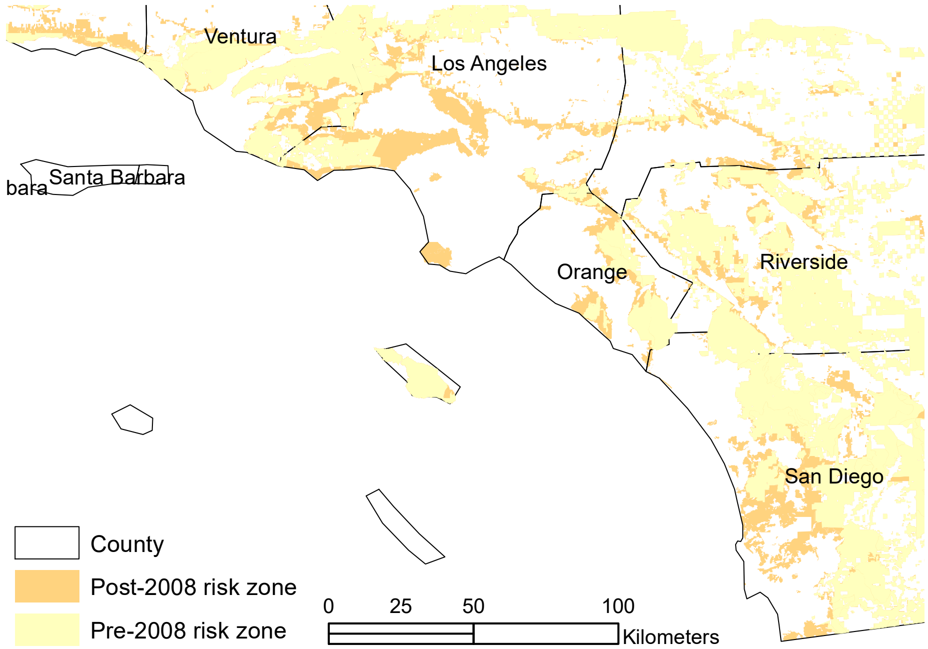


Figure 1 California wildfire risk zone designation, including the new risk designation adopted in November 2007.

the time of sale. While early maps for the state responsibility area were in place prior to 2000, a new risk designation (relying on updated data and models and, in general, expanding the risk zone) was adopted throughout California in November 2007 under Title 14 ordinance. One implication and impetus of the new designation is that new construction must comply with stricter building codes which are deemed safer by law (California building code 7a). In addition, following the 1992 Bates bill 337, CAL FIRE worked with 117 local governments in the six counties in our study area to develop fire hazard zones in local responsibility areas. After a public review and comment process, such maps were recommended for adoption starting in November 2008 for San Bernardino until as late as May 2012 for Los Angeles county. Yet, because CAL FIRE has no regulatory authority to enforce risk designation adoption in local responsibility areas, some local governments may never have adopted such designations. Because we do not know which local responsibility areas adopted the new maps (and if so when) and because of the potential endogeneity of such decisions, we discard sales in 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 discontinuously across the new risk designation. Because fire damages are covered as part of regular home insurance policies, answering this question would require access to individual homeowners' insurance policies, which we do not have. Indeed, home insurance policies are customized to each property based on a number of factors, including hazard rate and homeowners' risk mitigating actions. Because natural disaster risk represents a major part of insurance companies' business, in particular in California, insurance companies rely on sophisticated models taking into account hundreds of factors and spatial layers to estimate fire risk at a high-level of spatial resolution.[16] For example, a story in the Orange County Registar (March 5, 2012) by Mark Bouchy documents that an insurance agent that provides information to insurance underwriters does not use these hazard maps despite being publicly available. Furthermore, to reassure homeowners that the new risk designation would not bring about increases in insurance premium, the California Department of Insurance, CAL FIRE, and the insurance industry signed a Memorandum of Understanding on October 2007 (fire.ca.gov; insurance.ca.gov).

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 risk perceptions. As a result, the analysis includes 251 fires between 1998 and 2015. Burn scars range from 51 to 270,686 acres (with median and mean sizes of 695 and 5,634 acres, respectively; Table 1). The study includes some of the largest wildfires in California's history, for example, the 2003 Cedar Fire (271k acres; the third largest California fire), the 2007 Witch Fire (162k acres), and the 2009 Station Fire (161k acres). 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 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 2000 census tract boundaries and census characteristics come from the American Community Survey.

All properties are geo-coded to obtain exact latitude and longitude coordinates and link them 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.[17]

To determine which homes have a view of a burn scar, we follow McCoy and Walsh (2018) and

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

[17] 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 inside or within a 50m buffer outside a wildfire perimeter to ensure we exclude properties potentially exposed to structural damage by the fire. Note that during the study time period 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 entire state of California (California Department of Forestry and Fire Protection, 2018).

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

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$2015)	514.92	(568.75)	503.34	(304.67)
Age	38.65	(23.98)	36.81	(24.85)
Living area (k sqft)	1.84	(0.72)	1.88	(0.74)
# bedrooms	3.32	(0.82)	3.35	(0.82)
# bathrooms	2.34	(0.82)	2.39	(0.82)
Swimming pool (0/1)	0.20	(0.40)	0.20	(0.40)
Dist. green space (km)	0.56	(0.49)	0.57	(0.51)
Elevation (m)	241.10	(194.64)	261.11	(197.84)
Slope	2.92	(4.23)	2.94	(4.22)
FHSZ (0/1)	0.07	(0.26)	0.08	(0.27)
WUI (0/1)	0.47	(0.50)	0.50	(0.50)
Dist. main road (km)	1.42	(1.17)	1.45	(1.20)
Median hh. income (k$)	75.89	(28.02)	76.05	(27.81)
% white	65.47	(18.10)	65.84	(17.43)
% hispanic	38.29	(24.44)	38.68	(23.80)
Years between sales	3.27	(3.56)	5.31	(3.12)
# of sales	1,455,186		862,000	
# of census tracts	4,084		4,017	

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 what 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 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.[18]

3 Empirical strategy

We use the hedonic pricing method to value the effect of a new risk zone designation and views of wildfire damages on home prices (Rosen, 1974). 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 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 repeat-sales dataset to control for house and neighborhood time-invariant unobservables that may confound identification. In addition, in the sections below we discuss specific spatial sample restrictions chosen to improve the comparability of the treatment and control properties. Next, the empirical strategy lays out our approach to recover unbiased ATT of the new risk zone designation and wildfire treatments on home prices.

3.1 Effect of the new risk zone designation on salience

We exploit a new risk zone designation to compare the value of properties newly assigned to the risk zone relative to homes nearby that did not experience a change in designation. While the risk zone designation is discontinuous, arguably, the underlying risk is continuous, as illustrated in Figure 2.[19] Because we do not observe households' risk perceptions, the only inference one can draw is that if salience triggers a discontinuity in risk perceptions, then, either the households inside or outside the risk designation, or both, have biased risk perceptions. In particular, we cannot determine whether

[18] 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.

[19] Visual inspection of the new risk designation boundary reveals that it does not follow roads, streets, or rivers, but rather is driven by topography, reducing concerns that risk may be discontinuous across the risk designation boundary (CAL FIRE FHSZ web viewer).

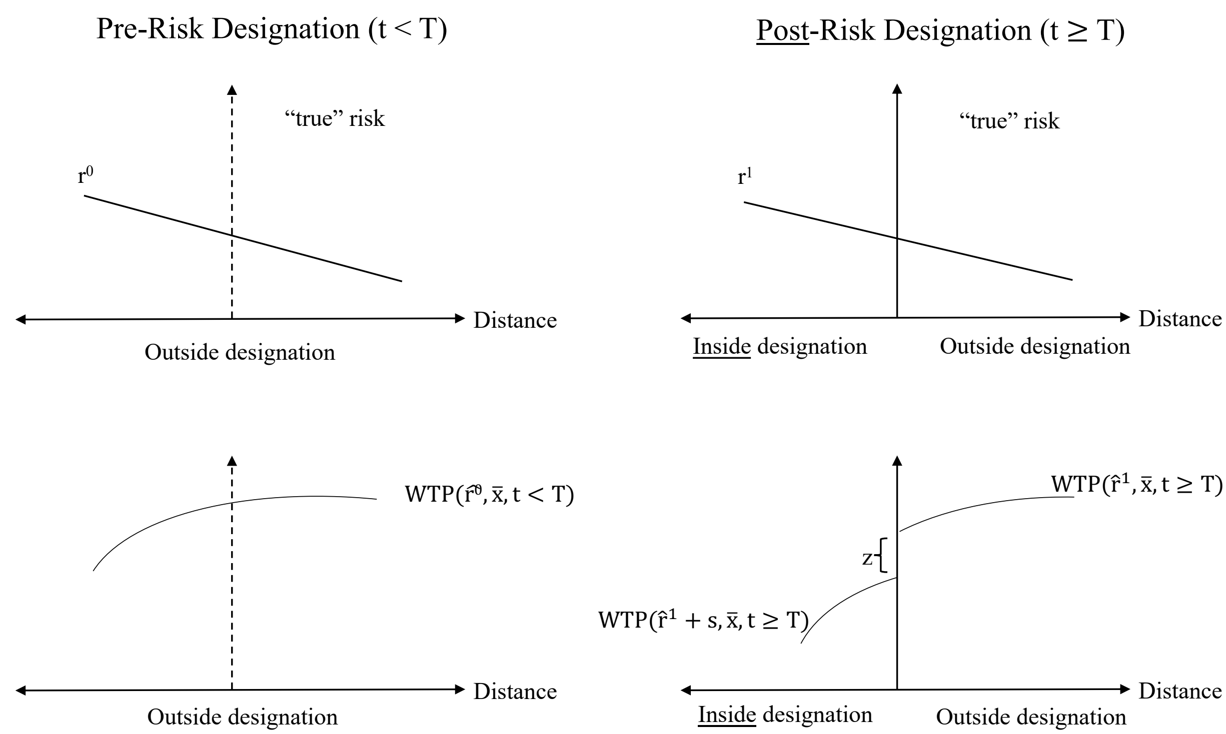


Figure 2 Illustration of the potential effect of a new risk zone designation on true and perceived risks and willingness-to-pay for housing.
Note: the top panels depict the true wildfire risk (r) for homes located along some wildfire risk gradient, e.g., based on elevation and/or proximity to the wilderness. The bottom panels depict homeowners' willingness-to-pay given their perceived wildfire risk ($\hat{r}$). Pre-designation, homeowners' perceived risk is solely informed by continuous variables that may influence risk ($\hat{r}^0$), e.g., elevation or proximity to the wilderness. In contrast, post-designation homeowners located inside the new risk designation receive additional information from the risk designation disclosure at the time of sale (s) when forming their risk perceptions ($\hat{r}^1 + s$). Homeowners located outside the new risk designation do not receive such information and solely rely on $\hat{r}^1$. Note that the true risk pre- and post-designation (r^0 and r^1) may remain constant or change. Likewise, homeowners' willingness-to-pay pre- and post-designation (WTP) could change in response to the new perceived risk (r^1).

the new designation induces households inside the new risk zone to over-, under- or adequately respond to the new information. Similarly, we cannot tell whether households outside the risk zone under-, over- or correctly estimate the risk. Making the risk salient may not necessarily induce households to correctly assess the risk. Indeed, in Bordalo et al. (2012)'s choice theory with decision weights, salient payoffs may lead decision-makers to under- or over-estimate the risk depending on the context. Inaccurate households' risk perceptions, even after a new designation, are plausible in the context of risks that are difficult to assess such as wildfire risk. (Insurance companies and the regulator (CAL FIRE) have access to extensive amounts of scientific data and models to estimate fine-scale resolution wildfire risk or hazard information, but most Southern California households likely do not.)

Thus, conditional on changes in insurance premiums being "not too" discontinuous across the risk zone (as discussed in Section 2), our estimate mostly picks up the effect of the new designation on risk salience. Another potential source of concern to our identification is if the risk zone designation triggers changes in the mortgage markets. Through personal communications with six bankers and mortgage brokers conducting business both inside and outside the risk designation (Table F1), risk zone status does not affect lending practices. (The mortgage brokers contacted underwrite mortgages to a large number of lenders in our study area, suggesting their behavior is representative of business practices in the region.)

Our quasi-experimental design consists of a difference-in-differences approach, while controlling for time-invariant attributes with property fixed effects, as shown in regression (1).

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

In this equation the dependent variable is the natural log of property i's sale price at time t. $NewDesignation_{it}$ denotes the treatment group, $Post_{it}$ is post treatment. The parameter of interest is δ. Here we define treatment, $NewDesignation_{it}$, as properties that are in the new risk designation while controls are nearby properties not affected by the new designation, either because they are always outside the new designation or because they were in the risk zone prior to the new designation. We show evidence of the common trends in pre-designation prices in Figure 4.[20] 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, we control for potential heterogeneity in temporal shocks across the region. For example, macro-level housing shocks could drive price changes and confound the effect of wildfires.[21] Thus, we rely on time varying fixed effects to 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).[22]

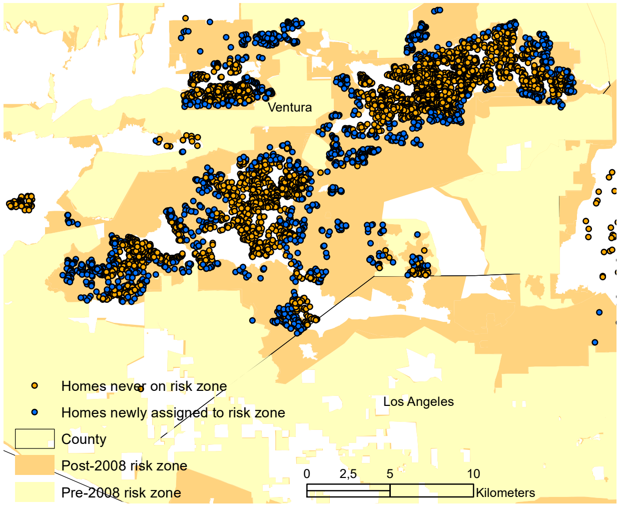
To reduce concerns about varying unobservable trends over space, we restrict the analysis to homes in the 0m to 500m bin and 500m to 1km bin on each side of the new risk designation boundary.[23] Summary statistics for the property samples used for this analysis are shown in Table A1. On average, properties in the new risk designation are at higher elevation, farther from a major road, and less expensive than properties outside the new designation. Figure 3 shows the spatial

[20]The difference in levels of treated and control may be due to imbalances in observable attributes. Our identification strategy is robust to these differences since we have property-level fixed effects.

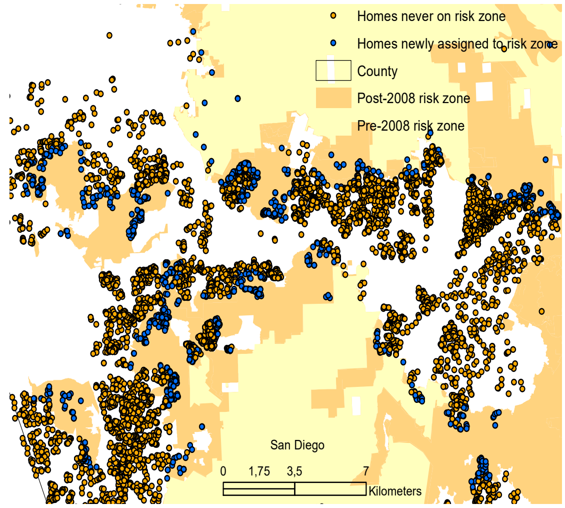
[21]We are not concerned about housing booms because housing supply is inelastic in the region due to the presence of steep-sloped terrain (Green et al., 2005; Saiz, 2010). Saiz (2010) reports MSA-level elasticities for Los Angeles-Long Beach, Riverside-San Bernardino, and San Diego are 0.63, 0.67, and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

[22]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.

[23]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 above 1000 acres within 10km during the three years prior to the time of sale. In addition, because we do not know precisely when or whether the 117 local governments in our six counties adopted the new risk zone designation for the local responsibility areas, we restrict the study to risk zones in the state responsibility area, which were updated by ordinance state-wide on November 2007.



(a)



(b)

Figure 3 Properties properties newly assigned to the risk designation and properties always outside the new designation. Examples in (a) Ventura County and (b) San Diego County.

distribution of two subsamples of properties in Ventura and San Diego Counties.

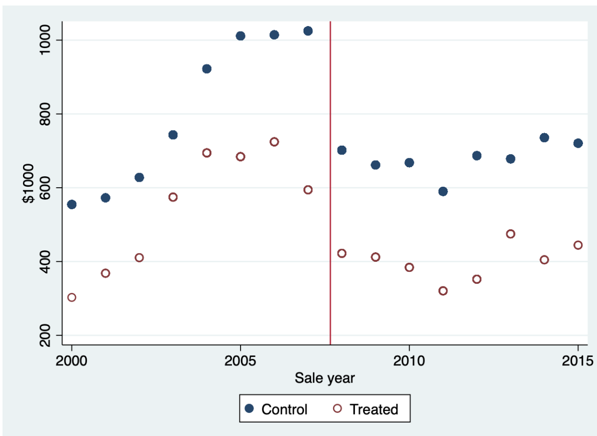
3.2 Effect of the burn scar view on risk salience

For our second treatment, we measure the effect of risk salience through visual cues of burn scars on property values. 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 $j = \{1, 2\}$.[24]

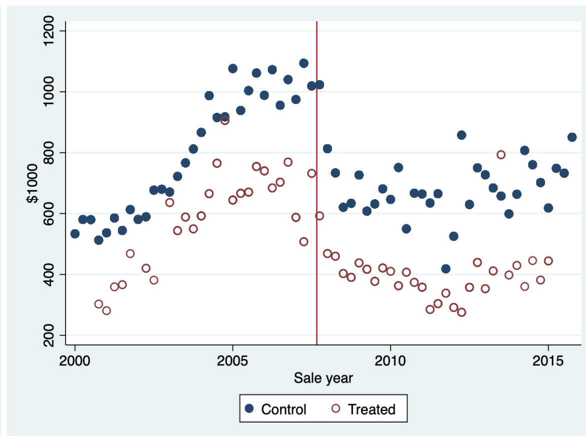
$$\ln p_{it} = \sum_j (\beta_j View_{jit} + \gamma_j View_{jit} \times Large_{jit}) + \lambda_i + \mu_{it} + \epsilon_{it}. \tag{2}$$

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. 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. Therefore, conditional on the trends for prices for homes with and without a burn scar view being identical, the estimates β_j capture a combination of visual disamenities and risk salience. To investigate the relative importance of these visual disamenities, we allow for heterogeneity in the burn scar view intensity, where γ_j denotes the effect of large burn scar views (above 10 acres) on property values. The hypothesis is that properties with large burn scar views may be impacted more severely than

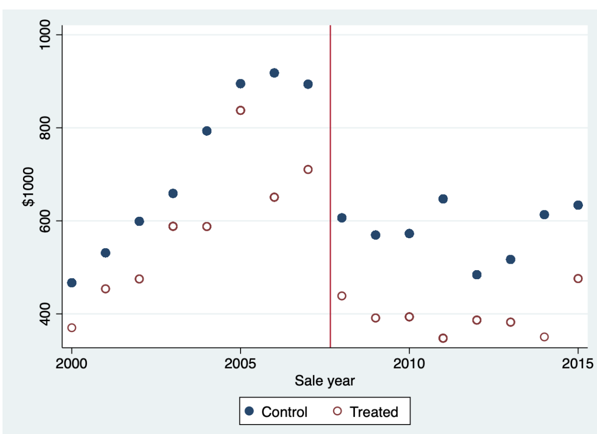
[24] In spite of burn scars taking many years to fully recover (Breslin, 2013), sales in the first two years post-fire are likely to capture the first-order impact on housing prices.



(a)



(b)



(c)

(d)

Figure 4 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 designation (treated group) and those not affected by the new designation (control group). The top panels include properties in the 0-500m from the risk designation boundary, while the bottom panels include properties in the 500m-1km from the boundary.

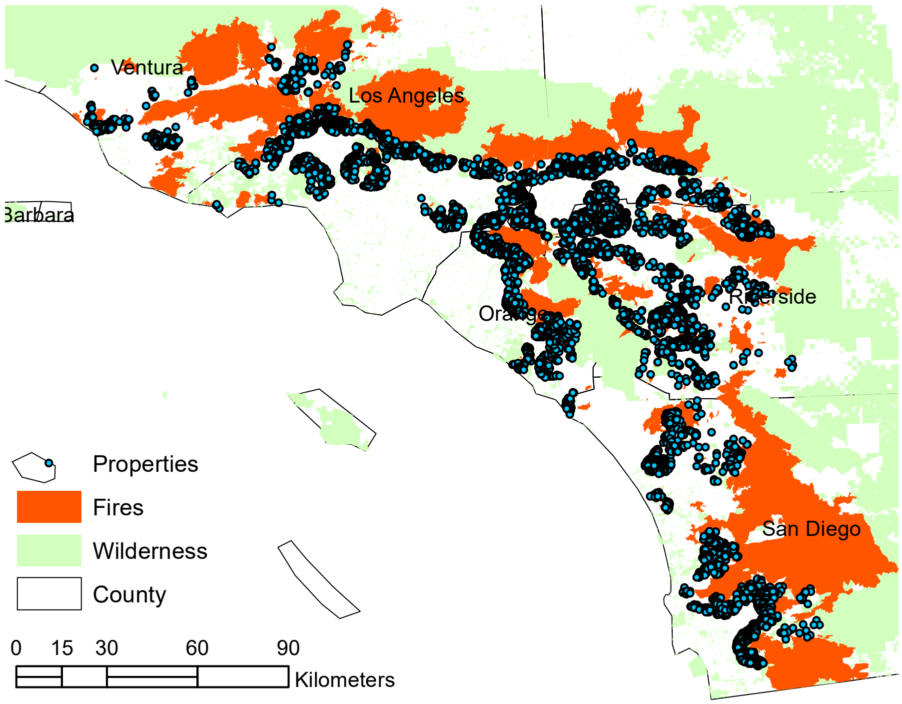


Figure 5 Wildfire perimeters between 1998 and 2015 and repeat-sales properties sold within 4km of burn scar and during the first two years post-fire.

properties from which the visible burn scar is small. In addition, to identify the effect of the visual cues of burn scars on property values, one must control for variables that vary along the distance from the burn scar and may confound the view effect, e.g., changes in risk or risk perceptions, and changes in proximity effects such as lost access to recreation sites. 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 variables that vary over space. 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.)

To estimate regression (1), the analysis focuses on repeat-sales homes for which one of the sales occurred within 4km of a burn scar and two years post-fire.[25] Summary statistics for the property samples for this analysis are shown in Table A2, with properties depicted in Figure 5.

Figure 6 illustrates the distribution of properties that are treated with a view of burn scars

[25]To isolate the effect of a single wildfire, 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 predominant vegetation type in the region) from more than a few kilometers away, we focus on burn scars within 4km. 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.

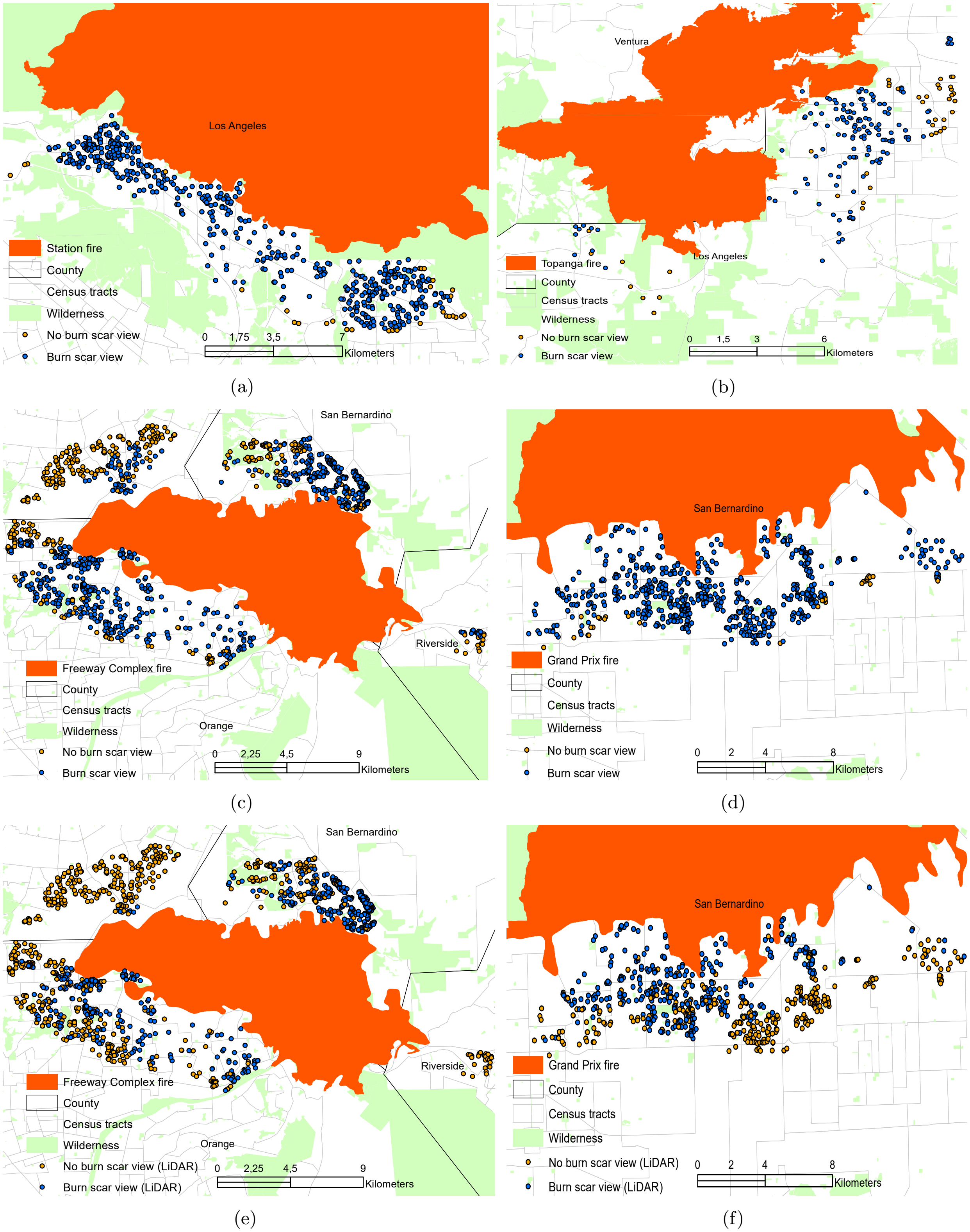


Figure 6 Properties with or without burn scar view sold within 4km and two years post-fire for: (a) the 2009 Station Fire in Los Angeles County, (b) the 2005 Topanga Fire in Ventura County, (c) the 2008 Freeway Complex Fire in Orange County, and (d) the 2003 Grand Prix Fire in Los Angeles County. LiDAR data are used to construct the viewshed for: (e) the 2008 Freeway Complex Fire and (f) the Grand Prix Fire.

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, e.g., distance to local amenities, via property fixed effects.

Effect of proximity to burn scar on salience

To further test whether salience affects home prices through other channels 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 a new risk zone designation. Second, we estimate the effect of having a view of a burn scar.

4.1 Effect of the new risk zone designation on salience

We find evidence that the new risk zone designation significantly affects the value of homes (Table 3). Our preferred sample definition restricts the analysis to properties as close to possible to the risk designation boundary (0-500m; columns (1) and (2)) to alleviate concerns of unobservable trends

Table 3 Effect of the new risk zone designation on home prices

	Sample restrictions around the new designation			
	0-500m		500m-1km	
	(1)	(2)	(3)	(4)
NewDesignation×Post	-0.112***	-0.105***	-0.104**	-0.121**
	(0.0226)	(0.0277)	(0.0430)	(0.0484)
Quadratic county trends	Yes		Yes	
Year×Quarter	Yes		Yes	
County×Year×Quarter		Yes		Yes
N	4560	4560	3320	3320
R^2_{adj}	0.765	0.786	0.855	0.867

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

varying over space across the treated and control properties. The effect of being newly assigned to the fire risk zone reduces property values by 10.5% to 11.2% in the 0-500m bin and by 10.4% to 12.1% in the 500m-1km bin. This effect combines homeowners' updated risk perceptions and, possibly, insurance premium increases if those vary differently for homes inside the new risk zone designation relative to nearby homes not affected by the new designation. Yet, conditional on changes in insurance premiums being "not too" discontinuous across the new risk zone designation, the estimates mostly reflect the effect of the new designation on risk salience (see discussion on factors allaying concerns about major changes in insurance in Sections 2 and 3.1). Because we exploit within-property variation for properties that sold once prior and once past the new 2007 designation (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 new designation persists over time.

A placebo test using properties inside the risk zone both pre- and post-new designation as 'treatment' compared to properties outside the new risk designation both pre- and post-new designation (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, non-treated homes in the area. This is important given that the new designation coincides with the beginning of the housing crisis.[26]

Since wildfire risk may have changed over the last 40 years in the study area there may be a concern about 'risky' areas capitalizing that risk in property prices during our time period. There could be similar concerns about population growth in 'risky' areas affecting our identification of the effect of the new designation. The common trends assumption would not hold if either of these problems existed in our empirical setting. Since visual evidence supports the common trends of treated and control properties on either side of the new risk zone designation it suggests that our estimates are not affected by these concerns. We would expect rather, that the trends of the treated and control properties would diverge from each other before and after the new risk designation.

[26] A placebo where we change the timing of the new designation would severely reduce our sample size since the repeat sales would have to occur pre- or post-November 2007 to obtain a clean placebo test.

Table 4 Placebo test - Effect of the new risk zone designation when homes in the risk zone both pre- and post-designation are assigned to the treatment

	Sample restrictions around the new designation			
	0-500m		500m-1km	
	(1)	(2)	(3)	(4)
NewDesignation×Post	0.0344	0.0299	-0.0700	-0.0306
	(0.0351)	(0.0416)	(0.0522)	(0.0665)
Quadratic county trends	Yes		Yes	
Year×Quarter	Yes		Yes	
County×Year×Quarter		Yes		Yes
N	4076	4076	3168	3168
R^2_{adj}	0.741	0.767	0.857	0.871

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

4.2 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.[27] The effect is in general attenuated 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 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 effect of a burn scar view differ from those found in McCoy and Walsh (2018) as they are highly robust only for the first year only and are small beyond 2km.

To put these 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. Thus,

[27] 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 upward our estimates. 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 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

because of the magnitude of the effect, it is difficult to imagine that it is fully attributable to the loss of visual amenities. In addition, burn scars can take ten years to fully recover and be barren of shrubs and trees for several years post-fire Breslin (2013). Thus, while the view of the burn scar is most extreme in the first-year post-fire, the visual disamenities are likely to improve gradually over multiple years following the wildfire. Furthermore, because the visual disamenity associated with a view of a burn scar may be hardly noticeable past a couple of kilometers and because the effect of a view of a burn scar is not higher for larger visible burn scars, it suggests the visual disamenity may not be driving the estimates. Our estimates suggest that views of recent 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. 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 the extent of this potential 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 (incl. buildings and vegetation); thereby assigning properties with less error to the treatment or control groups (Figure 6; bottom panels). The tradeoff is that LiDAR data are not available for all our study counties and therefore we face 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

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. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

post-fire, ranging from -2.6% to -3.3%. These results are not statistically different from the results in Table 5 at the 10% level and suggest that our main findings are robust to the definition of burn scar view using LiDAR data.

Effect of proximity to burn scar on salience

To test whether the salience of natural disaster damages mostly occurs through the visual cues channel (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.

4.3 Changes in neighborhood composition

A potential concern with identification of changes in housing prices using temporal variation in prices, as we do with repeat sales, is that preferences may change over time. For example, if

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)
$K_1 \times \text{View}_1$	0.0072	0.0090	0.0059	0.0044	0.0030	-0.0040
	(0.0239)	(0.0236)	(0.0168)	(0.0159)	(0.0151)	(0.0137)
$K_2 \times \text{View}_2$	-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. The subscript on coefficients denotes the year post fire the the coefficient captures.

neighborhoods change in response to risk zone assignment or fire events, our estimate would simply capture a capitalization effect rather than the marginal willingness-to-pay, or change in surplus, associated with a change in risk salience (Kuminoff and Pope, 2014). However, since the new risk designation is exogeneously determined and wildfires happen randomly over space and time across the wildland-urban interface in the region, changes in risk zone or burn scar view are not likely to result in large neighborhood changes. One way in which we may identify such shifts in the equilibrium of the hedonic price function is through inspection of the demographics of the buyers over time in the study area. Following Bayer et al. (2016), we use data from the Home Mortgage Disclosure Act to capture the buyers mortgage application information, including income, gender, race, and ethnicity of the applicant, as well as the loan amount and year, lender name, and census tract of the property. We do not find evidence that neighborhood composition, as measured by income, race, and ethnicity, is affected by changes in risk zone assignment or burn scar view (see Appendix D). To the extent that risk perceptions are influenced by these demographic characteristics, these results provide suggestive evidence that risk preferences may not dramatically change in response to the two treatments.

5 Conclusions

This paper provides evidence suggesting that households' risk perceptions respond to different forms of risk salience. To show that, we use Southern Californian real estate as a laboratory. We find suggestive evidence that the greater risk salience induced by a change in risk zone regulation can trigger a differential updating in households' risk perceptions across the new risk designation. Using the language of Loewenstein et al. (2001), the mechanism that can explain this form of salience is the "insensitivity to probability variations." As such, images associated with feelings of risk come to mind to households inside the risk designation, while these images are not present in the mind of households outside the risk designation. We further find that the view of a very recent burn scar negatively affects the prices of homes relative to those without a view. In this case, it is possible that the view of a charred landscape generates a visceral, gut feeling of dread, i.e., what Loewenstein et al. (2001) refers to as the "vividness" of risk. 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 (2018).

Furthermore, our findings suggest that different types of salience trigger differentially strong and long-lasting risk salience effects. For example, the wildfire risk zone designation treatment indicates that the effect of salience persists over time (possibly for as long as the new risk designation persists). In contrast, our second measure of salience, which operates through the visual cues of recent natural disaster damages, suggests that the vividness of risk induced by the view of a burn scar occurs only when the wildfire damages are most pronounced, i.e., when the vegetation is still charred and the ground barren. Indeed, despite the burn scar still being visible in the second year post-fire (Breslin, 2013), the visual cues of a recovering burn scar do not trigger differential prices across homes with or without a view.

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.

This study is subject to several caveats. First, the new risk designation measure may include differential insurance premium updates relative to homes just outside of the new designation. 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 potential changes in insurance premium. Similarly, our second measure of salience, likely confounds risk salience from visual cues of recent wildfire damages 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. Second, evidence of risk salience would suggest that at least some households have biased risk perceptions. Salience may make decision-makers overweight the bad outcome of a wildfire (Bordalo et al., 2012). Yet, without observing households' risk perceptions, it would not be possible to conclude whether households inside or outside the new risk designation, or both, have biased risk perceptions (or, with or without a burn scar view in the case of the second treatment). In addition, given that fine-scale wildfire risk information is not available to most households in Southern California, it is not unlikely that most households' subjective risk perceptions differ from the true underlying wildfire risk.

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A Additional figure and summary statistics

Table A1 Summary characteristics of the repeat-sales properties for different distance bins from the new risk designation boundary (properties are referred to "newly inside" or "always outside" the new risk designation)

	0-500m				500m-1km			
	Newly inside Means (sd)		Always outside Means (sd)		Newly inside Means (sd)		Always outside Means (sd)	
Sale price (k$2015)	519.26	(228.47)	773.92	(456.06)	509.92	(195.09)	691.21	(333.79)
Age	24.66	(14.45)	22.72	(16.17)	17.04	(8.26)	21.93	(17.53)
Living area (k sqft)	2.10	(0.52)	2.39	(0.85)	2.37	(0.50)	2.27	(0.78)
# bedrooms	3.39	(0.66)	3.51	(0.77)	3.62	(0.56)	3.53	(0.74)
# bathrooms	2.44	(0.68)	2.90	(0.89)	2.70	(0.64)	2.79	(0.81)
Swimming pool (0/1)	0.21	(0.41)	0.26	(0.44)	0.18	(0.39)	0.24	(0.42)
Dist. green space (km)	0.78	(0.41)	0.57	(0.48)	0.68	(0.51)	0.46	(0.43)
Elevation (m)	444.38	(65.76)	246.90	(127.64)	490.14	(53.34)	218.50	(110.49)
Slope	5.19	(3.33)	5.61	(4.41)	5.47	(2.64)	4.67	(4.12)
WUI (0/1)	1.00	(0.00)	0.99	(0.11)	1.00	(0.00)	0.92	(0.26)
Dist. main road (km)	3.74	(1.51)	2.01	(1.52)	4.10	(2.10)	1.56	(1.30)
Median hh. income (k$)	96.53	(13.42)	102.38	(29.07)	93.35	(11.94)	94.23	(26.18)
% white	93.85	(3.33)	81.35	(14.77)	94.80	(2.67)	77.70	(14.18)
% hispanic	11.01	(5.05)	17.41	(13.10)	12.37	(5.71)	22.02	(15.67)
Years between sales	6.04	(1.88)	3.78	(2.07)	7.28	(1.79)	3.36	(1.86)
# of sales	308		4074		100		3168	

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 sales	2174		8398		12234		12522	
# 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)
$\text{View}_1 \times \text{Large}_1$	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)
$\text{View}_2 \times \text{Large}_2$	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 in response to treatment. We adopt a difference-in-differences framework for sales within two years pre- and post-treatment to identify if treated properties are experiencing shifting demographics at the neighborhood level relative to control properties.

For the effect of the new risk designation, we start with the properties within 750m of the risk designation boundary. We drop observations with no mortgage year, no loan amount, no lendername, or indications that the lender was a private lender. Matching on mortgage year, lender name, loan amount and type, county, and census tract, and keeping properties with unique matches, we obtain a 50.2% matching success rate.[28] Table D1 shows no evidence of changes in neighborhood composition before and after the new designation. [29]

Table D1 Composition of buyers inside and outside the new risk designation pre- and post-new designation

	Within 250m		Within 500m		Within 750m	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Income			
NewDesignation×Post	-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			
NewDesignation×Post	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			
NewDesignation×Post	-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.[30] 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

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

[29] The results are robust to restricting the analysis to 1, 2, 3, or 4 year(s) around the time of the new risk designation.

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

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.

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 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.

E Mortgage Lending and Fire Risk Zones

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×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×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×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×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.

Table F1 Contacted Mortgage Lenders in Southern California

Name	Dan O'Brien	Jamie Cavanaugh	Bryan Hitchock	Maureen Martin	Jamie Mckeon
Company	Landmark Financial	Hillhurst Mortgage	Chase Bank	Maureen Martin	Community Mortgage
Method of contact	805-650-4999	800-570-5626	909-438-8823	619-857-7191	619-857-7192
Position	Mortgage Broker	Mortgage Broker	Senior Loan Officer	Mortgage Broker	Mortgage Broker
Market served	Ventura County	LA County	LA County	San Diego County	San Diego County
Years of experience	20+		20	20	6
Are fire risk zones used to set rates or mortgage limits?	No	No	No	No	No