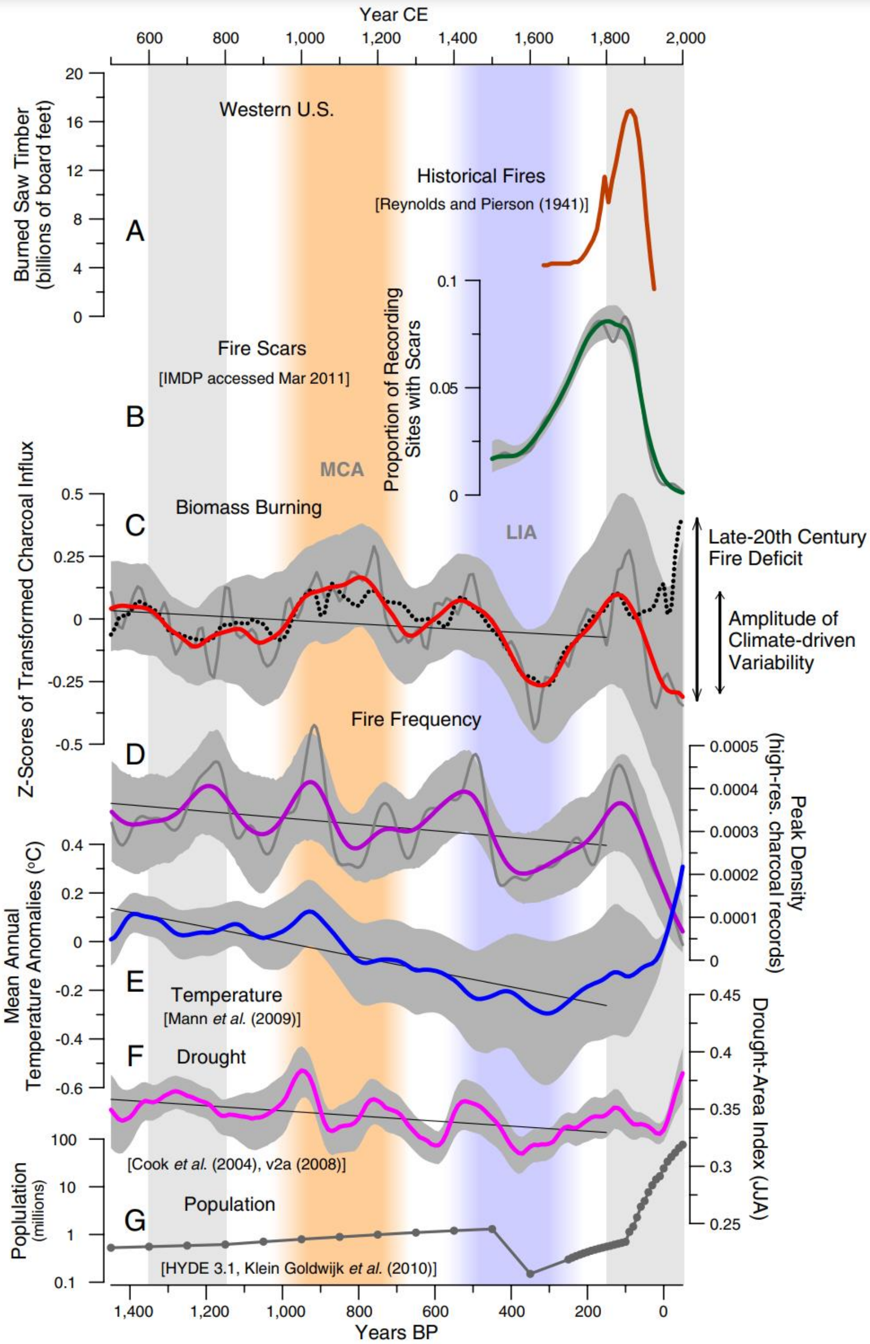
A State on Fire: Effect of California Wildfire on Perceived Risks and Home Values

I. Abstract

Due to land-use change, climate change and suppressive fire prevention measures, the fire in the west coast of the United States has been “a new seasonal normal” in the past few years. This project aims to shed light on people’s willingness to pay to avoid fire risks. Since nonmobile assets such as real estate are most directly affected by fires, this project analyzes housing value trends across cities that were hit by multiple severe fires to evaluate people’s willingness to pay to avoid the fire risk. In particular, this project provides a case study of the impact of wildfires in Santa Clarita over 2000 and 2010. The study finds that, compared to the neighboring city of Burbank, after several severe fires, the housing value in Santa Clarita decreased by 5% on average. Learning is observed following the fire, as after a severe fire, a smaller fire in the following year did not have a statistically significant effect on housing values. However, the effect of the fire is most significant in the following 1 or 2 years, if there are no further fires. After a few years without fires, another severe fire would lead to a steepper drop in housing prices. With the willingness to pay reflected on housing value depreciation in this study, and the learning curve of people’s perception of fire risks, we wish to give an estimated lower bound of the value of fire risk reduction, and thus serves to advise policymakers on the public spending of fire preventions.

II. Introduction

California, a state where wildfires are not news to us, have been naturally affected by wildfires in prehistoric times. Before mid-Holocene, lightning strikes were the most common cause of California Wildfires before the great population increase, and wildfires have been a part of and shaping California's ecosystem for thousands of years (Jones, 1992; Keeley, 2005). However, in recent decades, the frequency and severity of the wild-fire activities compounded with land-use change have dramatically impacted people's lives and the costs associated with fire mitigation. (Figure1)



(*A*) Estimated historical saw timber affected by fires (48). (*B*) Smoothed proportions of dendrochronological sites recording fire scars (the green curve is based on locally fitting nearest-neighbor parameter of 0.25, while the gray curve is based on a parameter value of 0.10. (*C*) Smoothed and standardized 25-year (gray) and 100-year (red) trend line through standardized biomass burning records ($n = 69$) along with predicted biomass burning based on a GAM (black dashed line) fit to the 100-year biomass burning records. (*D*) Smoothed peak density (inferred fire frequency) from charcoal values ($n = 41$). (*E*) Smoothed gridded temperature anomalies for the western United States (10). (*F*) Smoothed Palmer Drought Severity Index for the western United States (9) . (*G*) Population estimates for the western United States (11). All smoothed curves are plotted with 95% bootstrap confidence intervals.

Figure 1

From Figure 1, we can see that on a scale of a thousand years, the trend of fire frequencies, biomass burning and the temperature is downward. However, in the recent 200 years, we have a drastic increase in temperature, and accumulated lots of excess fire deficits, thus increasing future fire risks. Even though we are at the historic low for fire frequency, the frequency and severity of wildfires have already imposed huge damage to structures, lives, and health. Unfortunately, the frequency, damage and costs associated with fire mitigation and prevention are projected to grow. For instance, the fire suppression emergency fund has grown from around $10-20 million in the 1980s to hundreds of million dollars (California Department of Forestry and Fire Protection, 2019).

Not only in recent decades did fire severity and frequency increase, but this propensity is also most evident in recent years. In 2018, the Camp fire devastated almost 160,000 acres, destroyed nearly 20,000 structures, and took away more than 80 lives. In 2020, the year we witness the largest wildfire season, had over 9000 fires, and burned over 4 million acres, which is almost half of the nation-wide figure of 8.6 million (CAL FIRE, 2018; National Interagency Fire Center, 2018). A lot of Californians were stunned by the images of fire on media and described it as “the Hellfire”. California ranked the top at the number of acres burned, and the top 10 costliest fires in the U.S. are all California fires, six of which are during the year 2017 and 2018, as shown in figure 2 (Insurance Information Institute, 2018).

Top 10 Costliest Wildland Fires In The United States (1)
($ millions)

			Estimated insured loss	
Rank	Date	Name, Location	Dollars when occurred	In 2018 dollars (2)
1	Nov. 8-25, 2018	Camp Fire, CA (3)	$8,500-$10,500	$8,500-$10,500
2	Oct. 8-20, 2017	Tubbs Fire, CA (3)	7,500-9,700	7,700-9,900
3	Nov. 8-22, 2018	Woolsey Fire, CA (3)	3,000-5,000	3,000-5,000
4	Oct. 8-20, 2017	Atlas Fire, CA (3)	2,500-4,500	2,600-4,600
5	Dec 4-23, 2017	Thomas Fire, CA (3)	1,500-3,500	1,530-3,600
6	Oct. 20-21, 1991	Oakland Hills Fire, CA	1,700	2,851
7	Oct. 21-24, 2007	Witch Fire, CA	1,300	1,552
8	Jul. 23-Aug. 30, 2018	Carr Fire, CA (3)	1,000-1,500	1,000-1,500
9	Oct. 25-Nov. 4, 2003	Cedar Fire, CA	1,060	1,417
10	Oct. 25-Nov. 3, 2003	Old Fire, CA	975	1,304

Figure 2

In the list of 20 largest fires in California, ranked by CAL FIRE, 6 of which occurred in 2020, and 9 of which occurred between 2017 and 2020 (CAL FIRE, 2020). This result seems to be consistent with the trend of losses incurred by the wildfire, which took a huge jump in the year 2017, as shown in figure 3.

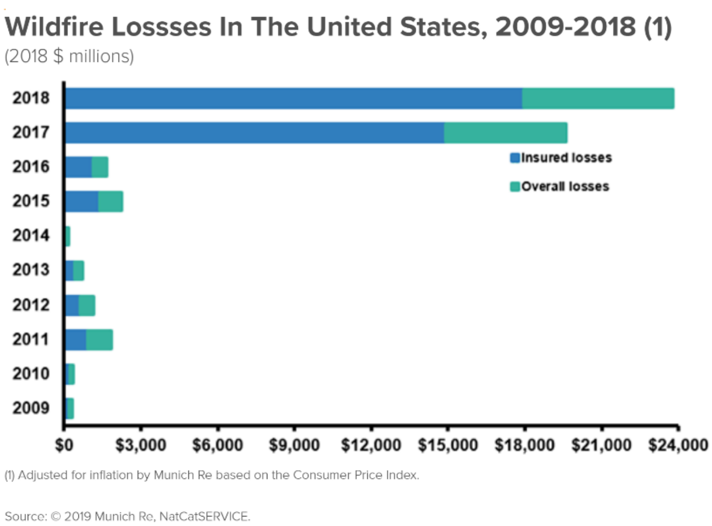


Figure 3

The sudden jumps of the wildfire loss can be explained in part by the increase in frequency of California fires, as the Camp fire alone accounts for $10,000 million, which is a quadruple of the wildfire loss in 2016. The unprecedented loss caused by wildfires along with the size of at-risk populations and properties caught media attention, and wildfires made the headlines frequently every year during fire seasons, with one record to be broken after another. Indeed, a large number of California homeowners are under extreme fire risks, according to the Insurance Information Institute.

We can see from figure 4 that California ranked top in “high to extreme fire risk”, with an estimated number of properties at risk of more than 2 million, nearly tripling the estimated number of Texas properties at risk, which ranked the second (Insurance Information Institute, 2019).

Top 10 States At High To Extreme Wildfire Risk, 2019 (1)

Rank	State	Estimated number of properties at risk	Rank	State	Percent of properties at risk
1	California	2,019,800	1	Montana	29%
2	Texas	717,800	2	Idaho	26
3	Colorado	371,100	3	Colorado	17
4	Arizona	237,900	4	California	15
5	Idaho	175,000	5	New Mexico	15
6	Washington	160,500	6	Utah	14
7	Oklahoma	153,400	7	Wyoming	14
8	Oregon	151,400	8	Oklahoma	9
9	Montana	137,800	9	Oregon	9
10	Utah	136,000	10	Arizona	8

Figure 4

Source: Insurance Information Institute

The growing cost and fire risks are a combination of a large population living near the risk-prone wildland-urban interface (WUI), and the resulting firefighting costs associated with protecting these residences (Boomhower, 2019). WUI is an area where houses are mixed with or adjacent to forests, grasslands, are created, and drastically increase the fire risks (Radeloff et al., 2018). Figure 5 below shows 2 types of WUI: wildland-urban interface and wildland-urban intermix. Both WUI types have large areas where many houses and wildland vegetation intermingle, which provides no barrier but excess fuels when the area is hit by a wildfire (USDA Forest Service, 2018).

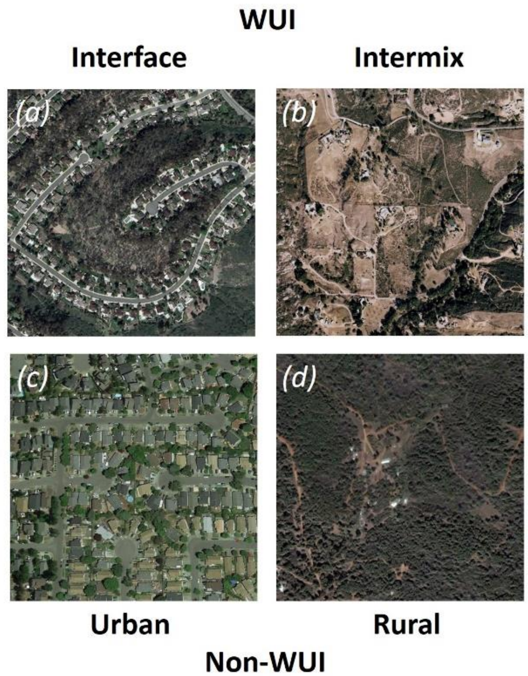


Figure 5

Despite the fire risks, in the recent several decades, we see an increasing trend of people moving away from cities and towards suburban WUI areas. From 1990 to 2010, the number of homes in WUI grew by 41%, the area of land in WUI grew by 33% nationwide, making WUI the fastest land-use type in the lower 48 states (United States Fire Administration, 2020). In California, the number of homes in WUI grew by 33.8% from 1990 to 2010 (USDA Forest Service, 2018).

On one hand, there are growing awareness and increasing attention and its impact on people's daily lives. On the other hand, an increasing number of people are moving into high-fire-risk WUI areas. This motivates us to think about if people are making informed decisions when they consider purchasing a home. If people are not aware of the risk of natural disasters when they decide to purchase a home, then a market failure is present and may need government intervention to internalize the externality from lack of information and underestimation of the expected loss of a wildfire event. Therefore, in this project, I look to recover people's evaluation of fire risks by analyzing the house price trend. Since wildfires pose a direct threat to immobile real estate, housing values will fairly accurately reflect people's willingness to pay to avoid wildfire risks. If the fire risks have not been priced in when people make purchasing decisions, then we should expect a significant drop in housing prices after the fires compared to the housing price trend in cities not affected by wildfires.

III. Research Subject & Methodology

This study focuses on the case study in Santa Clarita, a rapidly expanding WUI area in Southern California near Los Angeles. Described as a boomburb – booming suburb, Santa Clarita occupies the majority of the Santa Clarita valley. As shown in the map below, Santa Clarita is bounded by mountains, San Gabriel Mountains to the east, Santa Susana Mountains to the south and west, and Sierra Pelona Mountains to the North.

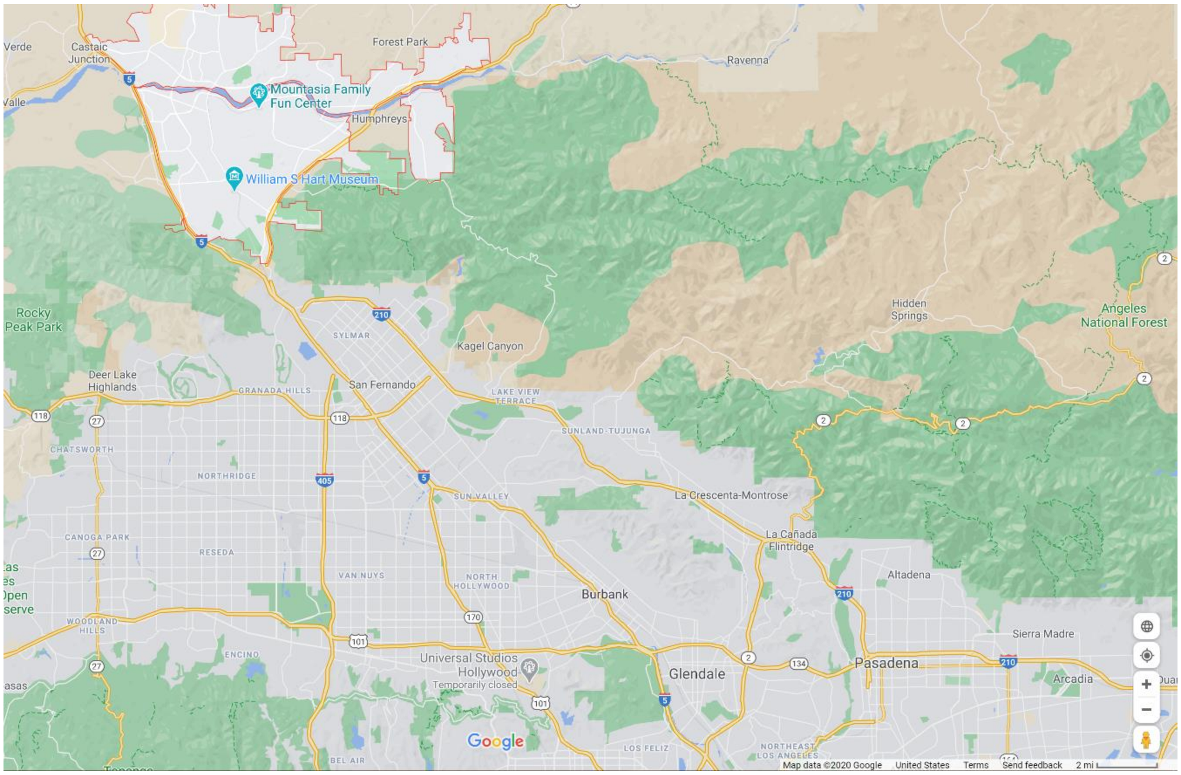


Figure 6

The mountains around Santa Clarita provided the conditions for wildfires to occur, and thus serves as the treatment group for this study. For the control group, we would like it to have similar characteristics to the treatment group and ideally to be geographically close to the treatment group to make sure the control group would accurately represent the treatment group without the fire. The nearby city of Burbank is chosen as the control group. The neighboring city of San Fernando was not chosen as the control group because it is too close to some of the fires we are looking at, and to avoid the control group to be secretly treated and underestimate the impact of fires on housing values, we decided to go further away and use Burbank as the control. The city of Pasadena is also used as a validity check, which will be mentioned in further sections.

The time frame of the study is chosen to be 2000-2010 to analyze the short-run effect of the fires on housing values. This study period is chosen due to the abundance of data and it is the time period that we witnessed the rapid expansion of houses into WUI areas, when the costs and impacts of wildfires took a relatively big leap compared to the pre-2000s. In addition, for Santa Clarita – our treatment group, there were multiple fires in this timeframe, which allows us to understand the recurring effect of wildfires on housing values. With data across multiple fires, we can then peek into how people respond to repeated fire events over years, and whether risk adjustment and mitigations happen.

The housing transaction data including the sales price amount, transaction time and housing characteristics are obtained from Zillow. The housing data were filtered to only focus on single-family homes between 1998 and 2012. The housing sales price values are normalized using the Housing Price Index for California to 2020 dollars to minimize the effect of business cycles and inflation/deflation muddling with the results over the years. The outliers and incomplete transaction data were removed by trimming 10% of the sales prices on both sides.

A histogram of housing prices across the treatment group Santa Clarita and control group Burbank is shown below in figure 7.

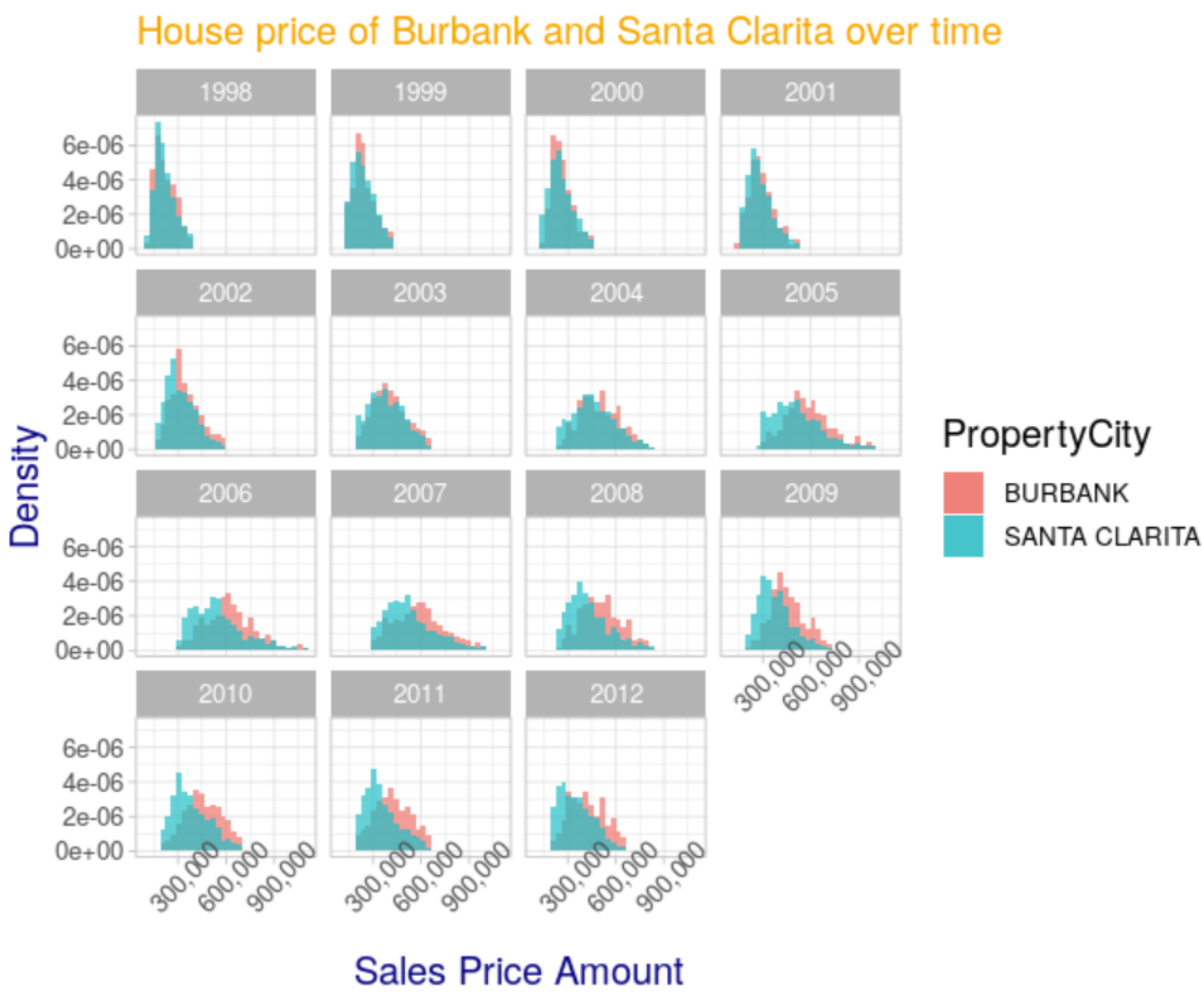


Figure 7

As shown from figure 7, the histograms of housing prices across Burbank and Santa Clarita are largely overlapping before the year 2002. After 2002, we can see the center of the histogram of housing values in Burbank shifted to the right of Santa Clarita. To clearly see the housing price trajectory evolving over the years, a line graph showing the average housing price each year in both the treatment and control groups is shown below in Figure 8 and 9.

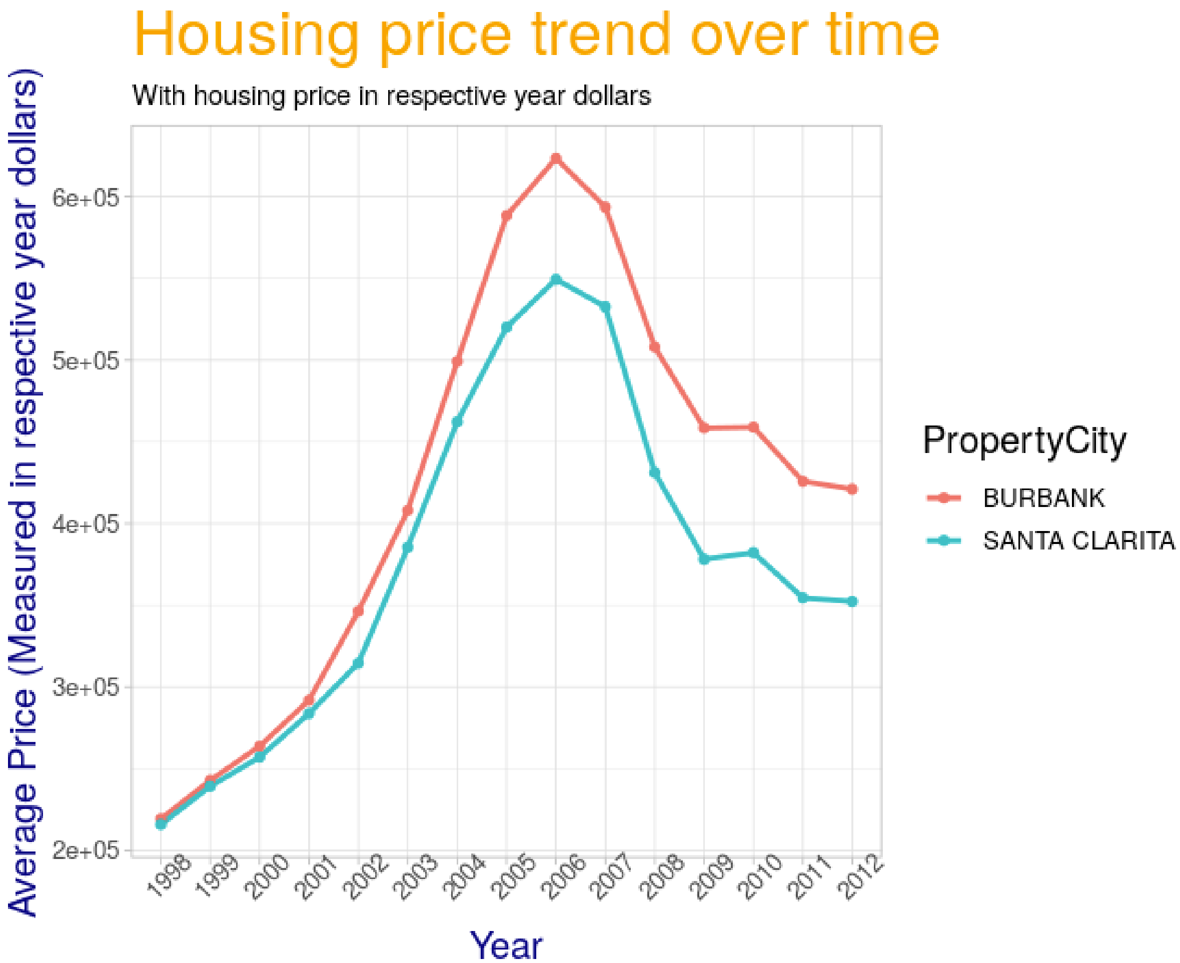

Housing price trend over time
With housing price in respective year dollars
Average Price (Measured in respective year dollars)
6e+05
5e+05
4e+05
3e+05
2e+05
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
Year
PropertyCity
BURBANK
SANTA CLARITA

Figure 8

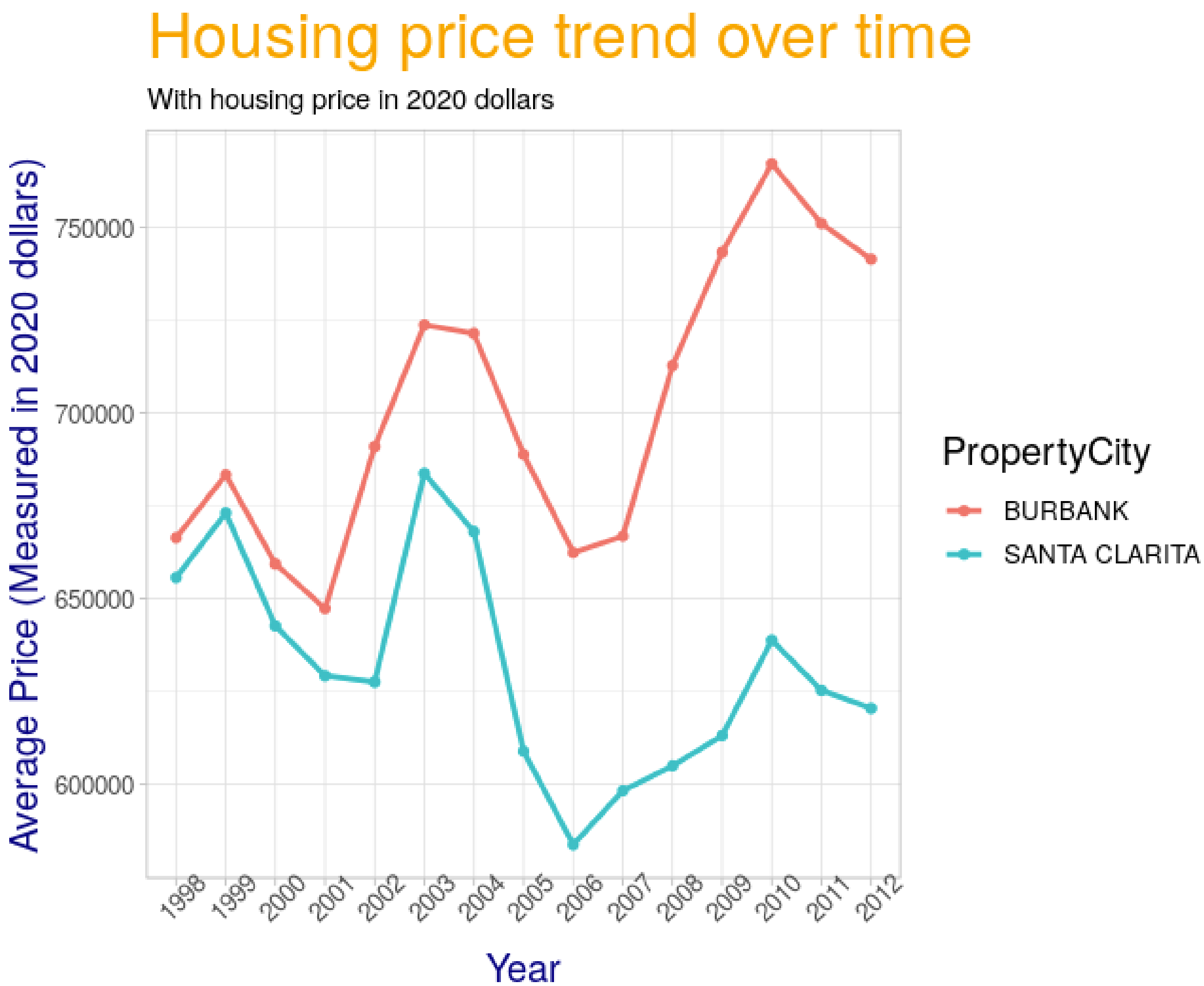


Figure 9

Figure 8 shows the nominal average housing value measured in dollars of the respective years. To see the real housing price and provide a clearer visual comparison, the normalized average housing value is shown in figure 9.

The fire data is acquired through CAL FIRE. During the study period, there were 4 major fires happening in the mountains surrounding Santa Clarita. The first major fire Simi took place in 2003. Simi fire ignited on Oct. 25th, 2003, which burned 108,204 acres. The second fire was in the following year of Simi in 2004. Foothill fire ignited on Jul. 15th, 2004 and burned around

6,002 acres. There were not any major fires near Santa Clarita in the next 2 years until 2007, when 2 major fires Buckweed and Magic fire took place near Santa Clarita. Buckweed and Magic fire ignited on Oct. 21st and 22nd, 2007, respectively, and burned more than 31,000 acres in total. The last fire included in this study is the Sayre fire, which ignited on Nov. 14th, 2008, and resulted in 11,262 acres burned and the loss of 489 homes, the most home loss due to fire in the city's history (CAL FIRE, 2020).

To quantitatively evaluate the impact of fires on housing values, a difference-in-differences research design is used to recover the causal effect of repeated wildfires on housing values. A general setup of the difference-in-difference regression is shown below, where y_{it} is the observed outcome variable that we observe, and we are interested in the coefficient β_3 that gives us the estimated causal effect of the treatment.

$$y_{it} = \beta_0 + \beta_1\, After_t + \beta_2 Treatment_i + \beta_3 After \cdot\ Treatment_{it}\ + u_{it}$$

The difference-in-differences model allows us to know if the fires lead to a differential trend in the trajectory of average housing prices in the treatment group compared to the control group. To achieve accurate results and avoid confounding variables, we must assume that the housing price trend in the treatment group should be no different from that of the control group had it not been for fires in the treatment group. This means the control group should be a good counterfactual to the treatment group and housing price trend before any fire happened should be evolving similarly across the treatment and control group. The control group Burbank is geographically close to the treatment group and both in the WUI areas, thus we think the housing price trend should be similar if not due to the fire. From figure 9, we do see before 2003, when the first fire hit the treatment group, the housing price trajectories do look similar across both treatment and control groups, which increases our confidence that the model is correct and the estimated effect of the fire on housing value is accurate and not due to something else that changes differently in time across the treatment and control groups. The estimated effect of the fires is given by:

$$[\hat{E}(price \mid Treatment = 1, Fire = 1) - \hat{E}(price \mid Treatment = 0, Fire = 1)] - [\hat{E}(price \mid Treatment = 1, Fire = 0) - \hat{E}(price \mid Treatment = 0, Fire = 0)]$$

This study includes several different model specifications and functional forms: linear and log-linear models with different variables being controlled.

$$\begin{aligned} norprice_{it} = {} & \beta_0 + \beta_1 treatment1_i + \beta_2 Simi_t + \beta_3 Foothill_t + \beta_4 BuckweedMagic \\ & + \beta_5 Sayre + \beta_6 treatment1 \cdot Simi_{it} + \beta_7 treatment1 \cdot Foothill_{it} \\ & + \beta_8 treatment1 \cdot BuckweedMagic_{it} + \beta_9 treatment1 \cdot Sayre_{it} + u_{it} \end{aligned}$$

$$\begin{aligned} norprice_{it} = {} & \beta_0 + \beta_1 treatment1_i + \beta_2 Simi_t + \beta_3 Foothill_t + \beta_4 BuckweedMagic \\ & + \beta_5 Sayre + \beta_6 treatment1 \cdot Simi_{it} + \beta_7 treatment1 \cdot Foothill_{it} \\ & + \beta_8 treatment1 \cdot BuckweedMagic_{it} + \beta_9 treatment1 \cdot Sayre_{it} \\ & + \beta_{10} LotSizeSquareFeet_{it} + \beta_{11} YearBuilt_{it} + \beta_{12} FullBeadrooms_{it} \\ & + \beta_{13} FullBath_{it} + u_{it} \end{aligned}$$

$$ln(norprice_{it}) = \beta_0 + \beta_1 treatment1_i + \beta_2 Simi_t + \beta_3 Foothill_t + \beta_4 BuckweedMagic + \beta_5 Sayre + \beta_6 treatment1 \cdot Simi_{it} + \beta_7 treatment1 \cdot Foothill_{it} + \beta_8 treatment1 \cdot BuckweedMagic_{it} + \beta_9 treatment1 \cdot Sayre_{it} + u_{it}$$

$$ln(norprice_{it}) = \beta_0 + \beta_1 treatment1_i + \beta_2 Simi_t + \beta_3 Foothill_t + \beta_4 BuckweedMagic + \beta_5 Sayre + \beta_6 treatment1 \cdot Simi_{it} + \beta_7 treatment1 \cdot Foothill_{it} + \beta_8 treatment1 \cdot BuckweedMagic_{it} + \beta_9 treatment1 \cdot Sayre_{it} + \beta_{10} LotSizeSquareFeet_{it} + \beta_{11} YearBuilt_{it} + \beta_{12} FullBeadrooms_{it} + \beta_{13} FullBath_{it} + u_{it}$$

In the first and third model specifications, both are not controlling for housing characteristics, in the second and fourth specifications, both control for common characteristics that people usually consider when they decide to purchase a home, namely the lot size of the house, the year the house was built, total number of bedrooms, and total number of full bathrooms. In the log-linear specification, we allow the marginal effect of fires on housing values to vary depending on the levels of the independent variables.

The fire and treatment dummy variables were created. For the treatment dummy, we encoded a 1 for houses sold in Santa Clarita, and 0 for houses sold in Burbank. For the fire dummy, we created a dummy variable for each fire that happened on the mountains around Santa Clarita. More specifically if a house is sold before the fire, then the dummy variable for that specific fire is set to 0, and if a house is sold after the fire, then the dummy variable for that specific fire is switched to a 1. In order to determine when to switch fire dummies to 1, the recording date of the house transaction is used. In fact, the recording date of a transaction is the date that a transaction is completely settled between the buyer and the seller and the information of the transaction is reported to the county clerk. However, this means the recording date is usually not the moment when the buyer decides to purchase a home, and there is usually an escrow period that usually lasts 30-60 days after the purchasing contract is signed, and when home inspections, appraisal, and insurance take place (Investopedia, 2020). Therefore, when creating the dummy variables for fires, the date that the fire dummies switches to 1 is 60 days after the actual date of the fire to capture the delayed effect of the fire on housing transactions.

The estimated causal effect of fires on housing values should be reflected in the coefficient of the interaction terms between treatment1 and respective fire dummies. The coefficients reflect the difference in slope of housing price trajectory between the treatment and control group. From figure 9, we can see that in 2004 and 2005, the slope in the treatment group is more negative than that of the control group. And in 2008 and 2009, the slope in the treatment group is less positive than that of the control group.

IV. Regression Results

The estimated effects of the fires on housing values are displayed in Table 1 below.

	norprice2020		log(norprice2020)	
	(1)	(2)	(3)	(4)
LotSizeSquareFeet		-0.187***		-0.00000***
		(0.006)		(0.000)
YearBuilt		874.501***		0.001***
		(67.322)		(0.0001)
TotalBedrooms		64,670.830***		0.105***
		(1,354.823)		(0.002)
FullBath		23,440.850***		0.031***
		(1,827.027)		(0.003)
treatment1	-28,939.620***	-105,800.600***	-0.047***	-0.165***
	(4,723.873)	(4,655.067)	(0.007)	(0.007)
Simi	37,628.260***	44,618.910***	0.059***	0.071***
	(11,180.570)	(9,724.162)	(0.017)	(0.015)
Foothill	-42,127.860***	-42,360.320***	-0.061***	-0.061***
	(11,310.900)	(9,837.970)	(0.017)	(0.015)
BuckweedMagic	32,095.680***	28,172.430***	0.047***	0.039***
	(9,006.496)	(8,054.947)	(0.014)	(0.012)
Sayre	42,123.370***	45,282.850***	0.057***	0.061***
	(8,716.357)	(7,837.023)	(0.013)	(0.012)
treatment1:Simi	-37,587.850***	-40,185.170***	-0.060***	-0.063***
	(12,540.400)	(10,905.940)	(0.019)	(0.016)
treatment1:Foothill	-793.614	10,423.430	-0.007	0.011
	(12,719.950)	(11,066.690)	(0.019)	(0.017)
treatment1:BuckweedMagic	-39,107.770***	-48,239.750***	-0.058***	-0.074***
	(10,583.110)	(9,408.610)	(0.016)	(0.014)
treatment1:Sayre	-20,072.380**	-31,789.830***	-0.020	-0.037***
	(10,240.380)	(9,152.560)	(0.016)	(0.014)
Constant	682,220.700***	-1,242,209.000***	13.396***	10.349***
	(4,060.433)	(130,742.700)	(0.006)	(0.197)
Observations	26,262	25,507	26,262	25,507
R^2	0.049	0.282	0.051	0.306
Adjusted R^2	0.049	0.282	0.050	0.306
Residual Std. Error	183,709.400 (df = 26252)	159,389.500 (df = 25493)	0.282 (df = 26252)	0.241 (df = 25493)
F Statistic	149.887*** (df = 9; 26252)	770.366*** (df = 13; 25493)	155.238*** (df = 9; 26252)	866.253*** (df = 13; 25493)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 1

In the linear model that controls for housing characteristics in column 2, we estimate that on average, when keeping other variables constant, fire Simi reduced the housing prices by

$40,185, with a standard error of $10,905, statistically significant at 1% level. The estimated effect of the second fire Foothill on housing prices is not statistically significant. The estimated effect of fire Buckweed and Magic on average reduced the housing prices by $48,239, statistically significant at 1% level. The estimated effect of fire Sayre on average reduced the housing prices by $31,789, statistically significant at 1% level. The linear model has an adjusted R^2 value of 0.282, with 25,507 observations, and 25493 degrees of freedom and all standard errors in the parentheses displaying the robust standard errors.

In the log-transformed model that controlled for housing characteristics displayed in column 4, the percent change of average housing price can be approximated by

$$\%\Delta y = 100 \cdot \left(e^{\beta_i} - 1\right)$$

Holding other variables constant, we estimate that Simi fire reduced housing prices by on average 6%, Buckweed and Magic fire reduced housing prices by on average 7%, Sayre fire reduced housing price by 3%, all at the significance level of 1%. Similar to the linear model, the estimated effect of Foothill fire on housing prices is statistically insignificant.

V. Model Validity Check

We checked visually that the housing prices trajectory before any fires in the treatment group evolves like that of the control group. To further check the validity of the model to make sure the treatment effect is not due to the specification of the model, a placebo test is run with a fake treatment group, the City of Pasadena. Since the City of Pasadena is geographically close to the treatment and control group, and also a rapidly expanding WUI at the time, we believe that housing prices should evolve similarly compared to the control group. Therefore, if we assign fire dummies to this fake treatment group, we should not see any statistically significant effect on housing prices if the model is correct. The regression result of the placebo regression is shown below in Table 2.

Placebo Regression Test

	norprice2020		log(norprice2020)	
	(1)	(2)	(3)	(4)
LotSizeSquareFeet		-0.631***		-0.00000***
		(0.038)		(0.00000)
YearBuilt		-1,418.916***		-0.002***
		(95.216)		(0.0001)
TotalBedrooms		24,704.600***		0.033***
		(2,481.992)		(0.003)
FullBath		60,289.980***		0.060***
		(2,938.568)		(0.003)
treatment1	77,851.550***	71,853.350***	0.077***	0.071***
	(8,732.114)	(8,100.418)	(0.010)	(0.009)
Simi	20,938.680	42,290.770**	0.032	0.058***
	(17,754.170)	(16,453.100)	(0.020)	(0.018)
Foothill	-30,273.890*	-29,345.870*	-0.039**	-0.038**
	(17,967.140)	(16,651.420)	(0.020)	(0.019)
BuckweedMagic	26,602.750*	26,780.620*	0.037**	0.035**
	(14,495.940)	(13,740.320)	(0.016)	(0.015)
Sayre	52,086.010***	54,650.470***	0.063***	0.066***
	(13,944.940)	(13,285.140)	(0.015)	(0.015)
treatment1:Simi	-12,363.150	-17,423.140	-0.022	-0.028
	(22,830.760)	(21,160.400)	(0.025)	(0.024)
treatment1:Foothill	-24,626.560	-24,000.960	-0.020	-0.019
	(23,063.310)	(21,384.440)	(0.026)	(0.024)
treatment1:BuckweedMagic	25,794.340	31,566.460*	0.022	0.032
	(18,953.740)	(17,994.640)	(0.021)	(0.020)
treatment1:Sayre	13,871.170	-4,880.343	0.015	-0.007
	(18,196.560)	(17,425.660)	(0.020)	(0.019)
Constant	759,012.700***	3,342,481.000***	13.491***	16.723***
	(6,564.456)	(185,871.900)	(0.007)	(0.207)
Observations	17,273	16,424	17,273	16,424
R^2	0.032	0.156	0.032	0.161
Adjusted R^2	0.032	0.156	0.031	0.160
Residual Std. Error	296,928.300 (df = 17263)	273,781.500 (df = 16410)	0.330 (df = 17263)	0.305 (df = 16410)
F Statistic	63.768*** (df = 9; 17263)	233.871*** (df = 13; 16410)	62.624*** (df = 9; 17263)	241.577*** (df = 13; 16410)
Note:				*p<0.1; **p<0.05; ***p<0.01

As shown in Table 2, the coefficients on the interaction terms between treatment1 and fire dummies are mostly insignificant, with a minor exception in column 2, where the coefficient on treatment1:BuckweedMagic is significant on 10% level. This placebo test confirmed that the model is correct and we can be more confident that the estimated coefficients on the interaction terms reflect the impact of fires on housing values fairly accurately.

VI. Conclusion

From the case study of repeated fire events in Santa Clarita Valley, we find that the fires do have a significant impact on housing values. When people make home purchasing decisions, it seems like they are unaware of or underestimate fire risks. In this specific case study, a fire reduces the housing price by on average 5%. This suggests that the risks of the fires have not yet been priced into the housing market, and thus proper governmental programs could help internalize the information externality. Currently, some governments implemented fire aid for homeowners affected or living near the high-risk areas, which we argue may lead to more people choose to live near fire-prone areas instead of moving away, since these programs act like subsidies and encourage people not to take mitigation strategies. These programs potentially lead to a larger public cost to fight the fires, as the costs of fighting against fires grow exponentially when the top goal is to protect properties. Better programs that discourage people to live near the fire-prone areas would help lower the public costs of fighting fire and make the market more efficient.

Despite the fact that the fire risks have not been priced in, we do observe learning and adjusting perceived fire risks after a severe fire event. For example, in 2004, Foothill fire which burned around 6 acres did not have any statistically significant effect on housing values, which we hypothesize is a result of people re-evaluating the fire risks after witnessing the Simi fire that burned around 100 acres in 2003.

In addition, we observe that the effect of the fire on housing prices diminishes quickly, since the housing price trajectory in the treatment group looks similar to that of the control group after 1 or 2 years of the fire, if there are no new fires. However, it seems like after a few years of no fires, another severe fire would lead to a bigger drop in housing prices. In our case study, there were no fires in 2005 and 2006, the Buckweed and Magic fire that happened in 2007 had a bigger effect on housing prices compared to fire Simi, even though the size and the damage of the fires in 2007 are both smaller than Simi fire in 2003.

VII. Limitations & Further Research Direction

Even though significant findings were discovered in this study, it is far from perfect. The lack of recent data limits us from getting a timelier result that reflects how people's evaluation of fire risks in recent years, when fire damages are unprecedented and growing attention and awareness emerge through the media headlines. In the next steps of the research, as the data becomes more available, we plan to scale up the case study and focus on multiple fire events in different places across the years to get a more comprehensive view of people's perception of fire risks. More control variables will also be added to the regression model to improve the fit and reduce omitted variable bias. In addition, this project focuses on the immediate effects of wildfires on housing values, and the nature of the treatment group, the fact that there are frequent fires over consecutive years, makes it impossible to separate out the long-term effect of fires because it would be impossible keep fire dummies constant over the years. This project also focuses on the local effect of the fire. Therefore, in the next step of the research, long term effects of the fire on housing values may be studied, and the impact of fires on health, and air qualities may be investigated.

Reference

Baylis, P., Boomhower, J., “Moral Hazard, Wildfires, and the Economic Incidence of Natural Disasters”. *National Bureau of Economic Research*. 2020. https://www.nber.org/papers/w26550

“Emergency Fund Fire Suppression Expenditures”. *California Department of Forestry and Fire Protection.* 2020. https://www.fire.ca.gov/media/8641/suppressioncostsonepage1.pdf

“Escrow”. *Investopedia.* 2020. https://www.investopedia.com/terms/e/escrow.asp

“Facts + Statistics: Wildfires”. *Insurance Information Institute*. 2020. https://www.iii.org/fact-statistic/facts-statistics-wildfires

“Incident Archive”. *CAL FIRE*. 2020. https://www.fire.ca.gov/incidents/2020

Jones, T.L., 1992. “Settlement trends along the California coast”. In: Jones, T.L. (Ed.), Essays on the Prehistory of Maritime California. *Center for Archaeological Research, University of California, Davis, pp. 1–37.*

Keeley, J.E., 1982. “Distributions of lightning and man-caused wildfire in California. In: Conrad, C.E., Oechel, W.C. (Eds.), Proceedings of the Symposium on Dynamics and Management of Mediterranean-Type Ecosystems”. *USDA Forest Service. General Technical Report PSW-58, Pacific Southwest Forest and Range Experiment Station, Berkeley, CA, pp. 431– 437.*

Keeley, J.E., 2005. “Fire history of the San Francisco east bay region and implications for landscape patterns”. *Int. J. Wildland Fire 14, 285–296.*

Keeley, J.E., 2006. South coast bioregion. In: Sugihara, N.G., van Wagtendonk, J., Shaffer, K.E., Fites-Kaufman, J., Thode, A.E. (Eds.), "Fire in California's Ecosystems". *University of California Press, Berkeley, California, pp. 350– 390*

Kramer, Heather Anu; Mockrin, Miranda H.; Alexandre, Patricia M.; Radeloff, Volker C. 2019. "High wildfire damage in interface communities in California". *International Journal of Wildland Fire. 28(9): 641-*. https://doi.org/10.1071/WF18108.

"National Preparedness Level 1". *National Interagency Fire Center*. 2020. https://www.nifc.gov/fireInfo/nfn.htm

Radeloff, Volker C.; Helmers, David P.; Kramer, H. Anu; Mockrin, Miranda H.; Alexandre, Patricia M.; Bar-Massada, Avi; Butsic, Van; Hawbaker, Todd J.; Martinuzzi, Sebastián; Syphard, Alexandra D.; Stewart, Susan I. 2018. "Rapid growth of the US wildland-urban interface raises wildfire risk". *Proceedings of the National Academy of Sciences. 24: 201718850-*. https://doi.org/10.1073/pnas.1718850115.

Radeloff, Volker C.; Helmers, David P.; Kramer, H. Anu; Mockrin, Miranda H.; Alexandre, Patricia M.; Bar Massada, Avi; Butsic, Van; Hawbaker, Todd J.; Martinuzzi, Sebastián; Syphard, Alexandra D.; Stewart, Susan I. 2017. "The 1990-2010 wildland-urban interface of the conterminous United States - geospatial data". 2nd Edition. *Fort Collins, CO: Forest Service Research Data Archive*. https://doi.org/10.2737/RDS-2015-0012-2.

"Top 20 Largest California Wildfires". *CAL FIRE*. 2020. https://www.fire.ca.gov/media/11416/top20_acres.pdf

"Incident Archive". *CAL FIRE*. 2020. https://www.fire.ca.gov/incidents/2020

"Wildland Urban Interface", *U.S. Fire Administration*. 2020. https://www.usfa.fema.gov/wui/

"Wildland Urban Interface (WUI) areas in the U.S.". *USDA Forest Service*. 2020. https://www.nrs.fs.fed.us/data/wui/state_summary/

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