The Cost of Wildfires in Heavily Urbanized Areas: A Hedonic Approach

Sophia Tanner and Cloé Garnache

Department of Agricultural, Food, and Resource Economics

Michigan State University

Abstract

The frequency and severity of wildfires in the United States has increased dramatically over the past few decades, with both climatic conditions and development into wildland areas fueling this trend. It is necessary to understand the potential impacts of this pattern on communities living in areas of significant wildland fire risk, especially in densely populated areas such as Southern California. We contribute to the literature on wildfire impacts by estimating the impact of a recent fire on property sales prices along two dimensions: properties close to the wildfire compared with properties farther away, and properties in designated areas of high fire risk. We find significant heterogenous impacts of wildfire depending on whether the property is located on high risk land, as well as evidence that proximity to a national forest can alter the risk perceptions of potential home buyers.

Introduction

Wildfires have increased dramatically in number, size, and destructive force over the past 30 years; especially hard hit is the American West, from forests of the Pacific Northwest through to dry shrub land that dominates at the U.S.-Mexico border. Two factors contribute to the increasing risk of wildfire. First, there are climatic or natural factors: warmer temperatures, earlier springs, insects and infestations affecting forests, and the associated buildup of available fuel, spark more frequent and intense wildfires (Westerling et al. 2006). Second, while climate change has encouraged conditions conducive to wildfires, development and expansion into the wildland-urban interface (WUI) has put more people directly into their path. Syphard et al. (2007) find that population density and distance from WUI are important factors in determining fire frequency in California, suggesting human patterns of development also determine exposure to risk. The wildfire burned area in California may grow by as much as 74% by 2085, putting many more people at risk (Westerling et al. 2011).

Wildfires have significant economic impact: federal agencies respond to tens of thousands of wildfires on roughly 7 million acres of land, spending a combined total of $1-2 billion each year on fire suppression (National Interagency Fire Center 2016). The US Forest Service expects its annual cost of fire suppression will reach an estimated $1.8 billion by 2025, and have growing concerns that other management efforts suffer when funds are re-directed towards fire suppression. In addition to the direct costs of wildfire suppression and damages, people living near wildfires, even if their house was not directly affected, experience indirect costs such as the aesthetic disamenity of the burn scar, loss of nearby recreation opportunities, and heightened perceived risk of wildfires.

This paper estimates the cost of wildfires to residents of southern California using a hedonic approach. Our study area is unique for a number of reasons: Southern California faces high levels of human development, with suburbs of Los Angeles and San Diego running straight into four fire-prone national forests. The ecosystems in these national forests are characterized by chaparral, a dense shrubland unique to this region with a natural high-intensity fire regime. The regulatory environment also sets California apart; the state is besieged by so many natural disasters that it is required by law to disclose potential risks to home buyers at the time of purchase. We employ difference-in-differences to identify the effect of proximity to a wildfire and risk perceptions associated with wildfires. We ask the following two questions: 1) How are the effects of a wildfire capitalized into nearby housing prices? And 2) Can we attribute the impact to increased perception of risk as opposed to decrease in aesthetic value?

Capitalization of Risk Perception into Housing Prices

This paper contributes to the literature on capitalization of risk perception into housing prices in response to natural disasters, which developed around discounts for properties located in flood plains following a major flood or storm. The major findings show that in general, information on risk provided at the time of sale, such as location in a special flood zone, can impact the price of properties at risk; however, people may only be paying attention to such information in the wake of recent catastrophic events. Atreya, Ferrerira, & Kriesel (2013) found the property sales prices located in a 100-year flood plain fell significantly after a flood, but that the price effect faded over a period of five to ten years. Similarly, Bin & Landry (2013) show a negative and increasing impact of multiple hurricanes on properties sold in flood plains in North Carolina. However, the effects of the storms also tapered off after several years.

As wildfires have grown in public conscience, the literature on effects of wildfires has also developed in the past decade. The broad direction of this research attempts to disentangle the aesthetic disamenity caused by a large wildfire from the effects of increased risk perception among potential buyers in addition to measuring the impact. In one of the earliest efforts, Loomis (2004) estimated the change in property values in a town near, but not directly affected by, a major wildfire in Colorado. He found that housing prices dropped 10-15% in the unburned town after the fire and that the effects were still present five years later. Following studies have innovated by incorporating more current econometric techniques, such as controlling for spatial lag and autocorrelation (Donovan, Champ, and Butry 2007; Mueller & Loomis 2008), or estimating the effects of repeated wildfires, a common problem for neighborhoods in the WUI (Mueller, Loomis, & Gonzalez-Caban 2009). Like the flood literature, they often find that risk is not capitalized into housing prices until after a disaster.

In a study on an area of northwest Montana rich with environmental amenities Stetler et al. (2010) estimated several hedonic price models with a suite of environmental controls, including distances to many amenities, canopy cover, location on wildland-urban interface, and view of the burned area. Their results suggest great importance of environmental amenities, and that there are significant differences for homes with a view of the burned area as opposed to without. They also found large and lasting effects of wildfires – home prices suffered at distances up to 10 km away from the nearest wildfire compared to homes at least 20km from a fire, and they did not find any significant attenuation in the effect for seven years after a wildfire.

Of relevance to this study is a paper by McCoy & Walsh (2014), which to our knowledge is the only hedonic pricing study on wildfires to use a quasi-experimental approach. They estimate the effect of a recent wildfire three distinct treatment groups: proximity to the fire, view of the burn scar, and location in an area of high latent wildfire risk. Wildfires had different consequences for each of these treatments: for houses close to a wildfire, negative effects of a fire were still present three years after a fire. Houses slightly farther away with a view, or farther still with no view but located in high latent risk areas also saw significant negative effects but theirs attenuated within three years.

Study Area and Data

Southern California has several distinguishing characteristics that makes it important to study. First, the state of California dwarves most others in terms of number of wildfires and acres burned per year. Second, even well-developed areas of southern California may have exposure to wildfire, and there is no reason to believe that the capitalization effects will be the same in urbanized areas as in the WUI. Third, there is a large amount of information on fire risk that is given to potential home buyers during the negotiating process: the cost of fire insurance in California has skyrocketed since 2007, and all homes are subject to a natural hazard disclosure law that includes information on underlying fire risk. Thus, it is possible that fire risk is capitalized into housing prices to a greater extent here than other areas regardless of a fire occurring.

Housing Data

We acquired property transactions data for homes sold between January 1, 2000 and December 31, 2015 in the area surrounded by the Los Padres, Angeles, San Bernardino, and Cleveland National Forests, spanning seven counties – Santa Barbara, Ventura, Los Angeles, San Bernardino, Riverside, Orange, and San Diego counties – and located in Zip Code Tabulation Areas (ZCTA) within 30km of the national forests on the coastal side. Housing data was purchased from CoreLogic, a company that provides real estate data obtained from public records to financial and research institutions. Along with sales date and price, the information provided includes property characteristics, address, and other transaction data. Transactions were limited to owner-occupied residential houses, duplexes, and condominiums. To identify arms-length transactions as opposed to transfers between family members or built-to-order homes, we excluded properties built in the same year as they were sold, that sold twice in 12 months, properties that were transferred using quit claim deeds or other unusual deeds, and those marked with a partial sale code.

After dropping houses in the top and bottom 1% by sale price in 2015 dollars, the top 1% of bedrooms, bathrooms, and total rooms, and the top 1% of square feet, from the sample, we have a full sample 1,272,363 properties.

Wildfire and Geographic Data

Using wildfire perimeter data available from California's Fire Resource and Assessment Program (FRAP), we select wildfires that occur between 1995-2015, and only fires at least 500 acres in size, assuming fires older than five years or smaller than 500 acres have a negligible effect on sales. We then match each property with all wildfires within 15 km for a sample of 288 wildfires. Figure 1 shows the selected study area and spatial distribution of wildfires in the area.

On average, these fires burned 10,900 acres and lasted roughly a week. The study period spans some of California's worst wildfire incidents, including the "California Fire Sieges" of 2003, in which 14 fires blazed through southern California over the course of two weeks, and 2007, which charred nearly one million acres between Santa Barbara and the US-Mexico border (Blackwell & Tuttle 2003; Cal Fire 2007).

Addresses were geocoded with Texas A&M Geoservices. Geographic data for properties, including distance to the nearest wildfire perimeter, distance to the closest National Forest boundary, and distances to other amenities for each individual property were obtained with geographic data from various sources, including the San Diego Association of Governments, city of Los Angeles, and California Protected Area Database.

Fire Hazard Data

Previous research has suggested that risk of wildfire is generally not salient to potential home buyers except shortly after an information shock such as publicly available risk ratings, or an actual fire (Champ, Donovan, & Butry 2009). We therefore identify effects of wildfires along two main dimensions: the effect of being close to a recent fire both on and off areas of high risk, using California's Fire Hazard Severity Zones as a measure of latent risk.

California Department of Forestry and Fire Protection (CAL FIRE) produces statewide maps of areas with significant fire hazards, called Fire Hazard Severity Zones (FHSZ), for land where the state has financial responsibility for wildland fire protection. Hazard zones are developed using information about the physical attributes of the area and fire history, including fuel availability, topography, typical weather, and models of ember production and movement. It does not take into consideration private actions to reduce fire risk on a given property, such as fuel reduction and defensible space. There have been efforts to map "state responsibility areas" (SRA), which are at greater risk of wildland fire, since the 1980s, with FHSZ mapping efforts in the early 2000s. Current FHSZ maps for SRA were proposed in 2007 and adopted by January 2008. Hazard Severity is rated moderate, high, or very high for SRAs. Hazard zones for local responsibility areas (LRA) were proposed in 2008 and adopted in 2009, and only map areas of very high hazard. Fire Hazard Severity Zones may be used in the development of building standards and defensible space requirements, but more importantly since 1998 California's Civil Code has required natural hazard disclosures at the time of property sale, including both location on areas of wildland fire risk (any SRA rating) and whether the property is in a "Very High" wildfire hazard zone (anywhere with a "very high" hazard rating). Location of Fire Hazard Severity Zones is shown in Figure 2.

Empirical Strategy

The hedonic price method is commonly used to value environmental amenities, from the benefits of open space to air quality to risks such as nuclear waste (Anderson & West 2006; Kim, Phipps, & Anselin 2003; Gawande & Jenkins-Smith 2001). However, a concern in the estimation of hedonic price functions is that coefficients will be biased if unobserved variables that influence price are correlated with observed variables. To address this, we turn to a difference-in-differences approach commonly used in in the risk literature (Hallstrom & Smith 2005; Gawande, Jenkins,-Smith, & Yuan 2012; McCoy & Walsh 2014).

We use difference-in-differences to evaluate the effect a wildfire houses in two treatment groups compared with a comparable control group of houses: proximity and high risk groups. After matching houses to all wildfire perimeters within 10 km of the property, we first remove confounding effects of multiple wildfires by dropping houses that experience more than one wildfire within 7 km in the five years preceding its sale date[1]. In line with McCoy & Walsh as well as other work on shale gas development and other risks that spill over confined boundaries (Muehlenbachs, Spiller, & Timmins 2014; Boslett, Guilfoos, & Lang 2015; Gawande, Jenkins-

[1] Mueller, Loomis, & Gonzalez-Caban estimate that it takes 5-7 years for housing prices to recover after a wildfire in Southern California.

Smith & Yuan 2012) we identify a distance cutoff to use as a proximity treatment group. Our main proximity treatment group consists of houses within 5 km of a wildfire, which are not located on FHSZ, with houses 5-10 km away from a fire used as controls.

After a fire, there may be a market-wide increase in risk salience among potential home buyers. We test for this effect using a high-risk treatment consists of houses located on land any Fire Hazard Severity Zone, either on state or local land. To keep estimates distinct from proximity effects, we only include properties 5-10 km from the nearest fire in these models. If home buyers generally are more aware of wildfire risk in the wake of recent disasters, there should be some saliency bump from seeing a property's wildland fire risk disclosure compared to pre-disaster.

Finally, we test the joint effect of adjacency and location in high risk areas using a third treatment group of properties that are both within 5 km of the nearest fire and located on FHSZ. Controls are properties 5-10 km from a fire, and not located in high risk areas. For each treatment group the model takes this form:

$$\ln \mathrm{P}_{it} = \beta_0 + \beta_1 Treat_{it} + \beta_2 Post_{it} + \beta_3 (Treat \times Post)_{it} + \beta_4 \boldsymbol{X}_{it} + \beta_5 \boldsymbol{A}_{\boldsymbol{i}} + \beta_6 \boldsymbol{N}_{\boldsymbol{it}} + \mathrm{FE} + \epsilon_{it}$$

Where $\ln P_{it}$ is the natural log of the sale price for house *i* selling in year *t*. $Treat_{it}=1$ if the property is treated, $Post_{it}=1$ if the property is sold at least 60 days after the nearest fire occurs, and β_3 is the difference-in-difference coefficient of interest. Our property controls **X** include square feet, acres, age, number of bedrooms and bathrooms, and type of property (single family residence, condo, or duplex). We also control for locational amenities **A** including distance to the nearest city center, either Los Angeles or San Diego, distance to the nearest major road, and distance to the nearest park or open area. To allow for nonlinear effects of distance to the nearest national forest, we include indicator variables for each 5km increment from the USFS-managed land. To control for neighborhood characteristics **N** we use data from the American Community Survey at the census tract level. Variables included are percent of the population 25 years or older with at least a Bachelor's degree, median household income, percent Hispanic residents, percent black residents, and unemployment rate. ACS data was available from 2009-2015. Finally, our preferred specifications use county fixed effects and year by quarter fixed effects.

Most previous wildfire literature has focused exclusively on wildland-urban interface rather than on more developed areas. We hypothesize that there will be heterogeneous treatment effects dependent on level of development, with a bigger change in risk salience in less densely populated areas than more urban ones. To extend on this basic model, we proxy for development by interacting the national forest distance bins with the difference-in-difference coefficient:

$$\ln \mathrm{P}_{it} = \beta_0 + \beta_1 Treat_{it} + \beta_2 Post_{it} + \sum_{j=1}^{5} \beta_{3j} \left(Treat \times Post \times Bin_j\right)_{it}$$

$$+\beta_4 \boldsymbol{X_{it}} + \beta_5 \boldsymbol{A_i} + \beta_6 \boldsymbol{N_{it}} + \mathrm{FE} + \epsilon_{it}$$

Identification of Treatment Groups

Prior studies testing the effect of wildfire proximity on housing prices have used a range of values from 2km (McCoy & Walsh 2014) to roughly 3.2 km (Loomis 2004). Other studies have shown a much wider effect of wildfires, up to 10 km from the perimeter (Stetler et al. 2014). To motivate the choice of distance band, closer to which the property experiences significant disamenities from location near a past wildfire, we estimate naïve hedonic model with property characteristics, amenities, neighborhood controls, county fixed effects, and year by quarter fixed effects. We explore the possibility of heterogeneous impacts for properties located in high risk zones by estimating separate regressions for properties inside and outside of FHSZ.

We then fit kernel-weighted local polynomials for each regression to the residuals of properties that sell before and after a fire. By plotting these residuals against distance from the nearest fire, we can clearly see an immediate negative impact of selling after a fire for properties close to the fire. For properties that are farther away and not on FHSZ, there seems to be an opposite effect, with sales prices increasing post fire, perhaps indicating a shift in the market away from immediately adjacent areas.

Though the visual identification suggests proximity effects taper out after a few kilometers, given the distance at which Stetler et al. (2010) found wildfire effects we test the sensitivity of our results with different proximity treatments by estimating model with treatment groups ranging from 1- 8 km. The results of this test are available in Table 1. We find there are significant negative effects for all control groups, but the magnitude declines sharply after 5 km. Therefore, our preferred model uses 5 km as the boundary for proximity treatment, and properties farther than 5 km used to define the risk treatment group.

Results

Wildfires had mixed effects over our study area, with some areas strongly and negatively affected by fire while others were not. We find a dynamic effect, with negative impacts close to a fire, and close to USFS land, while there is some evidence more developed areas farther away experienced a slight increase in prices, perhaps due to a shifting of the market away from more obviously hazardous places. Results for each treatment group are shown in tables 2-4 below, where the Treat by Post coefficient captures an average impact for the treatment group, and Treat by Post by Distances disaggregate differing effects over space.

Proximity Treatment

Table 2 presents the effect of selling after a wildfire on properties within 5 km compared to those in a control group of 5-10 km from a wildfire. Our analysis of proximity alone shows a significant but slight decrease in prices for houses close to a fire compared with those farther away. On average sales prices decreased by about 1% following a wildfire. Houses within 5 km of a national forest experienced a larger impact, a 2-2.4% drop in sales prices after a fire, while the price of houses at a more moderate distance from the forest (5-15 km from USFS land) increased by up to 3.4%. Unexpectedly, the greatest negative impacts are seen at the effect is again negative, at -6.8%. These models also show a high premium for properties near a national forest, 7.6% higher prices for properties within 5 km, compared to properties 25-30 km away.

Risk Treatment

In Table 3 are estimates for the effect of a recent fire on properties sold in a fire hazard zone, if they are not close to that fire. Surprisingly, in the model with year by quarter fixed effects there is a small, and slightly significant increase (1.1%) in property price after a fire. Disaggregating by distance to forest, we find that properties immediately adjacent to USFS land increase in price by 6.2% compared to those that sell before the fire. However, properties at a moderate distance, 5-10 km, or 10-15 km, decrease in price by 9.4 and 9.7% respectively. This magnitude is comparable with most other studies which show a price decrease on the order of 10% after a fire. The premium for forest-proximate properties does not exist on FHSZ land, with instead 1.7% lower prices for properties in a 5-km distance band from forests.

Risk and Proximity Combined Treatment

Table 4 shows coefficients for the combined close and high risk properties, those within 5 km of the nearest fire and on land at greater risk of wildland fire. This treatment group shows the expected pattern, with a 5.8% decrease in price for properties within 5 km of a forest and a 2.7%

decrease for those 5-10 km from a forest. However, farther away the difference-in-difference coefficient is positive and highly significant.

Discussion

Results show complicated effects of a wildfire on the housing market. Our study area consists of many heavily urbanized areas located within a 30-km band from the national forests of Southern California. Results suggest a slight negative effect on price after a nearby wildfire over the sample. As a simple proxy for less urbanized areas, we explore heterogenous treatment effects by distance from USFS land. Our hypothesis that being located closer to a national forest, where most wildfires in the area start, will cause a greater impact than farther away holds true, but only up until the 20 km from a national forest boundary.

We find evidence that the effect of a fire is significantly different on areas that have been identified as at greater risk of wildland fire, the Fire Hazard Severity Zones. This information is passed on to the buyer during the negotiation process. To test the hypothesis that there would be a market-wide bump in risk salience from a fire, we used a treatment group of properties somewhat near, but not in close proximity, to wildfires located on FHSZ. Our estimates do not fully support this claim, with some areas experiencing large decreases in prices, while others experienced increases. However, there may be some increase in risk salience for properties both in proximity to wildfire and located on FHSZ.

These results are preliminary: further extensions of this work will include additional geographic controls such as elevation, slope, and view of a wildfire burn scar, as well as housing density. However, there several distinguishing characteristics of this study which set it apart from past work surrounding wildfire effects. First, we look at a much broader study area geographically whereas previous literature has explored the impact of fires specifically on the wildland-urban interface. Second, we explicitly look at the differential impacts of fire on and off designated high risk land. Finally, our study encompasses a longer time period than most, with wildfire data spanning twenty years and sixteen years of transactions. In the past several years, homeowners have faced an increasingly worse insurance market, which is a direct source of information on wildfire risk. Future analysis should explore the potential confounding impacts of wildfire insurance.

Figure 1: Selected Zip Codes and Distribution of Wildfires

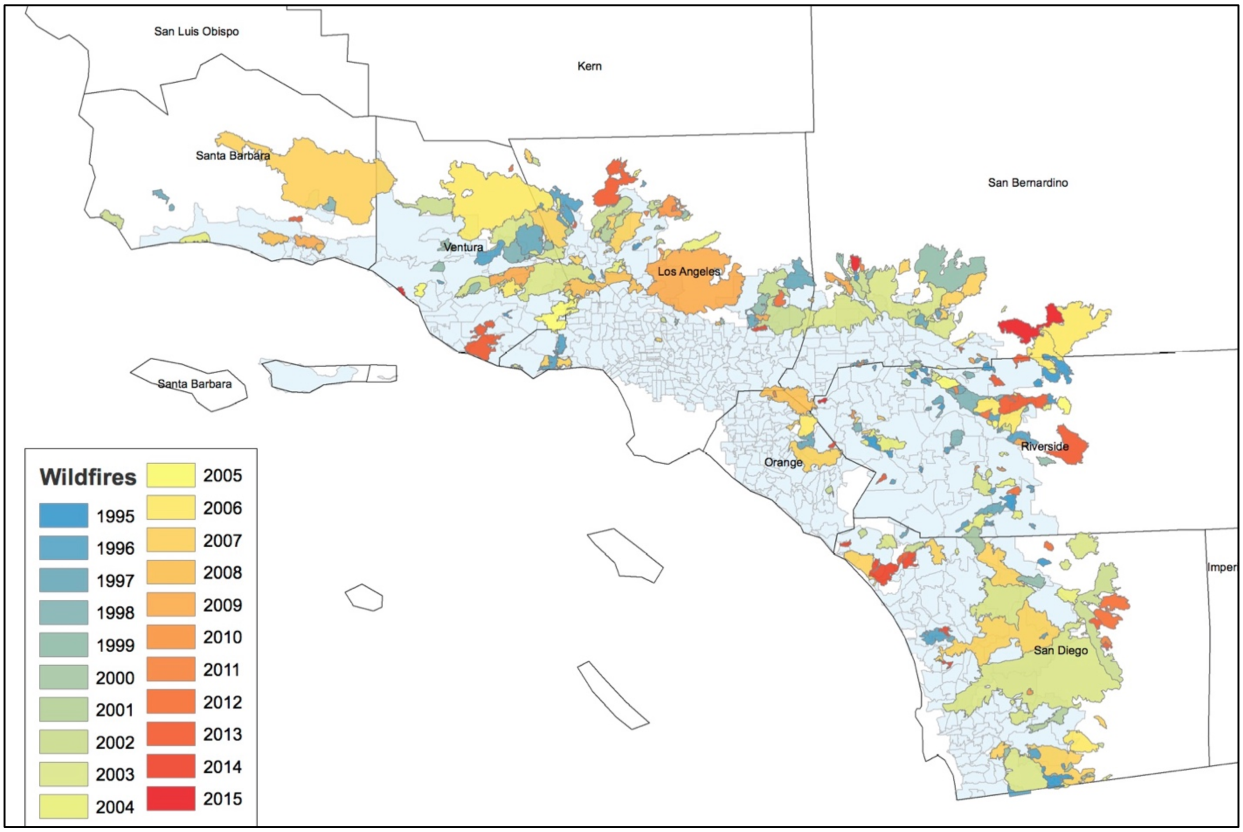

Figure 2: Location of Fire Hazard Severity Zones

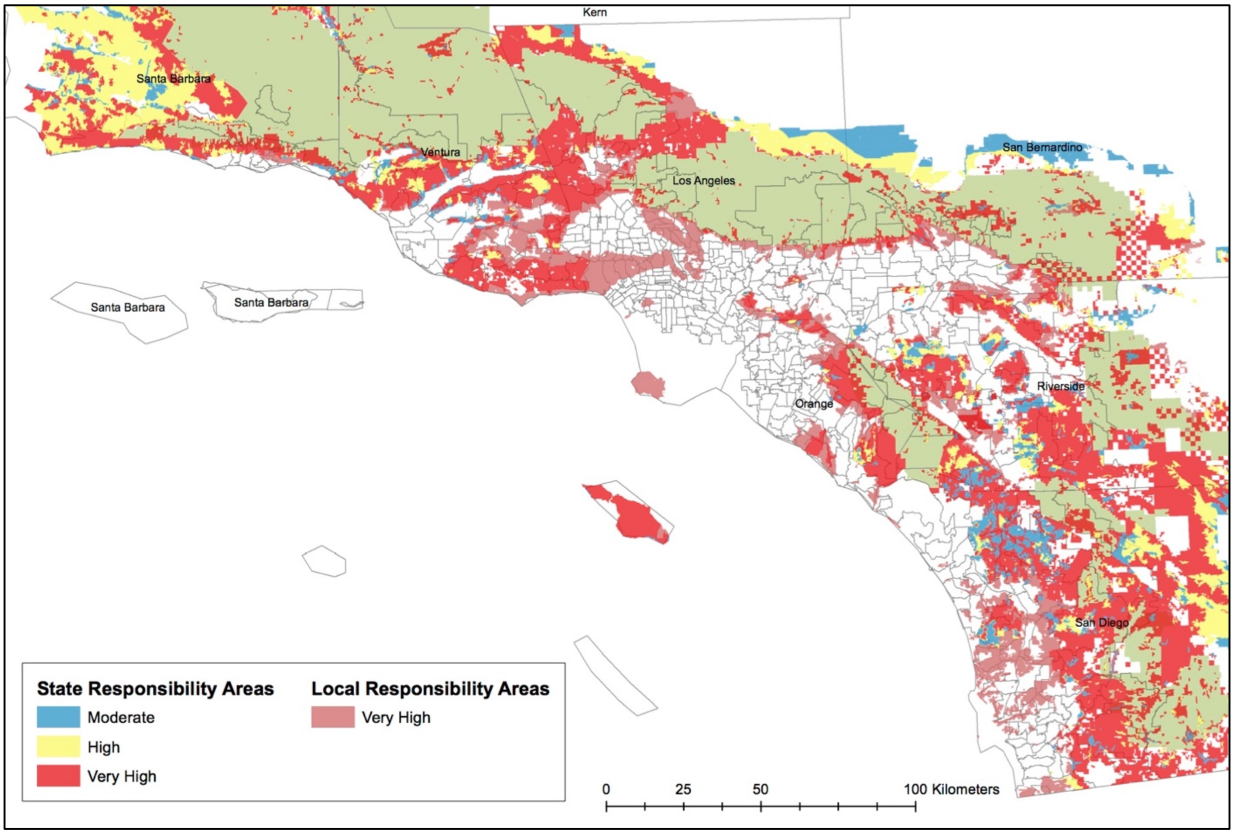

Table 1: Identification of Proximity Treatment

TREATMENT:	(1) 1 km	(2) 2 km	(3) 3 km	(4) 4 km	(5) 5 km	(6) 6 km	(7) 7 km	(8) 8 km
Treated	-0.026***	-0.028***	-0.029***	-0.025***	-0.023***	-0.030***	-0.034***	-0.037***
	(-9.469)	(-14.870)	(-18.667)	(-17.426)	(-16.204)	(-20.540)	(-21.503)	(-19.851)
Post Fire	0.014***	0.017***	0.017***	0.018***	0.020***	0.018***	0.019***	0.018***
	(13.573)	(15.174)	(14.585)	(14.437)	(14.019)	(11.371)	(10.155)	(7.381)
Treat by Post	-0.008**	-0.013***	-0.009***	-0.011***	-0.011***	-0.006***	-0.006***	-0.004*
	(-2.280)	(-5.668)	(-4.838)	(-5.963)	(-6.113)	(-3.258)	(-3.043)	(-1.657)
Observations	249,264	249,264	249,264	249,264	249,264	249,264	249,264	249,264
R-squared	0.776	0.776	0.777	0.776	0.776	0.777	0.777	0.777

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Proximity Treatment

VARIABLES	(1) Log Price	(2) Log Price	(3) Log Price	(4) Log Price
Treated	-0.026***	-0.023***	-0.030***	-0.028***
	(-17.712)	(-16.339)	(-20.474)	(-19.461)
Post Fire	0.015***	0.019***	0.015***	0.018***
	(10.624)	(13.220)	(10.663)	(13.158)
Treat by Post	-0.007***	-0.011***		
	(-3.872)	(-6.070)		
Treat by Post (0-5 km)			-0.020***	-0.024***
			(-7.510)	(-9.323)
Treat by Post (5-10 km)			0.005**	0.002
			(2.161)	(0.810)
Treat by Post (10-15 km)			0.036***	0.034***
			(13.280)	(12.695)
Treat by Post (15-20 km)			0.008***	0.006**
			(2.835)	(2.065)
Treat by Post (20-25 km)			-0.063***	-0.068***
			(-21.413)	(-23.372)
0-5 km from USFS	0.064***	0.064***	0.075***	0.076***
	(22.590)	(22.987)	(23.700)	(24.483)
5-10 km from USFS	0.045***	0.045***	0.043***	0.043***
	(17.726)	(18.008)	(16.176)	(16.571)
10-15 km from USFS	0.030***	0.031***	0.021***	0.022***
	(12.613)	(13.001)	(8.580)	(8.906)
15-20 km from USFS	0.036***	0.036***	0.034***	0.034***
	(15.317)	(15.525)	(13.741)	(13.973)
20-25 km from USFS	0.034***	0.034***	0.049***	0.049***
	(15.724)	(15.932)	(21.450)	(22.052)
Constant	12.086***	12.030***	12.086***	12.030***
	(1,656.789)	(1,493.715)	(1,652.669)	(1,489.205)
Observations	249,264	249,264	249,264	249,264
R-squared	0.769	0.776	0.770	0.777
Fixed Effects	Year	Year by Quarter	Year	Year by Quarter

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Risk Treatment

VARIABLES	(1) Log Price	(2) Log Price	(3) Log Price	(4) Log Price
Treated	0.018***	0.016***	0.041***	0.040***
	(3.701)	(3.297)	(9.360)	(9.141)
Post Fire	-0.007**	-0.007**	0.003	0.003
	(-2.477)	(-2.401)	(0.927)	(1.169)
Treat by Post	0.007	0.011*		
	(1.120)	(1.759)		
Treat by Post (0-5 km)			0.061**	0.062**
			(2.153)	(2.201)
Treat by Post (5-10 km)			-0.093***	-0.094***
			(-9.635)	(-9.885)
Treat by Post (10-15 km)			-0.103***	-0.097***
			(-11.770)	(-11.229)
Treat by Post (15-20 km)			0.002	0.005
			(0.194)	(0.644)
Treat by Post (20-25 km)			0.076***	0.077***
			(5.020)	(5.117)
0-5 km from USFS	-0.031***	-0.029***	-0.019***	-0.017***
	(-5.297)	(-4.927)	(-3.123)	(-2.835)
5-10 km from USFS	-0.063***	-0.059***	-0.040***	-0.037***
	(-11.026)	(-10.505)	(-6.880)	(-6.352)
10-15 km from USFS	0.015***	0.018***	0.036***	0.038***
	(2.795)	(3.449)	(6.602)	(7.056)
15-20 km from USFS	0.018***	0.020***	0.020***	0.022***
	(3.890)	(4.470)	(4.247)	(4.647)
20-25 km from USFS	-0.038***	-0.036***	-0.042***	-0.041***
	(-9.709)	(-9.421)	(-11.118)	(-10.908)
Constant	12.040***	11.997***	12.027***	11.983***
	(717.225)	(643.363)	(721.766)	(648.050)
Observations	46,209	46,209	46,209	46,209
R-squared	0.758	0.764	0.760	0.765
Fixed Effects	Year	Year by Quarter	Year	Year by Quarter

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Proximity & Risk Treatment

VARIABLES	(1) Log Price	(2) Log Price	(3) Log Price	(4) Log Price
Treated	-0.010***	-0.008***	-0.028***	-0.027***
	(-4.147)	(-3.376)	(-11.423)	(-11.230)
Post Fire	0.008***	0.011***	0.005***	0.008***
	(5.420)	(7.521)	(3.538)	(5.406)
Treat by Post	-0.024***	-0.028***		
	(-8.250)	(-9.662)		
Treat by Post (0-5 km)			-0.055***	-0.058***
			(-12.195)	(-12.969)
Treat by Post (5-10 km)			-0.026***	-0.027***
			(-5.620)	(-6.000)
Treat by Post (10-15 km)			0.106***	0.105***
			(19.489)	(19.437)
Treat by Post (15-20 km)			0.054***	0.054***
			(9.584)	(9.625)
Treat by Post (20-25 km)			-0.104***	-0.109***
			(-20.392)	(-21.494)
0-5 km from USFS	0.051***	0.052***	0.076***	0.078***
	(13.513)	(14.008)	(17.690)	(18.357)
5-10 km from USFS	0.017***	0.017***	0.014***	0.015***
	(5.590)	(5.894)	(4.597)	(4.900)
10-15 km from USFS	0.013***	0.014***	-0.000	0.001
	(4.533)	(4.969)	(-0.172)	(0.215)
15-20 km from USFS	0.032***	0.033***	0.025***	0.025***
	(12.045)	(12.444)	(8.885)	(9.250)
20-25 km from USFS	0.040***	0.040***	0.046***	0.047***
	(17.395)	(17.870)	(19.599)	(20.328)
Constant	12.069***	12.008***	12.072***	12.012***
	(1,309.272)	(1,155.119)	(1,310.196)	(1,152.352)
Observations	163,485	163,485	163,485	163,485
R-squared	0.778	0.785	0.780	0.786
Fixed Effects	Year	Year by Quarter	Year	Year by Quarter

References

Anderson, S. T., & West, S. E. (2006). Open space, residential property values, and spatial context. Regional Science and Urban Economics, 36(6), 773-789.

Atreya, A., Ferreira, S., & Kriesel, W. (2013). Forgetting the flood? An analysis of the flood risk discount over time. Land Economics, 89(4), 577-596.

Boslett, A., Guilfoos, T., & Lang, C. (2016). Valuation of expectations: A hedonic study of shale gas development and New York's moratorium. Journal of Environmental Economics and Management, 77, 14-30.

Bin, O., & Landry, C. E. (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. Journal of Environmental Economics and management, 65(3), 361-376.

Cal Fire. (2007). California Fire Siege 2007: An Overview.

Champ, P. A., Donovan, G. H., & Barth, C. M. (2009). Homebuyers and wildfire risk: a Colorado Springs case study. *Society & Natural Resources*, *23*(1), 58-70.

Donovan, G. H., Champ, P. A., & Butry, D. T. (2007). Wildfire risk and housing prices: a case study from Colorado Springs. Land Economics, 83(2), 217-233.

Gawande, K., & Jenkins-Smith, H. (2001). Nuclear waste transport and residential property values: estimating the effects of perceived risks. Journal of Environmental Economics and Management, 42(2), 207-233.

Gawande, K., Jenkins-Smith, H., & Yuan, M. (2013). The long-run impact of nuclear waste shipments on the property market: Evidence from a quasi-experiment. Journal of Environmental Economics and Management, 65(1), 56-73.

Hallstrom, D. G., & Smith, V. K. (2005). Market responses to hurricanes. Journal of

Environmental Economics and Management, 50(3), 541-561.

Kim, C. W., Phipps, T. T., & Anselin, L. (2003). Measuring the benefits of air quality improvement: a spatial hedonic approach. *Journal of environmental economics and management*, *45*(1), 24-39.

Loomis, J. (2004). Do nearby forest fires cause a reduction in residential property values?. Journal of forest economics, 10(3), 149-157.

McCoy, S. J., & Walsh, R. P. (2014). WUI on fire: Risk, salience & housing demand (No. w20644). National Bureau of Economic Research.

Muehlenbachs, L., Spiller, E., & Timmins, C. (2015). The housing market impacts of shale gas development. The American Economic Review, 105(12), 3633-3659.

Mueller, J. M., & Loomis, J. B. (2008). Spatial dependence in hedonic property models: Do different corrections for spatial dependence result in economically significant differences in estimated implicit prices?. Journal of Agricultural and Resource Economics, 212-231.

Mueller, J., Loomis, J., & González-Cabán, A. (2009). Do repeated wildfires change homebuyers' demand for homes in high-risk areas? A hedonic analysis of the short and long-term effects of repeated wildfires on house prices in Southern California. The Journal of Real Estate Finance and Economics, 38(2), 155-172.

National Interagency Fire Center. Federal Firefighting Costs (Suppression Only). https://www.nifc.gov/fireInfo/fireInfo_documents/SuppCosts.pdf. Last accessed 12 Jan 2017.

Stetler, K. M., Venn, T. J., & Calkin, D. E. (2010). The effects of wildfire and environmental amenities on property values in northwest Montana, USA. Ecological Economics, 69(11), 2233-2243.

Syphard, A. D., Radeloff, V. C., Keeley, J. E., Hawbaker, T. J., Clayton, M. K., Stewart, S. I., & Hammer, R. B. (2007). Human influence on California fire regimes. *Ecological applications*, *17*(5), 1388-1402.

Westerling, A. L., Bryant, B. P., Preisler, H. K., Holmes, T. P., Hidalgo, H. G., Das, T., & Shrestha, S. R. (2011). Climate change and growth scenarios for California wildfire. Climatic Change, 109(1), 445-463.

Westerling, A. L., Hidalgo, H. G., Cayan, D. R., & Swetnam, T. W. (2006). Warming and earlier spring increase western US forest wildfire activity. science, 313(5789), 940-943.