The Effect of Wildfire Proximity on Property Values: Evidence from the Western United States

by

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Abstract

This paper studies the dis-amenity effect of wildfire proximity on property values in the western United States by exploiting variation in the minimum distance to a wildfire perimeter from census block groups between 2005-2019. To isolate the effect of wildfire proximity on property values, I use a first difference regression to control for demographic, housing, and unobservable time-invariant factors (e.g. water, elevation, forests, etc.) that contribute to property values. I find that the implicit marginal price reduction for a block group being within 4km from a 2015 wildfire is $23,651.45. This translates into a 7.6% decrease in the growth rate of block group median property values within 4km from a 2015 wildfire perimeter. The estimate is found to be robust to pre-2015 wildfires and wildfire risk controls. I also find the dis-amenity effect from a 2015 wildfire on block group property values to be significant within 20km from a 2015 wildfire perimeter controlling wildfire risk. The results suggest that wildfire dis-amenity effects place downward pressure on property values, which homeowners may not realize due to strong positive amenity values in areas prone to wildfires.

1 Introduction

In the United States, no more than 7 million acres were lost annually to wildfires between 1994 and 1999. Since 2000, 11 of the last 19 years ended with more than 7 million acres burned. In 2015 and 2017, the United States lost 10 million acres to wildfires. All four (Oklahoma, Colorado, Utah, and Wyoming) of the 13 western states have experienced at least one year with over 1 million acres burned since 2010 (Jeffrey et al., 2019). As shown in Figure 10, the number of fires since 2000 (red bars) has remained relatively stable. However, there is a volatile trend in the total number of acres burned. This graph shows that wildfires are not only remaining intense, but the intensity of wildfires is becoming more volatile.

In 2017 homeowners in Sonoma County, California, faced the most destructive wildfire in Californian history, burning over 36,000 acres (i.e. Tubbs wildfire) (Barbaro and Flavelle, 2020). In 2019, the Kincade wildfire was the largest in Sonoma County, surpassing the Tubbs wildfire burning over 77,000 acres only to be surpassed again by the LNU Lighting Complex fires in 2020, burning over 363,000 acres. Despite these destructive wildfires year after year, housing shortages, affordability, and high rates of homelessness in California have incentivized the state government to approve new housing construction and speed up development (Hans Johnson, 2020). California's need to expand the housing supply resulted in the state governor passing 18 bills in 2019 to remove local barriers to housing development, including in the high wildfire risk wildland-urban interface (WUI) (Hans Johnson, 2020; Barbaro and Flavelle, 2020). Across the United States, development in the WUI is the "fastest-growing land-use type," with 97 percent of developments resulting from new housing, and is associated with more wildfire ignitions (Radeloff et al., 2018). Despite the increased wildfire risk and intensity in WUI areas, many homeowners decide not to move out due to competing incentives (e.g. California's housing and insurance policies) (Barbaro and Flavelle, 2020; Flavelle and Plumer, 2019). The trade-off homeowners face between the potential risk of a wildfire destroying their home versus the amenity value of living in a WUI area influences a homeowner's decision to live in a WUI area and property values. Developments in high wildfire risk WUI and rural localities generate moral hazards either because homeowners are misperceiving risk or are not fully internalizing wildfires' cost. Efforts to "price-in" the cost of fire suppression in high-risk areas have not been successful. In 2011, California introduced the Fire Protection Fee, which required all residents in the Cal Fire region to pay a fee of $152.33 to cover the costs of fire protection services. However, the fee did not differentiate between differentiated fire risk areas, so it was terminated in 2017. The incentive for municipalities and individuals not to consider fire risk mitigation measures because the benefits are not directly perceived is an area of research economists have not delved deep into (Baylis and Boomhower, 2019). More importantly, this paper studies how homeowners internalize the dis-amenity effects of wildfires[2] through property values.

This paper examines the effect of wildfire proximity on property values. Specifically, this paper asks what the environmental dis-amenity effect of wildfire proximity on property values is? The key estimation challenge is controlling for differential effects of wildfires on house prices over time (e.g. a wildfire may destroy the housing stock, which would raise prices, but also may make the community less desirable to live in lower property values) and parsing out the magnitude of wildfire dis-amenity effects from increased wildfire risk on property values. Using a first difference regression, I can control for various time-invariant confounding variables in both my treatment and control group by estimating the difference in property values between areas affected by a wildfire and areas not affected by wildfires.

I assume that the occurrence of a wildfire near properties is exogenous. By measuring across various property value attributes and controlling for wildfire risk, I can isolate the dis-amenity effect of wildfires on property values. Also, by parsing out wildfire dis-amenity effects in the analysis by controlling for an objective measure of wildfire risk, I can conclude if homeowners are "pricing in" dis-amenity from wildfires when making a location preference decision. I find that census block groups located within 4km from a 2015 wildfire perimeter face a 7.6% reduction in the growth rate of median property values compared to block groups located beyond 4km from a 2015 wildfire perimeter. This accounts for a marginal implicit price reduction of around $23,651.45 for properties in block groups

[2] Note wildfire dis-amenity effects refers to the cost of environmental destruction caused by wildfires on property values, while wildfire risk is the perceived threat or probability of a wildfire occurring.

situated within 4km from a 2015 wildfire perimeter. The main result is robust to pre-fire and wildfire risk controls. Controlling for wildfire risk the paper found the isolated dis-amenity effect on block group property values to be significant within 20km from a 2015 wildfire perimeter and negative. This paper adds to the literature in two important ways, a) this paper is the first[3] paper to look at the effect of wildfire proximity on property values across the western continental United States, and b) this paper considers the magnitudes of environmental dis-amenity effects separate from wildfire risk effects on attributes of property values. Understanding how homeowners internalize dis-amenity effects from wildfires is critical to developing fiscal policies to mitigate moral hazard generating location decisions[4].

2 Literature Review

The literature on the effect of wildfires on house prices finds a persistent negative effect ranging between a 9 and 16 percent drop in house prices in the year following a wildfire (see, for example, Loomis, 2004; Mueller et al., 2009; Mueller and Loomis, 2014; McCoy and Walsh, 2018; Stetler et al., 2010). A persistent gap in the literature as described by Mueller and Loomis (2014) is that "we do not have the ability to statistically determine what portion of the predicted sales price drop is due to the change in perceived risk versus the change in amenity values". Again, Mueller and Loomis (2014) also note that differences in perception of wildfire risk across the income distribution may be contributing to different effects of wildfires on house sale prices, but they did not perform this analysis and left it as an area for further research. McCoy and Walsh (2018) did find a significant 9.4 percent latent risk discount, as measured by the Colorado Wildfire Risk Assessment (CO-WRAP) Wildfire Threat Index (WTI), on home sale prices after a wildfire occurred. However, McCoy and Walsh (2018) did not look at the relationship between increased perceived risk and decreased amenity value due to wildfires on house prices. Boustan et al. (2020) looked at the effect of severe natural disasters on a series of economic

[3] Note: "First" to the best of my knowledge of the literature.

[4] For example, not accounting for wildfire dis-amenity effects when making a location preference decision would result in overvalued property values, which may encourage development in high wildfire risk areas.

outcomes (i.e. local wages, housing prices/rents, and net migration) within United States counties before and after a severe natural disaster by decade between 1920 and 2010 (i.e. 25 deaths or more, from wildfires, hurricanes, tornado, winter storm, and flood). Boustan et al. (2020) found that a severe disaster event leads to lower family income, heightened out-migration rates, lower housing prices and rents in a county over a decade. However, the paper only looked at severe natural disaster events with a significant focus on migration response effects. In addition, estimates for the effect of wildfires on house value and rent were positive, small, and imprecise, which is not consistent with the rest of the literature. Stetler et al. (2010) studied the effect of wildfires on house sale prices in northwest Montana between June 1996 and January 2007. Stetler et al. (2010) found house sale prices declined by 13.7 percent when comparing homes sold 20km from the wildfire to homes located 5 km from the wildfire. The study did not estimate how misguided risk perceptions may impact housing demand in the wildlife urban interface (WUI). Therefore, there is a gap in the literature on how the magnitude of reduced environmental amenity, and increased wildfire risk, affect property values. This paper will expand upon existing work by estimating the magnitude of wildfire dis-amenity effects on property values.

Most of the literature on the effect of wildfires on house pricing employs the hedonic property model (HPM) (see, Loomis, 2004; Mueller and Loomis, 2014; Huggett et al., 2008). The hedonic price model looks at the marginal amenity, or dis-amenity, effects of attributes (e.g. the number of bathrooms, square footage, amenities, etc.) on house prices (Loomis, 2004). However, one of the significant drawbacks of the hedonic price model is that it is necessary to assume buyers and sellers in the market have perfect information (Chau and Chin, 2003; Rosen, 1974). Patricia A. Champ and Barth (2013); McCoy and Walsh (2018) both respectively show that people underestimate wildfire risk in their area and that house price changes due to wildfires decline over one to two years. Patricia A. Champ and Barth (2013) studied the effect of the Firewise education campaign on risk-mitigating behaviours through a survey on wildfire risk perception in the Colorado Front Range, and they find the perception of wildfire risk and risk-mitigating behaviours to be jointly determined. However, they find a weak positive association between having accessed the Colorado Springs Fire Department (CSFD) Firewise website and fire mitigation levels. Their findings suggest that even when individuals are aware of the wildfire risk they may not take effective mitigation measures (Patricia A. Champ and Barth, 2013). Patricia A. Champ and Barth (2013) imply that an individual's willingness to take on wildfire risk mitigation measures is not purely determined by the awareness of such risks but also influenced by other factors, such as an individual's financial ability to invest in risk-mitigating measures. Patricia A. Champ and Barth (2013) found that 63 percent of respondents who did not access the Colorado Springs Fire Department (CSFD) Firewise website underestimated their home's wildfire risk. In comparison, 33 percent of respondents who had access to the CSFD Firewise website underestimated their home's wildfire risk. This shows that even in areas with a wildfire safety education program, a significant fraction of homeowners do not accurately perceive the level of objective fire risk. Patricia A. Champ and Barth (2013) study further supports the idea that measures of latent risk, such as used in McCoy and Walsh (2018), are not good estimates of risk perception when controlling for the measure of wildfire risk in property markets. An avenue of future research would be to compare the effect of wildfires across a series of economic outcomes and different measures of objective risk to understand the relationship between wildfires and potential changes in risk perceptions.

Capturing a complete picture of the effect of wildfires on housing demand Boustan et al. (2020) suggests looking at the effect of a change in housing demand (i.e. change in house prices) across a range of economic outcomes. For example, a decline in housing demand due to lower amenity levels should be associated with constant or rising wages as firms would want to attract workers back to the region affected by the disaster. In contrast, a decline in housing demand due to industry disruptions would be associated with a drop in firm productivity and decreased wages. The core identification assumption in Boustan et al. (2020) is that the presence of a disaster in a particular decade is not related to other economic changes at the county level. In my paper, I assume wildfires do not coincide with a drop in property values because wildfires are a naturally occurring phenomenon. The distributional aspects of natural disasters on community income, as noted by Boustan et al. (2020), occurs because lower house prices encourage some residents to stay and some to leave, with the strongest effect on the poor who may be willing to trade off the relocation cost of moving for staying in the area with greater wildfire risk (i.e. more affluent households would be more likely to move because they can afford to move, and they may be more risk-averse due to having more assets). Therefore, economic theory would expect that over time, natural disasters would disproportionately affect more impoverished communities. Boustan et al. (2020) did not look at the quantile distribution of the effect of wildfires on family income; however, their fixed effect regression estimates suggest wildfires slightly reduce net migration, slightly increases median family income, and slightly decreased the poverty rate at the decade level [5]. They did not find a significant effect on house value and rent; these results suggest that wildfires may increase median family income over the long term if there is a significant amount of individuals moving out of a wildfire risk region, causing wages to increase and poverty decrease, as firms compete for fewer workers. These results, although small, conflict with the HPM literature (for example, McCoy and Walsh, 2018; Mueller et al., 2009) that the effect of wildfires on house prices over time recover, but at a slower rate, to original prices as individuals become less risk salient towards wildfires, and that communities affected by wildfires would see an increase in poverty according to Boustan et al. (2020) theory. Future research on how changes in wildfire risk perception and environmental amenity value affect house prices can help in understanding how richer and poorer communities respond to such changes and its impact on local economies (e.g. poorer individuals may be more willing to take on wildfire risk despite the loss in environmental amenity value).

More closely related to the literature on housing markets Mueller and Loomis (2014) find that the standard ordinary least squares (OLS) hedonic property model overestimates the impact of wildfires on homes on the lower end of the housing price distribution and underestimates the impact of wildfires on housing prices for homes on the higher end of the housing price distribution. They were unable to calculate the portion of the housing price drop due to the loss in amenity value versus increased risk perceptions, and they noted this as a limitation of using HPM analysis (Mueller and Loomis, 2014). The core identification assumption in Mueller and Loomis (2014) is that properties within their study

[5] Coefficients were -0.013*** on net migration, 0.013** on median family income, and -0.004** on the poverty rate (Boustan et al., 2020).

area have similar location-specific environmental amenities and demographic characteristics, and by controlling for time trends and structural characteristics, they have isolated the risk effect of wildfires on property values. Stetler et al. (2010) also view the inability to separate risk perception and amenity value loss on prices as a limitation of their study in Montana. McCoy and Walsh (2018) did use a difference-in-differences model when studying the effects of wildfires on housing prices and changes in risk perceptions in the Colorado Front Range. Using a difference-in-differences model McCoy and Walsh (2018) was able to control for "contemporaneous shifts in local and macroeconomic housing markets". Consistent with the literature, they found a 12.6 percent reduction in housing values in the year following a fire and that risk salience towards wildfires are relatively short-lived (McCoy and Walsh, 2018). However, they did not study the potential economic factors (e.g. income) which influence people's choices and decisions people make under uncertainty. The core assumption in McCoy and Walsh (2018) is that measures of latent risk (i.e. the probability of a wildfire occurring based on topographical and vegetation data) does not suffer from dis-amenity spillover effects that distance to wildfires and view of burn scars suffer from because McCoy and Walsh (2018) selected properties that have a high latent wildfire risk but did not experience a wildfire. In my robustness section, I can control latent wildfire risk effects by including the USDA Wildfire Hazard Potential (WHP) index as a control to isolate the negative amenity effects of wildfires on property values.

To capture the risk effect of wildfires on house prices Loomis (2004) did a case study on the towns of Pine and Buffalo Creek in Colorado researching the reduction in house prices in the unburned town (i.e. Pine) that was near a town that experienced a wildfire (i.e. Buffalo Creek). Using an HPM Loomis (2004) found that home buyers that lived in the nearby town appeared to have updated their risk assessment given the new information about the fire in the other town. Loomis (2004) also found a reduction in the rate of increase in the price of houses located in forests in the unburned town. Most of the literature that uses HPM analysis examines localized effects of wildfires on property values and generally do not provide much analysis on the portion of price responses to changes in amenity values or risk perceptions (see, Loomis, 2004; McCoy and Walsh, 2018; Stetler et al., 2010; Mueller and

Loomis, 2014; Bouwer, 2011; Mueller et al., 2009). Also, Loomis (2004) was unable to measure the degree to which environmental amenity levels in Pine were reduced, so their estimate of wildfire risk was imperfect. The key identification assumptions in Loomis (2004) paper are: (1) the housing market is competitive such that no single buyer or seller can influence the market equilibrium price, and (2) by comparing similar communities, it is possible to control for neighbourhood and location-specific environmental amenity characteristics, such that the only factor that would result in differences in property values post-wildfire would be wildfire risk [6]. In my paper, I control for neighbourhood and location-specific environmental factors by including a set of demographic controls from the American Community Survey and by controlling time-invariant unobserved environmental factors in the first difference regression.

In related literature, Baylis and Boomhower (2019) look at the role external firefighting costs play in subsidizing development in high-risk areas. Baylis and Boomhower (2019) use variation in wildfire ignition locations to see how firefighting expenditures increase when homes are built in high-risk wildfire areas. In my paper, I will take advantage of variation in wildfire ignition locations to measure the dis-amenity effect on property values associated with wildfires. They found that fire fighting costs are non-rival (i.e. fighting an additional fire on the margin does not raise suppression costs), such that there is little difference in total fire fighting costs when comparing a fire that threatens many versus few homes (Baylis and Boomhower, 2019). They find that homes located in low-density areas on large lot sizes receive the largest indirect subsidy from federal firefighting expenditures (Baylis and Boomhower, 2019). The implicit subsidy received by homeowners means that they are not pricing the additional fire risk into the cost of living in a high-risk area as they do not face this cost directly (Baylis and Boomhower, 2019). Similar to federally provided flood insurance, Hino and Burke (2020) highlighted that uninformed home buyers do not account for the potential costs of living in a flood zone and are more likely to overvalue the property when making an offer. Hino and Burke (2020) exploit spatial and temporal variation in flood zone assignment to isolate the effect of floodplain maps on property values across the United States. They find homes located in floodplain areas in the United States are overvalued by a

[6] Assuming there are no negative spillover effects

total of $34 billion as housing prices are not accounting for the floodplain discount (Hino and Burke, 2020).

The findings from Baylis and Boomhower (2019); Hino and Burke (2020) suggest homes in the United States may not be fully internalizing the cost of natural disasters in their property values. There are many reasons why homeowners may not be internalizing the costs of natural disasters into housing prices, such as suppression costs being covered by federal agencies (see, Baylis and Boomhower, 2019; Hino and Burke, 2020), private homeowners only price costs they perceive (e.g. not taking into account the potential loss in community amenity value at the time of home purchase) (see, Loomis, 2004; Patricia A. Champ and Barth, 2013), and even if a fire occurs near a community the fire risk salience is only reflected in house prices for a short period (see, McCoy and Walsh, 2018). Homeowners should perceive fire risks over the long term because wildfires in the western United States are seasonal events, but the findings from Loomis (2004); McCoy and Walsh (2018) only show increased risk salience is over the short term. In addition the long-term effect of wildfires (for example, Boustan et al., 2020) contrast with existing HPM literature on how adjustments in risk perception change, and across various economic indicators (e.g. income, education, rent, etc.) (Mueller and Loomis, 2014; Loomis, 2004; McCoy and Walsh, 2018). Gaps exist in the literature that I hope to address by estimating the magnitude of wildfires' dis-amenity effects on property values.

3 Economic Theory: Hedonic Property Model [7]

A consumer derives utility U from housing and other goods. The utility from housing is a function of non-environmental neighbourhood characteristics $(N_1 \ldots N_n)$, housing characteristics such as number of bedrooms and year built $(S_1 \ldots S_m)$, environmental amenities such as clean air, water, trees $(Z_1 \ldots Z_i)$, and location-specific wildfire risk $(R_1 \ldots R_k)$ (Loomis, 2004). The household utility is an increasing function of desirable housing, neighbourhood, and environmental amenity char-

[7] This is based on Rosen (1974); Loomis (2004) hedonic property models.

acteristics $U_S > 0, U_N > 0, U_Z > 0$. The household utility is a decreasing function of wildfire risk $U_R < 0$. Consumers maximize their utility subject to market prices and their income (Loomis, 2004).

For a competitive housing market such that buyers' and sellers' individual decisions cannot influence the market price the hedonic price function takes the form:

$$P_h = f(N_1 \ldots N_n; S_1 \ldots S_m; Z_1 \ldots Z_i; R_1 \ldots R_k)$$

Regressing property value P_h on each of the attributes $(N_1 \ldots N_n; S_1 \ldots S_m; Z_1 \ldots Z_i; R_1 \ldots R_k)$ it is possible to estimate the change in property price given a one unit change in any of the characteristics (e.g.$\frac{dP_h}{dN_n}, \frac{dP_h}{dS_m}, \frac{dP_h}{dZ_i}, \frac{dP_h}{dR_r}$). These are known as the implicit marginal prices of each of the attributes associated with property value P_h. As mentioned by Loomis (2004) the "marginal implicit prices can be used to infer a households willingness to pay for marginal changes in the level of parcel attributes". The observed effect of wildfires proximity on property values P_h is the net effect of the change in environmental amenity attributes $(Z_1 \ldots Z_i)$ and the change in wildfire risk $(R_1 \ldots R_k)$. Loomis (2004) was primarily interested in measuring the effect of wildfire risk $(R_1 \ldots R_k)$ on property values P_h controlling for environmental amenity attributes $(Z_1 \ldots Z_i)$. Loomis (2004) did not explicitly control for the environmental dis-amenity effects from the nearby wildfires when isolating the effect of wildfire risk on property values. I argue that wildfires cause a decrease in the level of environmental amenity attributes $(Z_1 \ldots Z_i)$ in the nearby area, depressing prices P_h, and increase wildfire risk $(R_1 \ldots R_k)$ that raises property values P_h because I assume the cost of wildfire risk is known and is internalized by homeowners (e.g. fire and flood insurance).

4 Data Description and Summary Statistics

I got housing and demographic data from the American Community Survey (ACS) five-year estimates for 2005-2009, 2010-2014, and 2015-2019 periods, wildfire perimeter data from the National Interagency Fire Center, and wildfire hazard potential data from the United States Department of Agriculture (USDA) Forest Service Fire Modelling Institute (Manson et al., 2020; NIFC, 2020; Dillon and Gilbertson-Day, 2020). The Wildfire Hazard Potential (WHP) is not an explicit map of wildfire threat or risk, but it is a class scale [8], which represents areas with a high probability of experiencing extreme fire behaviour.

4.1 American Community Survey Dataset Description and Data Cleaning

The American Community Survey (ACS) 2005-2009, 2010-2014 and 2015-2019 five-year estimate block group housing data was retrieved from IPUMS NHGIS (Manson et al., 2020). I selected the Western United States as the geographic area of focus, including Arizona, California, Colorado, Idaho, Nebraska, New Mexico, Oklahoma, Oregon, South Dakota, Texas, Kansas, Wyoming, Montana, North Dakota, Utah, Nevada, and Washington. Looking at the bounding box area covered by wildfire perimeters between 2005-2018 [9] in Figure 1 we can see that majority of the wildfires occur in the western United States. Therefore, I limited my analysis to the western United States due to the lack of wildfires west of Oklahoma.

The ACS data covers all 2010 census block groups, and each block group contains between 600 and 3,000 people. Each observation in this data set is at the block group level. The five-year ACS data are period estimates which represent data collected over 2005-2019. The 2015-2019 five year estimates (ACS) data was merged with the provided 2019 Tiger/Line+ shapefiles, the 2010-2014 five-year

[8] Median WHP variable is an ordinal variable from 0 to 5, which represents the median WHP index for each block group. The variable is not specific to any particular season or forecast as it is based on historical and spatial datasets of wildfire likelihood and intensity, see USDA Wildfire Hazard Potential .

[9] I converted these from polygons because it is easier to see the boxes on the map

(ACS) estimates was merged with the 2014 Tiger/Line + shapefiles, and similarly, the 2005-2009 (ACS) estimates was merged with the 2010 Tiger/Line + shapefiles at the block group level. The five-year ACS estimates were merged by row on the unique GISJOIN identifier in the Tiger/Line + shapefiles provided by IPUMS NHGIS.

In the 2005-2009 and 2010-2014 ACS datasets, all dollar-denominated variables, such as median, upper, and lower home value, were inflation-adjusted according to the census documentation. That is, the 2009 and 2014 dollar-denominated variables were multiplied by the inflation adjustment factor, which is the ratio of the CPI-U-RS 2019 Annual Average to the CPI-U-RS 2009 and 2014 Annual Average. The CPI-U-RS is the estimate of the CPI for all Urban Consumers as provided by the U.S. Bureau of Labour Statistics.

Before merging the three ACS data-frames, I had to combine the estimate for the "Year Structure Built" and 2005-2009 "Educational Attainment for the Population 25 Years and Over" variables. The "Year Structure Built" variable in the 2015-2019 ACS had extra categories for homes built 2000 to 2009, built 2010 to 2013, and built 2014 or later compared to the 2005-2009 ACS estimates. Similarly, the 2010-2014 ACS had extra categories for homes built 2000 to 2009 and built 2010 or later compared to the 2005-2009 ACS estimates. The 2005-2009 ACS estimates had built 2000 to 2004 and built 2005 or later as the last categories for the Year Built variable. I added the last categories of Year Built variable in the 2005-2009, 2010-2014, and 2015-2019 ACS estimates to have one category for "Built 2000 or later" to be concatenated on across the ACS five year estimates. The 2005-2009 ACS estimates for "Educational Attainment for the Population 25 Years and Over" was split by sex and had Nursery School to 4th grade, grades 5 to 6, grades 7 to 8, high school diploma and GED categories combined in comparison to the 2010-2014 and 2015-2019 ACS estimates that had separate categories for nursery school, kindergarten, high school diploma, GED, and grades 1 to 8. After I combined the male and female categories by educational attainment in the 2005-2009 ACS, I combined the estimates for the 2010-2014 and 2015-2019 ACS estimates for educational attainment to match the 2005-2009 categories by adding across each variable in the 2005-2009 and 2010-2015 five year estimates.

Once 2005-2009, 2010-2014, and 2015-2019 ACS estimates were combined, I divided the total number of homes in each block group for each control variable to get the control variables of interest into percent format. The variables for Race, Travel Time to Work, Educational Attainment for the Population 25 Years and Over, Year Structure Built, Bedrooms and Mortgage Status only reported the number of homes within each category for each variable. For example, under Race, block group 1 may have 200 individuals under the "White alone" category. Each variable had a total column for the total number of individuals or housing units [10] in that block group reported on the variable. The variables for Race, Travel Time to Work, Educational Attainment for the Population 25 Years and Over, Year Structure Built, Bedrooms, and Mortgage Status were converted into percent format.

4.2 Calculating the Great Circle Distance and Wildfire Perimeter Data Description

The Geospatial Multi-Agency Coordination Group (GeoMAC) historical wildfire perimeter data from 2000 to 2018 was retrieved from the National Interagency Fire Center (NIFC) (NIFC, 2020; 2021). This data is compiled from various state and federal firefighting agencies in the United States and covers all recorded wildfires perimeters within the continental United States from 2000-2018. Each observation in this data-set corresponds to a recorded wildfire with detailed geometry (i.e. polygons and multipolygons) information on the wildfire perimeter's shape. To calculate the minimum distance from each block group in the 2010-2014 five-year estimates to the closest 2015 wildfire perimeter, I used the great circle distance formula. The great circle distance [11] measures the shortest distance between two points along the surface of a sphere instead of a straight line that would produce inaccurate distance calculations. The formula is given by:

[10] This depends on the universe of the variable. For example, Race is on the "Total Population" universe while Year Structure Built is based on the "Housing Units" universe.

[11] Great circle distance formula also known as the haversine formula.

$$d = 2r \arcsin\left[\sqrt{(\sin^2\left(\frac{\rho_2 - \rho_1}{2}\right) + \cos(\rho_1)\cos(\rho_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right]$$

- ρ_1 and ρ_2 are latitude of point one and latitude of point two in radians.
- λ_1 and λ_2 are longitude of point one and longitude of point two in radians.
- r is the earth's radius.
- d is the great circle distance between points (ρ_1, λ_1) and (ρ_2, λ_2).

It is important to note that the great circle distance does not consider the earth's terrain and should be interpreted "as the crow-flies" distance between two points. Also, the earth is not a perfect sphere, so there will be a certain degree of measurement error for far distances, but for this paper's purpose, the measurement error is negligible [12]. To make the distance computation within a reasonable period of time I had to simplify the wildfire perimeters' geometries using the simplify method for geopandas. The geopandas simplify method removes vertices or points from a complex polygon shape, which smooths the data [13]. Simplify method preserved the topology of the wildfire perimeters, and it did considerably reduce the complexity of the polygons and multipolygons. The geopandas simplify method was not the best method because it did misplace some interior holes in some of the multipolygon perimeters; however, it did provided a better approximation of the wildfire perimeter than the bounding box shapes [14]. Figure 5 shows the geopandas simplify wildfire perimeter shapes with a tolerance level of 5000[15] and Figure 6 shows the 2010-2018 wildfire perimeters with the most complex perimeters [16]. Developing a more systematic approach to simplify the multipolygon perimeters will

[12] For discussion on this see haversine measurement error

[13] Documentation on `GeoSeries.simplify|`.

[14] A bounding box is the smallest box around a wildfire perimeter which includes all of the polygon or multipolygon points. Figure 1 shows the wildfire perimeters as bounding boxes

[15] A higher tolerance level will make the polygons more simplified (i.e. less smooth).

[16] I was unable to load all wildfire from 2005-2018 so Figure 6 only shows wildfires from 2010-2018

need to be developed in future papers in case the distance measured to the wildfire perimeter from a census block is to a misplaced hole from a simplified multipolygon.

To get the minimum distance from the centre of a given block group to the wildfire perimeter, I used the Haversine formula to calculate the great circle distance. To measure the minimum distance from a single block group centroid to a single wildfire perimeter, I used a python function which calculates the great circle distance midpoint between any two points that make up the wildfire polygon (see Hofmann, 2021). I then iterated through all of the midpoint distances on a single wildfire perimeter to the block group center and selected the shortest distance from the block group center to the midpoint on the wildfire perimeter. This was for a single block group and a single wildfire perimeter.Figure 7 visually shows the calculation for a single property to three nearby wildfire perimeters, with the minimum distance to a wildfire perimeter being 15.7km. To get the shortest distance to the closets wildfire perimeter for each block group for that year I performed the midpoint calculation for every block group to every wildfire perimeter within the state the block group is located and to neighbouring states wildfire perimeters [17]. Once I got the list of minimum distances to every wildfire perimeter from every block group in the year the wildfires occurred, I selected the minimum distance to each wildfire perimeter for each block group (i.e. the closets wildfire to the block group in the given year). I then iterated through each wildfire year to get the minimum distance from every block group center to the closest wildfire perimeter for each year.

One of the downsides of selecting the midpoints on the edge of the polygons, as the point to measure the minimum distance to each block group, is that the distance may not be the actual minimum distance to the block group. However, it is a good approximation for a complex enough polygon and multipolygon. After computing the minimum distances to wildfires for each year between 2005 and 2018, I merged each minimum distance variable with the ACS five-year estimates on the unique `GISJOIN` (block group) identifier.

[17] This is to account for wildfires which cross state boundaries

4.3 Missing Data & Non-Constant Census Block Groups

There are 27,295 block groups that either did not have location data in the Tiger/Line+ shapefiles or had missing median property values out of a dataframe of 204,286 block groups across the 2005-2009, 2010-2014, and 2015-2019 periods [18]. In addition, when I merged the wildfire perimeters with the ACS five year estimates, there was an additional 47,245 block groups dropped due to changes in the composition of block groups over the years [19]. Out of the 47,245 missing block groups 3.98% are missing out of the 2005-2009 sample, 34.36% are missing out of the 2010-2014 sample, and 34.76% are missing out of the 2015-2019 sample [20]. Out of the total sample, excluding the block groups with missing median property values and location data (i.e. 27,295), 26.70% of the data is missing due to not having constant block groups between the time periods. However, only 10.11% of the data within 20km from a wildfire perimeter is missing across all the time periods [21]. I recognize having missing block groups across the years is a limitation to the analysis, but as shown in Figure 3 and Figure 4 we can see that most of the missing block groups are not concentrated in a single state. For future research, it would be ideal to account for the redefined block group geometries by using constant census tracts instead of block groups.

4.4 Summary Tables & Data Visualizations

Table 1 shows the summary statistics of block groups' median property values and some key housing characteristics. It is clear there is little percentage growth in property values between 2005 and

[18] Figure 2 includes tabulations of the missing block groups by state and year

[19] The ACS may change the geographic boundary of block groups year to year to account for demographic changes Figure 3. The original sample of block groups in the western United States across 2005-2009, 2010-2014, and 2015-2019 had 204,286 block groups (counting each block group for every year). Subtracting out the block groups with missing median property values, location data, and inconsistent geographic boundaries the sample is 129,746 block groups (counting each block group for every year) (i.e. $204,286 - 27,295 - 47,245 = 129,746$)

[20] 45,541 block groups in 2005-2009 sample and 334 of the 1817 missing are within 20km from a wildfire perimeter. 66,619 block groups in the 2010-2014 sample and 10,142 out of the 22,895 missing are within 20km from a wildfire perimeter. 64,831 block groups in the 2015-2019 sample and 7,409 out of the 22,533 missing are within 20km from a wildfire perimeter.

[21] Sum missing within 20km from wildfire perimeter and divide by total sample excluding block groups with missing property values and location data $\frac{334+10,142+7,409}{176,991} = 10.11\%$

2019 with the difference in the natural logarithm of median property values [22] having an average of zero. This suggests median property values between 2005 and 2019 across the western United States have been relatively constant, or there was a period of negative and positive growth. Table 2, Table 3, and Table 4 show the number of block groups within 4km, 4km to 20km, and beyond 20km from a wildfire perimeter. It is shown that most of the block groups are beyond 20km from a wildfire perimeter and that most block groups within 20km experience a wildfire in each period (i.e. very few block groups experience a single wildfire over the three periods). Figure 8 shows the average minimum distance to a wildfire perimeter for each year wildfire perimeter data is available. There is a clear decrease in the average minimum distance to wildfires, which suggests wildfires are occurring more frequently closer to block groups. The increasing prevalence of wildfires closer to population centers is also shown in the interquartile range becoming more narrow over the study period in Figure 8. Table 5 shows the difference in the average median property values between block groups located within 4km from any wildfire between 2005-2018 and homes not located within 4km from a wildfire between 2005-2018. It is clear block groups located within 4km from any wildfire on average have a higher median property value than block groups not located within 4km from any wildfire. This is suggests that properties located near wildfires have a higher property value because of being located in areas with a high amenity value (e.g. being close to a forest increases a homes property value). Table 6 shows us that the 2020 average median Wildfire Hazard Potential (WHP) across all of the block groups in the dataset. Block groups located within 4km of a wildfire perimeter have a higher median WHP on average compared to block groups not within 4km from a wildfire perimeter. Table 5 and Table 6 suggests that property values close to wildfire perimeters are not pricing in wildfire risk or the amenity value from living in high wildfire risk areas is greater than the potential costs wildfires pose (i.e. negative environmental dis-amenity effects). Table 5 also shows that the majority of block groups are not located within 4km from a wildfire perimeter.

In Figure 9 we can see that the states that experience the most frequent wildfires between

[22] Difference in natural logarithm is approximate to percentage change in property values. I defined difference in natural logarithm of median property values as $\ln(\text{Median Value}_{2014-2010}) - \ln(\text{Median Value}_{2005-2009})$ and $\ln(\text{Median Value}_{2015-2019}) - \ln(\text{Median Value}_{2010-2014})$

2000 and 2018 and the total number of acres burned. Figure 9 suggests the number of wildfires is not a good indicator of the total number of acres burned, and the association of wildfires on property values may be more pronounced for states that have a large number of acres burned per year. In Figure 10 the same data is plotted as in Figure 9 but over years with acres burned reaching a peak in 2015, suggesting the intensity of wildfires is increasing despite the number of wildfires remaining relatively stable year to year.

For a more visual representation Figure 11, Figure 12, and Figure 13 are maps of the western United States with data plotted for block group property values and wildfires. The coloured dots represent each block group's center, and the colour represents how high (light green/white) or low (purple/blue) the 2005-2009, 2010-2014, and 2015-2019 median property value estimate is. I also plotted the respective wildfire perimeter polygons in shades of orange and red, which represent the number of acres burned (i.e. the darker red implies a large wildfire). This visual representation of the data shows us that the highest median home prices are located in Los Angeles and San Francisco areas that also appear to be the most densely populated. Looking at Figure 11, Figure 12, and Figure 13 it appears that wildfires do not directly affect urban population centers. This brings up a concern that block groups not affected by a wildfire are more likely to be located in urban areas that could have higher or lower property values. In my analysis, I will control for variation in urban-rural median property values by comparing control and treatment groups within a set minimum and maximum distance from a wildfire perimeter. However, Table 5 shows block groups located near wildfires on average have a higher median property value, which may result from higher amenity values in the areas wildfires occur. By including a set of housing characteristics, demographic characteristics, and removing time-invariant unobservable factors (e.g. distance to water or elevation, etc.) it is possible to control housing and neighbourhood amenity factors that raise property values. In addition to the housing characteristics in Table 1 I will also include controls for proportion educated, race, mortgage and travel time to control for differences in property values due to community makeup and positive amenity value from having good public transportation/infrastructure. In my robustness section, I will include the time-invariant measurement of wildfire potential, using the median Wildfire Potential Hazard (WPH) as a proxy control for wildfire risk to isolate the direct environmental dis-amenity effects of wildfires on median block group property values. By exploiting variation in distance to wildfire perimeters, it may be possible to draw inferences on how the dis-amenity effect from wildfires impact median property values across the western United States.

5 Estimation & Results

In this paper I study the dis-amenity effect of wildfire proximity on property values across the western United States [23]. This paper uses the first difference estimator to control for time-invariant factors that influence property values in estimating the association of wildfire proximity on property values. In addition to the first difference regression, I run the baseline ordinary least squares (OLS) regression which is standard in the hedonic property model literature (see, for example, Loomis, 2004; Mueller et al., 2009; Mueller and Loomis, 2014).

The pooled OLS specification is given by:

$$\begin{aligned}\text{Median Value}_{it} &= \beta_0 + \beta_1 \text{4km 2015 Ring}_{it} + \beta_2 \text{race}_{it} + \beta_3 \text{travel}_{it} + \beta_4 \text{educ}_{it} + \\ &\quad \beta_5 \text{yearbuilt}_{it} + \beta_6 \text{bedrooms}_{it} + \beta_7 \text{mortgagestatus}_{it} + \lambda_t + \delta_s + \epsilon_{it} \quad (1)\end{aligned}$$

For brevity, I will refer to the 2005-2009 period as 2007, the 2010-2014 period as 2012, and the 2015-2019 period as 2017. t in the above regression can take on values of 2007, 2012, and 2017 periods. i represents an individual block group. Median Value$_{it}$ is the median property value for block group i in period t. 4km 2015 Ring$_{it}$ is a dummy variable that takes on a value of 1 if the block group

[23] i.e. block groups located in Arizona, California, Colorado, Idaho, Nebraska, New Mexico, Oklahoma, Oregon, South Dakota, Texas, Kansas, Wyoming, Montana, North Dakota, Utah, Nevada, and Washington

was only within 4km from a 2015 wildfire perimeter, or was within 4km from a 2015 wildfire perimeter and was within 4km from at least one other wildfire before 2015. For example, if a block group was within 4km from a 2015 wildfire perimeter the dummy 4km 2015 Ring_{it} would indicate 1. It is also true, if the block group was within 4km from a 2015 wildfire perimeter and was within 4km from at least one wildfire perimeter between 2005 to 2014 the dummy 4km 2015 Ring_{it} would indicate 1. The dummy 4km 2015 Ring_{it} is 0 for observations that are not within 4km from a 2015 wildfire or only was within 4km from a wildfire perimeter in the years before 2015 (i.e. 2005 to 2014). Block groups that experienced wildfires in the period before 2015 will be explicitly controlled for in the robustness specification (i.e. regression equations 4 and 5). λ_t are time fixed effects, and δ_s are state fixed effects. The controls are for race, travel, education, year home built, number of bedrooms, and mortgage status in proportion terms of each block group. The decision of how to deal with wildfires in the pre-period will be addressed in the robustness section by directly controlling for the wildfires in the pre-periods. For the main baseline specification, I used 4km 2015 Ring_{it} as the treatment dummy. The identifying assumption of the Hedonic Property Model OLS regression is that by controlling for property, demographic, and time-varying trends, it is possible to estimate the implicit marginal price of wildfires on property values (i.e. both risk and dis-amenity costs to property values) (Loomis, 2004; Rosen, 1974).

To control for time invariant factors which influence property values, such as distance to water, mountains, forests, and public services, etc. I used the first difference regression given by:

$$\begin{aligned}\Delta\text{Median Value}_{it} = {} & \beta_1 \text{4km 2015 Ring}_{it} + \beta_2\Delta\text{race}_{it} + \beta_3\Delta\text{travel}_{it} + \beta_4\Delta\text{educ}_{it} + \\ & \beta_5\Delta\text{yearbuilt}_{it} + \beta_6\Delta\text{bedrooms}_{it} + \beta_7\Delta\text{mortgagestatus}_{it} + \Delta\lambda_t + \Delta\nu_{it} \qquad (2)\end{aligned}$$

Where Δ is the first-difference operator. If we let $\epsilon_{it} = \gamma_i + \nu_{it}$ where γ_i is a time invariant unobserved factor that influences property values, such as distance to water, we can see that first differencing is equivalent to, where x_{it} is the vector of controls:

$$\text{Median Value}_{it} - \text{Median Value}_{it-1} = \beta_1 \text{4km 2015 Ring}_{it} + x_{it}\beta - x_{it-1}\beta + \lambda_t - \lambda_{t-1} + (\delta_s - \delta_s) + (\gamma_i - \gamma_i) + \nu_{it} - \nu_{it-1} \quad (3)$$

So $\Delta\text{Median Value}_{it} = \text{Median Value}_{it} - \text{Median Value}_{it-1}$ denotes the change in the median block group property value. Note that 4km 2015 Ring_{it} has not been first differenced because some block groups did experience a wildfire before 2015 and not during or after 2015. In this case, first differencing 4km 2015 Ring_{it} would result in both positive (+1) and negative (-1) values for the dummy variable and would make the regression difficult to interpret. Instead, in the robustness section, I look at block groups that were treated in 2015 controlling for the pre-period wildfires. To address serially correlation in the first difference residuals I clustered the standard errors on block groups i (see, Angrist and Pischke, 2008). The main identifying assumption of the first-difference regression is controlling for unobservable time-invariant factors and time variant demographic and housing characteristics, between block groups affected and not affected by a wildfire, the only time-varying change left is the treatment effect of a 2015 wildfire. However, the effect of wildfires on property values is driven by the dis-amenity effects of wildfires on the surrounding environment and homeowners perceptions (i.e. risk saliency) of a wildfire occurring. The above specification does not control for time-varying wildfire risk salience because I did not have time to process the United States Geological Survey (USGS) Large Wildfire Probability raster data to create a time varying index of wildfire risk. However, in the robustness section, I included the 2020 block group median Wildfire Hazard Potential (WHP) variable as a proxy for wildfire risk salience in the OLS regression.

To be clear, the treatment dummy 4km 2015 Ring_{it} is not defined the same as the treatment dummies 4km 2015 & 2015-2019_{it}, 4km-20km 2015 & 2015-2019_{it} and the pre-period wildfire controls Pre-Fire 4km 2005-2009_{it}, Pre-Fire 4km 2010-2014_{it}, Pre-Fire 4km-20km 2005-2009_{it}, Pre-Fire 4km-20km 2010-2014_{it} in regression equation (4). 4km 2015 & 2015-2019_{it} is a dummy for wildfires within 4km from a 2015 wildfire perimeter in the 2015-2019 period. 4km 2015 & 2015-2019$_{it}$ is 1 if a census block group was within 4km from a 2015 wildfire perimeter and the period is 2015-2019. Otherwise, 4km 2015 & 2015-2019$_{it}$ is zero. Similarly, 4km-20km 2015 & 2015-2019$_{it}$ is a dummy for census block groups between 4km and 20km from a 2015 wildfire perimeter (i.e. greater than 4km and less than or equal to 20km from a 2015 wildfire perimeter) in the 2015-2019 period. 4km-20km 2015 & 2015-2019$_{it}$ is 1 if a census block group was between 4km and 20km from a 2015 wildfire perimeter and the period is 2015-2019. Pre-Fire 4km 2005-2009$_{it}$ is a pre-fire control dummy variable for block groups within 4km from a 2005, 2006, 2007, 2008, or 2009 wildfire perimeter in the first period (i.e. 2005-2009). Pre-Fire 4km 2005-2009$_{it}$ is 1 if a block group is within 4km from a 2005, 2006, 2007, 2008, or 2009 wildfire perimeter and the period is 2005-2009. Likewise, Pre-Fire 4km 2010-2014$_{it}$ is a pre-fire control dummy variable for block groups within 4km from a 2010, 2011, 2012, 2013, or 2014 wildfire perimeter in the second period (i.e. 2010-2014). Pre-Fire 4km 2010-2014$_{it}$ is 1 if a block group is within 4km from a 2010, 2011, 2012, 2013, or 2014 wildfire perimeter and the period is 2010-2014. Pre-Fire 4km-20km 2005-2009$_{it}$ and Pre-Fire 4km-20km 2010-2014$_{it}$ are defined the same way as Pre-Fire 4km 2005-2009$_{it}$ and Pre-Fire 4km 2010-2014$_{it}$ for block groups within 4km to 20km from a wildfire perimeter (i.e. greater than 4km and within 20km from a wildfire perimeter). In the first difference, regression equation 5, in section 6.2 4km 2015 & 2015-2019$_{it}$ and 4km-20km 2015 & 2015-2019$_{it}$ are defined the same as above. However, Pre-Fire 4km 2005-2014$_{it}$ is a pre-fire control dummy variable that indicates block groups within 4km from a 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, or 2014 wildfire perimeter in the first two periods (i.e. 2005-2009, 2010-2014). Pre-Fire 4km-20km 2005-2014$_{it}$ is a pre-fire control dummy variable that indicates block groups between 4km and 20km (i.e. greater than 4km and less than or equal to 20km) from a 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, or 2014 wildfire perimeter in the first two periods (i.e. 2005-2009, 2010-2014). In the first difference, regression equation 5, I combined the first two periods in the pre-wildfire control dummies (i.e. Pre-Fire 4km 2005-2014$_{it}$, Pre-Fire 4km-20km 2005-2014$_{it}$) because wildfires in the 2005-2009 period would not be captured in the dummy variable if it was left in the format specified for the OLS regression (i.e. the first difference would subtract out the 2005-2009 wildfire perimeter distances because it needs a base period). The treatment dummies and pre-wildfire controls in Table 14 are defined the same as the treatment variables (i.e. 4km 2015 & 2015-2019$_{it}$, 4km-20km 2015 & 2015-2019$_{it}$) and OLS pre-wildfire control variables (i.e. Pre-Fire 4km 2005-2009$_{it}$, Pre-Fire 4km 2010-2014$_{it}$, Pre-Fire 4km-20km 2005-2009$_{it}$,Pre-Fire 4km-20km 2005-2014$_{it}$), but for different non-overlapping categories. For example, 10km-15km 2015 & 2015-2019 is a treatment dummy for block groups within 10km and 15km (i.e. greater than 10km and less than or equal to 15km) from a 2015 wildfire perimeter in the last period (i.e. 2015-2019). 10km-15km 2015 & 2015-2019 is 1 if a block group is greater than 10km and less than or equal to 15km from a 2015 wildfire perimeter and the period is 2015-2019. Likewise, the pre-wildfire control Pre-Fire 10km-15km 2010-2014 in Table 14 is a dummy variable for block groups located greater than 10km and less than or equal to 15km from a 2010, 2011, 2012, 2013, or 2014 wildfire perimeter in the 2010-2014 period. Pre-Fire 10km-15km 2010-2014 is 1 if a block group is greater than 10km and less than or equal to 15km from a 2010, 2011, 2012, 2013, or 2014 wildfire perimeter and the period is 2010-2014. The other pre-wildfire control dummy variables in Table 14 are defined the same as Pre-Fire 10km-15km 2010-2014 but for different periods and non-overlapping distance categories. The other treatment dummy variables in Table 14 are defined the same as 10km-15km 2015 & 2015-2019 but for different non-overlapping distance categories. The key take away from the description of dummy treatment and pre-wildfire controls variables is that the OLS and first difference regressions switch between different definitions of dummy treatment variables, and the pre-wildfire controls in the first difference regression combine the two pre-periods (i.e. 2005-2009, 2010-2014) to capture the distances to the 2005-2009 wildfire perimeters.

Table 7 column (1) shows the results for the baseline OLS regression, and columns (2)-(5) show the baseline results for the first difference regressions. I took the difference in natural logarithms of the median property value because it is approximate to percentage growth in median block group property values. We can see that the baseline OLS in column (1) is not statistically significant when not controlling for time-invariant factors that influence median block group property values. Moving across to columns (2) and (3) there is a 7.6% reduction in the growth rate of median property values for block groups within 4km from a 2015 wildfire perimeter [24] in comparison to block groups beyond 4km from a wildfire perimeter. The marginal implicit price reduction from being within 4km from a 2015 wildfire is around \$23,651.45 [25]. In column (2) the reduction in the change in median property value by being within 4km from a 2015 wildfire perimeter of $\$26,644.80$ is close to the marginal implicit price reduction of \$23,651.45. Columns (4) and (5) limit the sample to only block groups within 20km of a 2015 wildfire perimeter, comparing block groups within 4km from a 2015 wildfire perimeter to block groups within 4km-20km of a 2015 wildfire perimeter. Column (5) shows a 6.03% reduction in the growth rate of median property values for block groups within 4km of a 2015 wildfire perimeter versus block groups within 4km-20km of a 2015 wildfire perimeter. The marginal implicit price reduction on the new sample is \$21,178.48 [26] for block groups within 4km of a 2015 wildfire perimeter, which is consistent with the change in median property value estimate of -\$22,318.1 in Table 7 column (4). The estimates in Table 7 is consistent with findings in the literature finding a marginal implicit price reduction between \$14,000 and \$20,000 (Loomis, 2004; McCoy and Walsh, 2018; Mueller et al., 2009). In the robustness section, I will include pre-fire controls, a set of distance dummies, and the median WHP as a proxy control for wildfire risk to test the findings' sensitivity.

[24] This is for block groups within 4km from a 2015 wildfire perimeter, or within 4km from a 2015 wildfire perimeter and were 4km from at least one wildfire perimeter in the years before 2015

[25] Marginal Implicit Price $= \hat{\beta}\bar{\text{Median Value}}_{it} = -0.0760 \times 311,203.25 = -23,651.45$

[26] $-0.0603 \times 351,218.70 = -21,178.48$

6 Robustness & Discussion

6.1 Overview of Robustness Specifications and Tests

The 4km cutoff value from a wildfire perimeter was an arbitrary decision. To test the sensitivity of the choice of cutoff values, I first run the OLS and first difference regressions with non-overlapping groups of within 4km, within 4km-20km, and beyond 20km from a wildfire perimeter. I also add pre-fire controls to control for observations that experienced a previous wildfire. I then repeat the analysis for non-overlapping block group categories within 4km, 4km-10km, 10km-15km, and 15km-20km, and beyond 20km from a wildfire perimeter. I cannot show that there are no wildfires before and after the 2015 wildfire treatment because wildfires occur every year. By controlling for wildfires in the pre-period, I isolate the association of 2015 wildfires on 2015-2019 median property values. In the Colorado Front Range McCoy and Walsh (2018) shows a significant 9.4% latent risk discount on property sales prices in the first year following a wildfire, but the effect decreases and becomes insignificant in the second year. McCoy and Walsh (2018) also find that the effect of an increased sales rate, due to the occurrence of wildfires, diminishes to zero after three years. Mueller et al. (2009) found that after a second wildfire house prices after 5 to 7 years recover, but this depends on the amount of time between wildfires. More time between separate wildfires means it would take longer for prices to recover than if both wildfires hit simultaneously. Therefore, I have not added controls for wildfires that occur after 2015 because those controls may absorb a portion of the 2015 wildfire effect.

The first-difference regression's core assumption is that there are no time-varying factors within a block-group that are correlated with both property values and being within 4km away from a 2015 wildfire perimeter. To test this assumption, I regressed the growth rate of house prices between the 2005-2009 and 2010-2014 periods on the baseline specification to see if there is any significant association. To show that the treatment is random and that I am capturing the association of wildfire proximity on property values (i.e. the association is not being driven by an omitted variable), I regressed the treatment dummy 4km 2015 Ring_{it} on the controls and ran a two sample t-test on the control variables by treatment.

Table 8 refers to the following specification:

$$\begin{aligned}\text{Median Value}_{it} = \beta_0 + \beta_1 \text{4km 2015 \& 2015-2019}_{it} + \beta_3 \text{4km-20km 2015 \& 2015-2019}_{it} + \\ \beta_4 \text{Pre-Fire 4km 2005-2009}_{it} + \beta_5 \text{Pre-Fire 4km 2010-2014}_{it} + \beta_6 \text{Pre-Fire 4km-20km 2005-2009}_{it} + \\ \beta_7 \text{Pre-Fire 4km-20km 2010-2014}_{it} + \beta_8 \text{race}_{it} + \beta_9 \text{travel}_{it} + \beta_{10} \text{educ}_{it} + \\ \beta_{11} \text{yearbuilt}_{it} + \beta_{12} \text{bedrooms}_{it} + \beta_{13} \text{mortgagestatus}_{it} + \lambda_t + \delta_s + \epsilon_{it} \quad (4)\end{aligned}$$

4km 2015 & 2015-2019_{it} is a dummy variable for a block group being within 4km from a 2015 wildfire and is in the 2015-2019 period, 4km-20km 2015 & 2015-2019_{it} is a dummy variable for a block group being within 4km-20km from a 2015 wildfire perimeter and is in the 2015-2019 period. Pre-Fire 4km 2005-2009_{it} is a dummy variable control for a block group within 4km from a wildfire in the 2005-2009 period and the period is 2005-2009. Pre-Fire 4km 2010-2014_{it} is a dummy variable control for a block group within 4km from a wildfire perimeter in the 2010-2014 period and the period is 2010-2014. Pre-Fire 4km-20km 2005-2009_{it} is a dummy variable control for a block group within 4km to 20km from a wildfire perimeter in the 2005-2009 and the period is 2005-2009. Pre-Fire 4km-20km 2010-2014_{it} is a dummy variable control for a block group within 4km to 20km from a wildfire perimeter in the 2010-2014 period and the period is 2010-2014.

6.2 Sensitivity of Distance Cutoff Values & Non-Overlapping Categories

Table 8 shows the result for regression equation (4). Table 8 column (1) and (2) show the OLS regression with only the 4km 2015 & 2015-2019_{it} treatment and column (2) has the same regression with pre-fire controls Pre-Fire 4km 2005-2009_{it} and Pre-Fire 4km 2010-2014_{it}. We can see that these estimates are not statistically significant within 4km of a 2015 wildfire perimeter, but the pre-fire controls are absorbing the effect of wildfire proximity in the pre-period. Columns (3) and (4) in Table 8 show the association with the added non-overlapping category for 4km-20km (i.e.4km-20km 2015 & 2015-2019$_{it}$ variable). We can see that controlling for wildfires in the pre-period there is a significant estimate for home located within 4km-20km from a 2015 wildfire perimeter in column (4). The change in the association is relatively small when comparing columns (4) and (5) for the 4km-20km 2015 & 2015-2019$_{it}$ variable. In comparison to Table 7 column (1) the point estimate on 4km 2015 Ring$_{it}$ is consistent with Table 8 column (4) point estimate on 4km 2015 & 2015-2019$_{it}$.

Table 9 refers to the following specification:

$$\Delta \text{Median Value}_{it} = \beta_1 \text{4km 2015 \& 2015-2019}_{it} + \beta_2 \text{4km-20km 2015 \& 2015-2019}_{it} + \beta_3 \text{Pre-Fire 4km 2005-2014}_{it} + \beta_4 \text{Pre-Fire 4km-20km 2005-2014}_{it} + \beta_5 \Delta \text{race}_{it} + \beta_6 \Delta \text{travel}_{it} + \beta_7 \Delta \text{educ}_{it} + \beta_8 \Delta \text{yearbuilt}_{it} + \beta_9 \Delta \text{bedrooms}_{it} + \beta_{10} \Delta \text{mortgagestatus}_{it} + \Delta\lambda_t + \Delta\nu_{it} \quad (5)$$

To avoid the situation where block groups become untreated the wildfire perimeter distance variables and pre-fire control variables are not differenced. Pre-Fire 4km 2005-2014$_{it}$ is a dummy variable for a block group within 4km from a wildfire perimeter in the 2005-2014 period. Pre-Fire 4km-20km 2005-2014$_{it}$ is a dummy variable for a block group within 4km-20km from a wildfire perimeter in the 2005-2014 period. I grouped the 2005-2009 and 2010-2014 years because the 2005-2009 pre-fire control would otherwise drop out in the first difference regression. These two dummy variables indicate homes that were near a wildfire perimeter in both before periods.

Moving left to right in Table 9 I add the 4km-20km category and pre-period fire controls. We can see that the estimates for Pre-Fire 4km 2005-2014$_{it}$ and Pre-Fire 4km-20km 2005-2014$_{it}$ are robust to adding more pre-period fire controls. This shows that property prices for block groups close to a wildfire perimeter recover within the five-year period, and the effect of previous wildfires on property values is relatively short-lived. In column (4) of Table 9 we can see that the estimate are consistent with the estimates in Table 7 column (2) and (3). Table 10 shows the same result as Table 9, but with the difference in the natural logarithm as the dependent variable to approximate the growth rate of median property values. Table 10 column (4) shows us that being within 4km-20km from a 2015 wildfire perimeter results in a 1.88% reduction in the growth rate of median property values in comparison to block groups beyond 20km from a 2015 wildfire perimeter. There is an additional 7.774% reduction in the growth rate of median property values for block groups within 4km from a 2015 wildfire perimeter. These estimates are consistent with the findings in Table 7.

To test the cutoff values' sensitivity for the treatment dummies Table 11 shows the regression results for non-overlapping categories within 4km, 4km-10km, 10km-15km, and 15km-20km. In addition, Figure 14 and Figure 15 shows how the cutoff estimate changes for the coefficient β_1 [27] for 500 meter increases in the cutoff value between 2km and 30km from a wildfire perimeter. Figure 14 and Figure 15 show that as the cutoff value is closer to the wildfire perimeter the confidence intervals are large, and within 30km the incremental cutoff values are within the 95% confidence interval estimate for the 4km cutoff. This shows that within 30km the estimate is not statistically different from the original 4km cutoff value chosen. However, the point estimate decreases as the cutoff value gets smaller (i.e. wildfires are associated with a decrease in property values). Figure 16 and Figure 17 show how the cutoff estimate changes for the coefficient β_1 for 500-meter increases in the cutoff value between 2km and 100km from a wildfire perimeter. Figure 16 show that around 40km from a wildfire perimeter the point estimate moves outside of the 4km confidence interval, which suggests block groups located within 40km of a 2015 wildfire perimeter have depressed property values controlling for other amenity factors because they experience repeated wildfires. Figure 17 shows that the increase in the point estimate as the cutoff value increases is relatively linear. Table 11 columns (5) and (6) show that the point estimates on 4km 2015 & 2015-2019$_{it}$, 4km-10km 2015 & 2015-2019$_{it}$, 10km-15km 2015 & 2015-2019$_{it}$, and 15km-20km 2015 & 2015-2019$_{it}$ are robust to controlling for wildfires in the years before 2015. However, the association becomes statistically insignificant beyond 10km from a wildfire perimeter. This finding is consistent with the literature on the localized case studies of the effect of wildfire prox-

[27] Referring to regression equation (2)

imity on property values [28] (McCoy and Walsh, 2018; Stetler et al., 2010). This suggests that any potential effect of wildfire proximity on property values (i.e. either environmental dis-amenity effects or risk perception) is localized within 10km of a wildfire perimeter.

6.3 Omitted Variables Sensitivity

To test that there are no time-varying factors within a block-group that are correlated with both property values Table 12 shows the results for the first difference regressions of all the treatment dummy categories on the percentage change in median property values between the 2005-2009 and 2010-2014 periods [29]. Table 12 shows that there is no association between having a 2015 wildfire within 4km of a block group on the growth rate of median property values between 2005-2009 and 2010-2014. Comparing Table 12 columns (4) and (5) shows that the result is robust to adding pre-fire controls. This suggests that within 4km from a 2015 wildfire perimeter, it is likely that there are no other time-varying unobserved variables correlated with both property values and being within 4km from a 2015 wildfire perimeter. However, the assertion that there are no other time-varying variables correlated with property values and wildfire proximity cannot be made for block groups within 4km-10km, 10km-15km, and 15km-20km from a wildfire perimeter. As shown in Table 12 column (4) the coefficient on 4km-10km 2015 & 2015-2019$_{it}$, 10km-15km 2015 & 2015-2019$_{it}$, and 15km-20km 2015 & 2015-2019$_{it}$ are statistically significant, which means there is evidence to suggest that there are time-varying omitted variables that are correlated with property values for block groups within 4km-20km from a 2015 wildfire perimeter.

[28] McCoy and Walsh (2018) find that after 5km away from a wildfire the effect on property sale prices goes to zero. Stetler et al. (2010) find the effect of wildfire proximity on the sale price of homes in northwestern Montana diminishes to zero beyond 10km

[29] In Table 12 $\%\Delta\text{Median Value} = \frac{\text{Median Value}_{it=2010/2014} - \text{Median Value}_{it=2005/2009}}{\text{Median Value}_{it=2005/2009}}$

6.4 Controlling for Wildfire Hazard Potential as a Proxy for Wildfire Risk

As mentioned earlier, the effect of wildfire proximity on property values has a negative dis-amenity effect on environmental attributes that will lower property values (i.e. areas less desirable to live in will have lower property values), and a positive risk effect on property values (i.e. high wildfire risk increases the cost of living in a wildfire risk area). To isolate the negative dis-amenity effect of wildfire proximity on property values it is necessary to control wildfire risk, because wildfire risk puts upward pressure on residential property values. Table 14 shows the results for regression equation (4) with the added control for Wildfire Hazard Potential (WHP) as a proxy for wildfire risk. Block groups with a higher WHP index have a higher probability of experiencing extreme wildfires based on historical wildfires, vegetation, and landscape attributes. I did not use the WHP as a control in the first difference regression because the WHP estimate is not a measure of wildfire risk at any single point in time since it is based on historical wildfire data (i.e. WHP is time-invariant). Therefore, the OLS in Table 14 provides a rough estimate of the adverse dis-amenity effects from wildfires for block groups within the non-overlapping treatment categories. We can see that controlling for wildfire risk via the WHP index improves the OLS estimate with statistical significance at 95% within 4km from a 2015 wildfire perimeter. Adding in pre-fire controls in columns (2),(4), and (6) of Table 14 shows that the estimates are robust to controlling for previous wildfires. Table 14 shows the dis-amenity association is strictly negative within 20km from a wildfire perimeter, which suggests the effects from wildfire risk were putting upward pressure on property values between 10km-20km from a wildfire perimeter. The results in Table 14 does not control for unobservable time-invariant variables, which may put upward pressure on property values (e.g. distance to water, elevation etc.). To get a more accurate estimate of wildfires' environmental dis-amenity effects on property values it would be necessary to process time-varying raster data on wildfire risk, such as the USGS measure of Large Fire Probability. However, the OLS results in Table 14 suggest that negative environmental dis-amenity association from wildfires cover a greater area than the combined association when not controlling for wildfire risk.

The regressions in Table 14 controls for a time-invariant measure of wildfire risk proxied by the Wildfire Hazard Potential (WHP) index. In contrast, the first difference regression in Table 7, Table 9, Table 10, and Table 11 removes any unobservable time-invariant variables including the WHP proxy of wildfire risk. I included the time-invariant proxy for wildfire risk in the OLS regressions in Table 14 because I had limited time to process the raster data for the time-varying measure of wildfire risk, which would ideally be included as a control in the first difference regression. In Table 11 columns (4) and (6), the first difference regression controls for the effect of wildfire proximity before 2015 on the 2015-2019 median block group property values, changes in demographic composition between the periods (i.e. changes in race and education composition of a block group), changes in property characteristics (i.e. changes in year built, number of bedrooms, and mortgage status), and changes in travel time to work as a neighbourhood amenity characteristic. Also, the first difference regression controls for any unobservable time-invariant variables, such as distance to bodies of water, distance to forest perimeter, elevation, latent measures of wildfire risk (e.g. the WHP index), and any other location-specific property market characteristics that do not change over time. In the first difference regression, I included time-fixed effects to control for any other time-varying trends between 2005-2009, 2010-2014, and 2015-2019 in the housing market (e.g. 2008 subprime crisis). The variation left in the first difference regression would be any change in property values over time from changes in the distance to the closest wildfire perimeter. The effect of changes in wildfire perimeter proximity on property values includes both wildfire risk (i.e. If a wildfire is closer to properties, there is a heightened sense of wildfire risk) and wildfire dis-amenity effects (i.e. The area where a wildfire occurs will be less desirable to live in after the wildfire happens). Although I did not control for time-varying measures of wildfire risk in the first difference regression to isolate the pure dis-amenity effect, by comparing row one column (4) of Table 11 with row one column (6) of Table 14[30] we can see that the estimate only increases by $2,630 when controlling for wildfire risk in the OLS versus the first difference without time-varying controls for wildfire risk (i.e. Point estimates of -$27,187 in the first difference versus -$24,557 in the OLS with the time-invariant wildfire risk control). This suggests that any time-varying measure of wildfire risk may be putting upward pressure on median block group property values in the first difference regressions.

[30] Note that both of these regressions control for wildfires that occur before 2015.

6.5 Test for Exogenous Treatment

To test that the treatment is random (i.e. being within a certain distance of a wildfire perimeter is not being driven by an omitted variable), I performed a two-sample t-test on the control variables and regressed the 4km 2015 Ring$_{it}$ treatment on the controls. Table 13 shows that there appear to be statistically significant differences in the means of the control variables between block groups within and not within 4km from a 2015 wildfire perimeter. The differences in the mean comparisons of the control variables may be driven by the fact that block groups where wildfires occur have a higher amenity value and are more desirable areas to live in. Table 18, Table 19, and Table 20 [31] shows the regression of the 4km 2014 Ring$_{it}$ and 4km 2015 & 2015-2019$_{it}$ on the controls. We can see that in Table 18, Table 19, and Table 20 a lot of the controls are not significant or the estimates are close to zero. Also, the results in Table 18, Table 19, and Table 20 are explaining very little of the variation in treatment. Similarly, in Table 15, Table 16, and Table 17 [32] show the first difference regression of treatment on the controls. Again, there is minimal variation explained in the model, and all of the coefficients are close to zero or are not statistically significant. Table 18, Table 19, Table 20, Table 15, Table 16, and Table 17 provides evidence to suggest that the wildfire treatment variable for within 4km from a 2015 wildfire perimeter is random and is not determined by other variables in the model.

6.6 Additional Robustness Checks

As an additional robustness check, I also performed a box-cox test on the median property value variable to test the appropriate power transformation. As shown in Figure 18 none of the powers are not statistically different from the best (i.e. the smoothed curve does not go above the red line) [33], which suggests there is no optimal transformation of the median property values variable. The choice of the natural logarithm and linear functional forms of property values is also consistent with the litera-

[31] Note Table 18, Table 19, and Table 20 is the same table, I split it over three pages to see all of the coefficients.
[32] Note Table 15, Table 16, and Table 17 is the same table, I split it over three pages to see all of the coefficients.
[33] This is using the 95% critical value for a chi-squared distribution with 100 degrees of freedom of 124.34.

ture, where Cropper et al. (1988); Loomis (2004) find that "simpler functional forms such as linear and semi-log transformation outperformed more complex functional forms in the face of omitted variable bias". Lastly, as a quick robustness check, I scrapped Zillow data of Sonoma, Nappa, and Solona County California sold listings for March 2021 to look at the effect of the fall 2020 Wallbridge, Hennessey, and Glass wildfires on house price sales. The summary statistics and results are provided in Table 21 and Table 22, but none of the results are statistically significant given a lack of controls and inability to scrap property values from the website before the wildfires occurred[34].

7 Conclusion

This study aimed to understand wildfire dis-amenity effects on property values. Using a first difference estimation strategy to control for unobservable time-invariant factors that determine property values, the study isolated the association of wildfire proximity on property values across the continental western United States. The paper found that block groups located within 4km from a 2015 wildfire perimeter face a 7.6% reduction in the growth rate of median property values compared to block groups located beyond 4km from a 2015 wildfire perimeter. This accounts for an implicit marginal price reduction of around $23,651.45 for properties in block groups situated within 4km from a 2015 wildfire perimeter. The main result was found to be robust to pre-fire and wildfire risk controls. Controlling for wildfire risk, the paper found the isolated dis-amenity effect on block group property values to be significant within 20km from a 2015 wildfire perimeter and negative. This study is the first of its kind in the literature to analyze the effect of wildfire proximity on property values across the entire western United States, and it contributes to understanding the environmental dis-amenity effect of wildfires on property values. The major limitations of this study is that: i) It was unable to control for time-varying measures of wildfire risk, ii) the paper was not able to look at year over year changes in median block group property values, because the ACS only provided the five-year estimates at the block group level, iii) the

[34] Zillow removes old listings from their website, so I was not able to get property data before the Fall 2020 wildfires occurred.

study was unable to look at the post-wildfire trends to measure how persistent the pure dis-amenity effect of wildfires on property values is, and iv) although the paper did control for time-invariant factors in the first difference it would be ideal to have a richer set of geographic, vegetation, and neighbourhood amenity controls to more precisely estimate the pure dis-amenity effect. In addition to using more specific time and amenity data, future research should take advantage of detailed time-varying geographic data[35]for more precise controls for wildfire risk in isolating the pure dis-amenity effect of wildfires on property values.

[35] For example, USGS Large Fire Probability and Fire Potential Index raster data.

8 Tables

Table 1: Summary Statistics Property Value and Block Group Housing Characteristics

	Mean	Standard Deviation	Min	Max
Median Property Value	311203.25	250820.51	6450.19	2000001.00
Natural Log Median Property Value	12.34	0.81	8.77	14.51
Difference in Median Property Value	830.06	126561.27	-1034938.25	1513566.88
Natural Log Difference in Median Property Value	0.00	0.39	-3.87	3.97
Median WHP 2020	0.48	0.99	0.00	5.00
Average Minimum Distance to a Wildfire Perimeter	138.23	145.12	4.34	600.55
Built 2000 or later	0.22	0.30	0.00	29.33
Built 1990 to 1999	0.11	0.13	0.00	1.00
Built 1980 to 1989	0.14	0.15	0.00	1.00
Built 1970 to 1979	0.19	0.17	0.00	1.00
Built 1960 to 1969	0.14	0.14	0.00	1.00
Built 1950 to 1959	0.15	0.18	0.00	1.00
Built 1940 to 1949	0.07	0.10	0.00	0.97
Built 1939 or earlier	0.11	0.17	0.00	1.00
1 bedroom	0.10	0.12	0.00	0.87
2 bedrooms	0.27	0.17	0.00	1.00
3 bedrooms	0.41	0.18	0.00	1.00
4 bedrooms	0.16	0.14	0.00	0.96
5 or more bedrooms	0.04	0.06	0.00	0.85
Housing units with a mortgage contract to purchase or similar debt	0.64	0.19	0.00	1.00
Housing units without a mortgage	0.36	0.19	0.00	1.00
Observations	129746			

*All variables below 'Average Minimum Distance to a Wildfire Perimeter'are in proportion terms of the block group (e.g. 1 bedroom is proportion of homes in the block group with one bedroom)

Table 2: Number of Block Groups Within Each Distance Category

		2010-2014			
		<=4km	4km<=20km	>20km	Total
	<=4km	1475	4390	949	6814
2005-2009	4km<=20km	2721	26076	16557	45354
	>20km	2536	18647	56395	77578
	Total	6732	49113	73901	129746
	Observations	129746			

Table 3: Number of Block Groups Within Each Distance Category

		2015-2018			
		<=4km	4km<=20km	>20km	Total
	<=4km	1320	4415	1079	6814
2005-2009	4km<=20km	1745	25081	18528	45354
	>20km	361	6052	71165	77578
	Total	3426	35548	90772	129746
	Observations	129746			

Table 4: Number of Block Groups Within Each Distance Category

		2015-2018			
		<=4km	4km<=20km	>20km	Total
	<=4km	772	2801	3159	6732
2010-2014	4km<=20km	2286	22948	23879	49113
	>20km	368	9799	63734	73901
	Total	3426	35548	90772	129746
	Observations	129746			

Table 5: Average Median Property Values Within and Not Within 4 km Distance from Wildfire Perimeter

	Within 4km From a Wildfire Perimeter				
	No	Yes	N No	N Yes	p-Value
Median Property Value 2005-2009	321,676	408,280	39,062	4,662	0.00
Median Property Value 2010-2014	260,160	309,644	39,062	4,662	0.00
Median Property Value 2015-2019	332,680	383,864	37,784	4,514	0.00

N is the number of observations.

Table 6: Comparison of Wildfire Hazard Potential (WHP) 2020 Within 4 km Distance from Wildfire Perimeter

	Within 4km From a Wildfire Perimeter		
Within 4 km	No	Yes	Total
Mean 2005-2009	0.4486311	0.9628983	0.4756296
N	43724		
Mean 2010-2014	0.4375499	1.169604	0.4756296
N	43724		
Mean 2015-2019	0.4562906	1.306798	0.4788129
N	42298		

*WHP is not a forecast or outlook to any particular time or season.

I split it by periods so that this table can be compared with the above table.

Table 7: Block Group Median Property Values on Within 4km from a 2015 Wildfire Perimeter

	(1)	(2)	(3)	(4)	(5)
	Median Value	Δ Median Value	Δ $\ln$(Median Value)	Δ Median Value	Δ $\ln$(Median Value)
4km 2015 Ring	-15147.8	-26644.8***	-0.0760***	-22318.1***	-0.0603**
	(-1.52)	(-4.47)	(-3.85)	(-3.51)	(-2.92)
Observations	129741	86016	86016	6842	6842
R^2	0.664	0.328	0.301	0.459	0.386

t statistics in parentheses

Model (1) use state and time fixed effects, and robust standard errors.

Models (2)-(5) use time fixed effects and standard errors are clustered on block groups.

Models (4) and (5) exclude block groups greater than 20km from a wildfire perimeter.

Controls: Percent Race, Percent Educated, Percent Travel Time to Work, Percent Year Built, Percent Number of Bedrooms, Percent With Mortgage.

Model (1)-(3) base category beyond 4km. Model (4)-(5) base category beyond 4km.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: OLS Block Group Median Property Values on Within 4km and 4km-20km from a 2015 Wildfire Perimeter

	(1) Median Value	(2) Median Value	(3) Median Value	(4) Median Value
4km 2015 & 2015-2019	-15147.8	-14726.4	-17893.7	-15349.6
	(-1.52)	(-1.47)	(-1.79)	(-1.54)
4km-20km 2015 & 2015-2019			-26551.0***	-23036.0***
			(-10.33)	(-8.88)
Pre-Fire 4km 2005-2009		42406.8***		18699.6***
		(10.83)		(4.66)
Pre-Fire 4km 2010-2014		-13244.7***		-8924.1***
		(-4.86)		(-3.43)
Pre-Fire 4km-20km 2005-2009				54620.1***
				(27.73)
Pre-Fire 4km-20km 2010-2014				-24068.4***
				(-17.64)
Observations	129741	129741	129741	129741
R^2	0.664	0.664	0.664	0.668

t statistics in parentheses

Model (1),(2),(3),(4) use state and time fixed effects, and robust standard errors.

Models (2) and (4) include controls for wildfires that happened within 4km and 4km-20km in the 2005-2009 and 2010-2014 pre-periods.

Controls: Percent Race, Percent Educated, Percent Travel Time to Work, Percent Year Built, Percent Number of Bedrooms, Percent With Mortgage.

Model (1)-(2) distance base category is beyond 4km. Model (3)-(4) distance base category beyond 20km.

$^{*}\ p < 0.05, ^{**}\ p < 0.01, ^{***}\ p < 0.001$

Table 9: First Difference Block Group Median Property Values on Within 4km and 4km-20km from a 2015 Wildfire Perimeter

	(1) Δ Median Value	(2) Δ Median Value	(3) Δ Median Value	(4) Δ Median Value
4km 2015 & 2015-2019	-26644.8***	-26672.0***	-27112.5***	-27123.0***
	(-4.47)	(-4.48)	(-4.55)	(-4.55)
4km-20km 2015 & 2015-2019			-6085.3***	-6183.2***
			(-3.96)	(-4.04)
Pre-Fire 4km 2005-2014		-38087.9***		-24904.9***
		(-19.77)		(-13.42)
Pre-Fire 4km-20km 2005-2014				-49936.4***
				(-51.91)
Observations	86016	86016	86016	86016
R^2	0.328	0.332	0.328	0.350

t statistics in parentheses

Models (1)-(4) use time fixed effects, and standard errors clustered on block groups.

Models (2) and (4) include controls for wildfires that happened within 4km and 4km-20km in the 2005-2009 and 2010-2014 pre-periods.

Controls: Percent Race, Percent Educated, Percent Travel Time to Work, Percent Year Built, Percent Number of Bedrooms, Percent With Mortgage.

Model (1)-(2) distance base category is beyond 4km. Model (3)-(4) distance base category beyond 20km.

$^{*}\ p < 0.05, ^{**}\ p < 0.01, ^{***}\ p < 0.001$

Table 10: First Difference Block Group Median Property Values on Within 4km and 4km-20km from a 2015 Wildfire Perimeter

	(1)	(2)	(3)	(4)
	Δ ln(Median Value)	Δ ln(Median Value)	Δ ln(Median Value)	Δ ln(Median Value)
4km 2015 & 2015-2019	-0.0760***	-0.0760***	-0.0774***	-0.0774***
	(-3.85)	(-3.86)	(-3.93)	(-3.93)
4km-20km 2015 & 2015-2019			-0.0186***	-0.0188***
			(-3.83)	(-3.88)
Pre-Fire 4km 2005-2014		-0.0718***		-0.0440***
		(-11.91)		(-7.38)
Pre-Fire 4km-20km 2005-2014				-0.105***
				(-29.28)
Observations	86016	86016	86016	86016
R^2	0.301	0.302	0.301	0.311

t statistics in parentheses

Models (1)-(4) use time fixed effects, and standard errors clustered on block groups.

Models (2) and (4) include controls for wildfires that happened within 4km and 4km-20km in the 2005-2009 and 2010-2014 pre-periods.

Controls: Percent Race, Percent Educated, Percent Travel Time to Work, Percent Year Built, Percent Number of Bedrooms, Percent With Mortgage.

Model (1)-(2) distance base category is beyond 4km. Model (3)-(4) distance base category beyond 20km.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: OLS & First Difference Block Group Median Property Values on Within 4km, 4km-10km, 10km-15km, and 15km-20km from a 2015 Wildfire Perimeter

	(1)	(2)	(3)	(4)	(5)	(6)
	Median Value	Median Value	Δ Median Value	Δ Median Value	Δ ln(Median Value)	Δ ln(Median Value)
4km 2015 & 2015-2019	-17841.9	-17079.1	-27113.6***	-27187.2***	-0.0774***	-0.0776***
	(-1.78)	(-1.71)	(-4.55)	(-4.57)	(-3.93)	(-3.94)
4km-10km 2015 & 2015-2019	-11341.6	-10216.2	-16473.6***	-16610.0***	-0.0552***	-0.0555***
	(-1.91)	(-1.71)	(-4.94)	(-5.00)	(-5.28)	(-5.32)
10km-15km 2015 & 2015-2019	-27653.9***	-26268.2***	-6733.3*	-6860.4**	-0.00939	-0.00969
	(-7.27)	(-6.88)	(-2.56)	(-2.62)	(-1.13)	(-1.16)
15km-20km 2015 & 2015-2019	-32870.6***	-31162.1***	-688.7	-963.9	-0.00817	-0.00881
	(-9.04)	(-8.54)	(-0.33)	(-0.46)	(-1.21)	(-1.30)
Pre-Fire 4km 2005-2014				-14506.4***		-0.0197**
				(-7.78)		(-3.27)
Pre-Fire 4km-10km 2005-2014				-18388.9***		-0.0340***
				(-13.82)		(-7.74)
Pre-Fire 10km-15km 2005-2014				-29540.1***		-0.0659***
				(-22.67)		(-15.10)
Pre-Fire 15km-20km 2005-2014				-41842.6***		-0.104***
				(-34.70)		(-25.60)
Observations	129741	129741	86016	86016	86016	86016
R^2	0.664	0.669	0.328	0.362	0.301	0.320

t statistics in parentheses

Models (3)-(6) use time fixed effects, and standard errors clustered on block groups.

Models (1)-(2) use time and state fixed effects with robust standard errors.

Model (2),(4), and (6) controls for previous wildfires in the 2005-2009 and 2010-2014 periods within 4km, 4km-10km, 10km-15km, and 15km-20km from block group

Controls: Percent Race, Percent Educated, Percent Travel Time to Work, Percent Year Built, Percent Number of Bedrooms, Percent With Mortgage.

Model (1)-(6) distance base category is beyond 20km.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: First Difference Regressions Percentage Change in Median Value between 2005-2009 and 2010-2014 Periods on Distance from a 2015 Wildfire Perimeter

	(1)	(2)	(3)	(4)
	% Δ Median Value	% Δ Median Value	% Δ Median Value	% Δ Median Value
4km 2015 Ring	-0.0450	0.0167		
	(-1.49)	(0.52)		
4km 2015 & 2015-2019			-0.0502	-0.0503
			(-1.67)	(-1.67)
4km-10km 2015 & 2015-2019			-0.0471**	-0.0473**
			(-2.99)	(-3.01)
10km-15km 2015 & 2015-2019			-0.0600**	-0.0602**
			(-2.65)	(-2.66)
15km-20km 2015 & 2015-2019			-0.0827***	-0.0832***
			(-5.73)	(-5.77)
Pre-Fire 4km 2005-2014				-0.0255***
				(-3.51)
Pre-Fire 4km-10km 2005-2014				-0.0291***
				(-3.79)
Pre-Fire 10km-15km 2005-2014				-0.0492***
				(-6.09)
Pre-Fire 15km-20km 2005-2014				-0.0744***
				(-10.52)
Observations	86016	6842	86016	86016
R^2	0.0175	0.0326	0.0179	0.0221

t statistics in parentheses

Models (1)-(4) use time fixed effects, and standard errors clustered on block groups.

Model (2) excludes block groups further than 20km from a 2015 wildfire perimeter

Model (4) controls for previous wildfires in the 2005-2009 and 2010-2014 periods within 4km, 4km-10km, 10km-15km, and 15km-20km from a block group

Controls: Percent Race, Percent Educated, Percent Travel Time to Work, Percent Year Built, Percent Number of Bedrooms, Percent With Mortgage.

Model (1)-(2) distance base category is beyond 4km. Model (3)-(4) distance base category is beyond 20km.

$^{*}\ p < 0.05,^{**}\ p < 0.01,^{***}\ p < 0.001$

Table 13: Two Sample t-test with Unequal Variances on Control Variables by Within 4km from a 2015 Wildfire

	diff.	t-statistic
White alone	-0.0868***	(-7.38)
Black or African American alone	0.0489***	(21.15)
American Indian and Alaska Native alone	-0.0103	(-1.49)
Asian alone	0.0390***	(13.34)
Native Hawaiian and Other Pacific Islander alone	-0.000923	(-0.68)
Some other race alone	0.0186*	(2.27)
Two or more races	-0.00850*	(-2.19)
Less than 5 minutes	-0.0232**	(-2.62)
5 to 9 minutes	-0.0301**	(-2.66)
10 to 14 minutes	0.00629	(0.68)
15 to 19 minutes	0.00811	(0.80)
20 to 24 minutes	0.0450***	(6.06)
25 to 29 minutes	0.00888	(1.82)
30 to 34 minutes	0.0410***	(5.83)
35 to 39 minutes	-0.00312	(-0.82)
40 to 44 minutes	-0.000238	(-0.06)
45 to 59 minutes	-0.0160*	(-2.21)
60 to 89 minutes	-0.0252***	(-3.37)
90 or more minutes	-0.0114*	(-2.02)
No schooling completed	0.102***	(59.38)
Nursery to 4th grade	0.104***	(45.43)
5th and 6th grade	0.0976***	(31.54)
7th and 8th grade	0.0873***	(46.80)
9th grade	0.0915***	(51.97)
10th grade	0.0813***	(40.36)
11th grade	0.0839***	(42.94)
12th grade no diploma	0.0766***	(33.26)
High school graduate, GED, or alternative	-0.0428***	(-4.84)
Some college less than 1 year	0.0200***	(5.28)
Some college 1 or more years no degree	-0.0210***	(-3.41)
Associates degree	0.0116*	(2.49)
Bachelors degree	0.0164*	(2.31)
Masters degree	0.0421***	(8.03)
Professional school degree	0.0877***	(31.26)
Doctorate degree	0.0996***	(58.67)
Built 2000 or later	0.0719***	(6.64)
Built 1990 to 1999	-0.0324**	(-3.19)
Built 1980 to 1989	-0.0159	(-1.34)
Built 1970 to 1979	-0.0365**	(-2.72)
Built 1960 to 1969	0.0130	(1.11)
Built 1950 to 1959	0.0726***	(10.26)
Built 1940 to 1949	0.0268***	(5.40)
Built 1939 or earlier	0.0168	(1.68)
No bedroom	-0.0127*	(-2.40)
1 bedroom	0.00301	(0.34)
2 bedrooms	0.0166	(1.34)
3 bedrooms	0.0180	(1.39)
4 bedrooms	-0.0171	(-1.71)
5 or more bedrooms	-0.00782	(-1.42)
Housing units with a mortgage contract to purchase or similar debt	0.0397**	(2.63)
Housing units without a mortgage	-0.0397**	(-2.63)
Observations	129746	

t statistics in parentheses
4km 2015 Ring dummy variable is used to create the two samples between within and not within 4km from a 2015 wildfire perimeter
diff. is difference in means between control and treated groups (i.e. not within 4km - within 4km)
*All variables above are in proportion terms of the block group (e.g. 1 bedroom is proportion of homes in the block group with one bedroom)
$^{*}\ p < 0.05, ^{**}\ p < 0.01, ^{***}\ p < 0.001$

Table 14: OLS Block Group Median Property Values on Within 4km, 4km-10km, 10km-15km, and 15km-20km from a 2015 Wildfire Perimeter With WHP Controls

	(1) Median Value	(2) Median Value	(3) Median Value	(4) Median Value	(5) Median Value	(6) Median Value
4km 2015 & 2015-2019	-22049.1*	-21532.1*	-25284.2*	-22534.4*	-25213.1*	-24557.1*
	(-2.22)	(-2.17)	(-2.55)	(-2.28)	(-2.54)	(-2.48)
4km-20km 2015 & 2015-2019			-28329.7***	-24856.1***		
			(-11.10)	(-9.65)		
4km-10km 2015 & 2015-2019					-14886.9*	-13865.9*
					(-2.52)	(-2.34)
10km-15km 2015 & 2015-2019					-29088.1***	-27823.7***
					(-7.66)	(-7.29)
15km-20km 2015 & 2015-2019					-34060.5***	-32488.5***
					(-9.47)	(-9.00)
Pre-Fire 4km 2005-2009		40535.5***		17203.2***		17591.2***
		(10.37)		(4.30)		(4.32)
Pre-Fire 4km 2010-2014		-17258.4***		-12969.0***		-10667.8***
		(-6.40)		(-5.02)		(-4.19)
Pre-Fire 4km-20km 2005-2009				53141.2***		
				(27.02)		
Pre-Fire 4km-20km 2010-2014				-24779.8***		
				(-18.28)		
Pre-Fire 4km-10km 2005-2009						26068.5***
						(9.86)
Pre-Fire 4km-10km 2010-2014						-20659.4***
						(-12.24)
Pre-Fire 10km-15km 2005-2009						24113.3***
						(10.37)
Pre-Fire 10km-15km 2010-2014						-21846.2***
						(-13.14)
Pre-Fire 15km-20km 2005-2009						22963.5***
						(10.77)
Pre-Fire 15km-20km 2010-2014						-28372.5***
						(-17.90)
Median WHP 2020=1	29835.6***	29863.9***	29746.8***	29704.8***	29730.1***	29386.3***
	(24.26)	(24.32)	(24.18)	(24.22)	(24.17)	(23.98)
Median WHP 2020=2	29911.8***	30041.1***	30164.7***	29775.1***	30154.7***	30460.4***
	(16.99)	(17.09)	(17.15)	(17.05)	(17.14)	(17.44)
Median WHP 2020=3	39091.3***	38932.3***	39926.5***	38928.0***	39815.2***	39771.5***
	(16.95)	(16.84)	(17.33)	(16.92)	(17.27)	(17.30)
Median WHP 2020=4	26726.9***	25475.5***	28137.5***	26189.2***	28047.2***	27357.8***
	(8.71)	(8.32)	(9.19)	(8.60)	(9.16)	(8.94)
Median WHP 2020=5	25242.8**	24614.0**	27408.3**	25375.8**	27250.5**	25845.7**
	(2.85)	(2.77)	(3.11)	(2.90)	(3.09)	(2.93)
Observations	129492	129492	129492	129492	129492	129492
R^2	0.666	0.666	0.666	0.670	0.666	0.671

t statistics in parentheses

Models (1)-(6) use state and time fixed effects with robust standard errors.

Model (2) controls for previous wilfires in 2005-2009 and 2010-2014 within 4km.

Model (4) controls for previous wilfires in 2005-2009 and 2010-2014 within 4km and 4km-20km.

Model (6) controls for previous wildfires in the 2005-2009 and 2010-2014 periods within 4km, 4km-10km, 10km-15km, and 15km-20km from block group.

Controls: Percent Race, Percent Educated, Percent Travel Time to Work, Percent Year Built, Percent Number of Bedrooms, Percent With Mortgage.

Model (1)-(2) distance base category beyond 4km. Model (3)-(6) distance base category is beyond 20km.

$^{*}\ p < 0.05, ^{**}\ p < 0.01, ^{***}\ p < 0.001$

Table 15: First Difference Regression Within 4km from a 2015 Wildfire Perimeter on Controls

	(1) 4km 2015 Ring	(2) 4km 2015 & 2015-2019	(3) 4km 2015 & 2015-2019
Pre-Fire 4km 2005-2014			-0.0000300
			(-0.84)
Δ Black or African American alone	0.00167	0.00167	0.00167
	(1.66)	(1.66)	(1.66)
Δ American Indian and Alaska Native alone	0.00555	0.00555	0.00555
	(1.10)	(1.10)	(1.10)
Δ Asian alone	-0.00206	-0.00206	-0.00206
	(-1.48)	(-1.48)	(-1.48)
Δ Native Hawaiian and Other Pacific Islander alone	0.0104	0.0104	0.0104
	(1.29)	(1.29)	(1.29)
Δ Some other race alone	0.00139	0.00139	0.00139
	(1.00)	(1.00)	(1.00)
Δ Two or more races	0.00129	0.00129	0.00129
	(0.35)	(0.35)	(0.35)
Δ 5 to 9 minutes	0.000853	0.000853	0.000853
	(0.18)	(0.18)	(0.18)
Δ 10 to 14 minutes	0.000563	0.000563	0.000563
	(0.13)	(0.13)	(0.13)
Δ 15 to 19 minutes	0.00184	0.00184	0.00184
	(0.42)	(0.42)	(0.42)
Δ 20 to 24 minutes	-0.000259	-0.000259	-0.000259
	(-0.06)	(-0.06)	(-0.06)
Δ 25 to 29 minutes	0.000601	0.000601	0.000601
	(0.12)	(0.12)	(0.12)
Δ 30 to 34 minutes	-0.00124	-0.00124	-0.00124
	(-0.27)	(-0.27)	(-0.27)
Δ 35 to 39 minutes	0.00470	0.00470	0.00470
	(0.87)	(0.87)	(0.87)
Δ 40 to 44 minutes	-0.00649	-0.00649	-0.00649
	(-1.24)	(-1.24)	(-1.24)
Δ 45 to 59 minutes	0.0000690	0.0000690	0.0000686
	(0.01)	(0.01)	(0.01)
Δ 60 to 89 minutes	-0.000276	-0.000276	-0.000276
	(-0.05)	(-0.05)	(-0.05)
Δ 90 or more minutes	-0.000962	-0.000962	-0.000962
	(-0.16)	(-0.16)	(-0.16)
Observations	86016	86016	86016
R^2	0.00235	0.00235	0.00235

t statistics in parentheses
Models (1)-(3) use time fixed effects and standard errors clustered on block groups.
$^{*}\ p < 0.05, ^{**}\ p < 0.01, ^{***}\ p < 0.001$

Table 16: First Difference Regression Within 4km from a 2015 Wildfire Perimeter on Controls. Cont.

	(1) 4km 2015 Ring	(2) 4km 2015 & 2015-2019	(3) 4km 2015 & 2015-2019
Δ Nursery to 4th grade	0.000509	0.000509	0.000509
	(0.65)	(0.65)	(0.65)
Δ 5th and 6th grade	0.000724	0.000724	0.000724
	(0.99)	(0.99)	(0.99)
Δ 7th and 8th grade	-0.000595	-0.000595	-0.000598
	(-0.88)	(-0.88)	(-0.88)
Δ 9th grade	-0.000146	-0.000146	-0.000147
	(-0.23)	(-0.23)	(-0.23)
Δ 10th grade	0.000692	0.000692	0.000692
	(1.20)	(1.20)	(1.20)
Δ 11th grade	-0.00110	-0.00110	-0.00109
	(-1.62)	(-1.62)	(-1.62)
Δ 12th grade no diploma	0.000404	0.000404	0.000404
	(0.67)	(0.67)	(0.67)
Δ High school graduate, GED, or alternative	-0.000573	-0.000573	-0.000574
	(-0.57)	(-0.57)	(-0.57)
Δ Some college less than 1 year	0.000898	0.000898	0.000899
	(0.93)	(0.93)	(0.93)
Δ Some college 1 or more years no degree	-0.00119	-0.00119	-0.00119
	(-1.12)	(-1.12)	(-1.12)
Δ Associates degree	0.00111	0.00111	0.00111
	(1.20)	(1.20)	(1.21)
Δ Bachelors degree	-0.000683	-0.000683	-0.000684
	(-0.79)	(-0.79)	(-0.79)
Δ Masters degree	0.000514	0.000514	0.000514
	(0.71)	(0.71)	(0.71)
Δ Professional school degree	-0.000743	-0.000743	-0.000743
	(-1.10)	(-1.10)	(-1.10)
Δ Doctorate degree	-0.000281	-0.000281	-0.000280
	(-0.42)	(-0.42)	(-0.42)
Observations	86016	86016	86016
R^2	0.00235	0.00235	0.00235

t statistics in parentheses
Models (1)-(3) use time fixed effects and standard errors clustered on block groups.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: First Difference Regression Within 4km from a 2015 Wildfire Perimeter on Controls. Cont.

	(1) 4km 2015 Ring	(2) 4km 2015 & 2015-2019	(3) 4km 2015 & 2015-2019
Δ Built 1990 to 1999	-0.00405*	-0.00405*	-0.00406*
	(-1.98)	(-1.98)	(-1.98)
Δ Built 1980 to 1989	-0.00574***	-0.00574***	-0.00574***
	(-3.33)	(-3.33)	(-3.33)
Δ Built 1970 to 1979	-0.00260	-0.00260	-0.00260
	(-1.40)	(-1.40)	(-1.40)
Δ Built 1960 to 1969	-0.00475**	-0.00475**	-0.00475**
	(-2.69)	(-2.69)	(-2.69)
Δ Built 1950 to 1959	-0.00473**	-0.00473**	-0.00473**
	(-2.93)	(-2.93)	(-2.93)
Δ Built 1940 to 1949	-0.00310	-0.00310	-0.00310
	(-1.73)	(-1.73)	(-1.73)
Δ Built 1939 or earlier	-0.00201	-0.00201	-0.00201
	(-1.01)	(-1.01)	(-1.01)
Δ 1 bedroom	-0.00423	-0.00423	-0.00423
	(-0.82)	(-0.82)	(-0.82)
Δ 2 bedrooms	-0.00474	-0.00474	-0.00474
	(-0.96)	(-0.96)	(-0.96)
Δ 3 bedrooms	-0.00497	-0.00497	-0.00497
	(-1.02)	(-1.02)	(-1.02)
Δ 4 bedrooms	-0.00437	-0.00437	-0.00437
	(-0.85)	(-0.85)	(-0.85)
Δ 5 or more bedrooms	-0.00825	-0.00825	-0.00825
	(-1.33)	(-1.33)	(-1.33)
Δ Housing units with a mortgage contract to purchase or similar debt Both	0.00692	0.00692	0.00692
	(1.69)	(1.69)	(1.69)
Δ Housing units with a mortgage contract to purchase or similar debt	0.00144	0.00144	0.00144
	(1.37)	(1.37)	(1.37)
Δ Housing units without a mortgage	0.00192	0.00192	0.00193
	(1.52)	(1.52)	(1.52)
Observations	86016	86016	86016
R^2	0.00235	0.00235	0.00235

t statistics in parentheses
Models (1)-(3) use time fixed effects and standard errors clustered on block groups.
$^{*}\ p < 0.05, ^{**}\ p < 0.01, ^{***}\ p < 0.001$

Table 18: OLS Regression Within 4km from a 2015 Wildfire Perimeter on Controls

	(1) 4km 2015 Ring	(2) 4km 2015 & 2015-2019	(3) 4km 2015 & 2015-2019	(4) 4km 2015 & 2015-2019
Pre-Fire 4km 2005-2009			-0.000949***	-0.00161***
			(-5.71)	(-6.94)
Pre-Fire 4km 2010-2014			-0.000690***	-0.00154***
			(-5.68)	(-7.61)
Black or African American alone	-0.00140***	-0.00140***	-0.00142***	-0.000504
	(-4.72)	(-4.72)	(-4.76)	(-1.76)
American Indian and Alaska Native alone	0.00120	0.00120	0.00120	0.000273
	(0.51)	(0.51)	(0.51)	(0.12)
Asian alone	-0.00563***	-0.00563***	-0.00572***	-0.00377***
	(-8.14)	(-8.14)	(-8.17)	(-5.77)
Native Hawaiian and Other Pacific Islander alone	0.00175	0.00175	0.00163	0.00328
	(0.20)	(0.20)	(0.19)	(0.38)
Some other race alone	-0.00142	-0.00142	-0.00146	0.000251
	(-1.46)	(-1.46)	(-1.50)	(0.26)
Two or more races	0.000263	0.000263	0.000266	0.00132
	(0.09)	(0.09)	(0.09)	(0.45)
5 to 9 minutes	-0.00346	-0.00346	-0.00345	-0.00172
	(-0.87)	(-0.87)	(-0.87)	(-0.43)
10 to 14 minutes	-0.00573	-0.00573	-0.00573	-0.00383
	(-1.69)	(-1.69)	(-1.69)	(-1.14)
15 to 19 minutes	-0.00352	-0.00352	-0.00354	-0.00193
	(-1.08)	(-1.08)	(-1.09)	(-0.59)
20 to 24 minutes	-0.00793*	-0.00793*	-0.00797*	-0.00630
	(-2.33)	(-2.33)	(-2.35)	(-1.87)
25 to 29 minutes	-0.00629	-0.00629	-0.00632	-0.00504
	(-1.67)	(-1.67)	(-1.68)	(-1.34)
30 to 34 minutes	-0.00898**	-0.00898**	-0.00901**	-0.00747*
	(-2.66)	(-2.66)	(-2.67)	(-2.23)
35 to 39 minutes	-0.00379	-0.00379	-0.00378	-0.00319
	(-0.78)	(-0.78)	(-0.78)	(-0.66)
40 to 44 minutes	-0.00775	-0.00775	-0.00776	-0.00685
	(-1.90)	(-1.90)	(-1.91)	(-1.70)
45 to 59 minutes	-0.00334	-0.00334	-0.00331	-0.00291
	(-0.82)	(-0.82)	(-0.81)	(-0.71)
60 to 89 minutes	-0.000883	-0.000883	-0.000834	-0.000586
	(-0.21)	(-0.21)	(-0.19)	(-0.14)
90 or more minutes	-0.00614	-0.00614	-0.00612	-0.00717
	(-1.11)	(-1.11)	(-1.10)	(-1.29)
Observations	129741	129741	129741	129492
R^2	0.00542	0.00542	0.00544	0.00695

t statistics in parentheses
Models (1)-(4) use state and time fixed effects with robust standard errors.
Model (3) and (4) have pre-fire controls for wildfires within 4km from a block group in 2005-2009 and 2010-2014 periods.
Model (4) includes the 2020 Wildfire Hazard Potential (WHP) control.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: OLS Regression Within 4km from a 2015 Wildfire Perimeter on Controls. Cont.

	(1) 4km 2015 Ring	(2) 4km 2015 & 2015-2019	(3) 4km 2015 & 2015-2019	(4) 4km 2015 & 2015-2019
Nursery to 4th grade	-0.0000153	-0.0000153	-0.0000180	-0.000244
	(-0.02)	(-0.02)	(-0.03)	(-0.39)
5th and 6th grade	-0.00192**	-0.00192**	-0.00194**	-0.00189**
	(-3.02)	(-3.02)	(-3.05)	(-2.98)
7th and 8th grade	-0.000787	-0.000787	-0.000741	-0.000732
	(-1.73)	(-1.73)	(-1.63)	(-1.60)
9th grade	-0.000882	-0.000882	-0.000855	-0.000807
	(-1.94)	(-1.94)	(-1.89)	(-1.78)
10th grade	0.000884	0.000884	0.000893	0.00107*
	(1.78)	(1.78)	(1.80)	(2.12)
11th grade	-0.000783	-0.000783	-0.000784	-0.000607
	(-1.60)	(-1.60)	(-1.61)	(-1.23)
12th grade no diploma	0.000304	0.000304	0.000295	0.000432
	(0.61)	(0.61)	(0.59)	(0.86)
High school graduate, GED, or alternative	0.00147	0.00147	0.00151	0.00117
	(1.65)	(1.65)	(1.69)	(1.32)
Some college less than 1 year	0.000887	0.000887	0.000879	0.000975
	(1.10)	(1.10)	(1.09)	(1.21)
Some college 1 or more years no degree	0.00183	0.00183	0.00184	0.00160
	(1.81)	(1.81)	(1.81)	(1.60)
Associates degree	0.00172*	0.00172*	0.00170*	0.00161*
	(2.11)	(2.11)	(2.08)	(1.97)
Bachelors degree	-0.00252***	-0.00252***	-0.00253***	-0.00239**
	(-3.41)	(-3.41)	(-3.41)	(-3.24)
Masters degree	0.000466	0.000466	0.000466	0.000455
	(0.68)	(0.68)	(0.68)	(0.66)
Professional school degree	0.000782	0.000782	0.000751	0.000557
	(1.23)	(1.23)	(1.18)	(0.87)
Doctorate degree	-0.000264	-0.000264	-0.000270	-0.000305
	(-0.52)	(-0.52)	(-0.53)	(-0.60)
Built 1990 to 1999	0.000135	0.000135	0.000114	0.000494
	(0.12)	(0.12)	(0.10)	(0.42)
Built 1980 to 1989	-0.000538	-0.000538	-0.000544	0.000344
	(-0.53)	(-0.53)	(-0.54)	(0.34)
Built 1970 to 1979	0.000146	0.000146	0.000123	0.00131
	(0.15)	(0.15)	(0.13)	(1.36)
Built 1960 to 1969	-0.000628	-0.000628	-0.000647	0.000941
	(-0.62)	(-0.62)	(-0.64)	(0.94)
Built 1950 to 1959	-0.00231**	-0.00231**	-0.00235**	-0.000579
	(-2.93)	(-2.93)	(-2.97)	(-0.74)
Built 1940 to 1949	-0.00155	-0.00155	-0.00160	-0.000145
	(-1.65)	(-1.65)	(-1.69)	(-0.16)
Built 1939 or earlier	-0.00134	-0.00134	-0.00137	-0.000144
	(-1.53)	(-1.53)	(-1.57)	(-0.17)
Observations	129741	129741	129741	129492
R^2	0.00542	0.00542	0.00544	0.00695

t statistics in parentheses
Models (1)-(4) use state and time fixed effects with robust standard errors.
Model (3) and (4) have pre-fire controls for wildfires within 4km from a block group in 2005-2009 and 2010-2014 periods.
Model (4) includes the 2020 Wildfire Hazard Potential (WHP) control.
$^{*}\ p < 0.05, ^{**}\ p < 0.01, ^{***}\ p < 0.001$

Table 20: OLS Regression Within 4km from a 2015 Wildfire Perimeter on Controls. Cont.

	(1) 4km 2015 Ring	(2) 4km 2015 & 2015-2019	(3) 4km 2015 & 2015-2019	(4) 4km 2015 & 2015-2019
1 bedroom	-0.00392	-0.00392	-0.00391	-0.00379
	(-0.99)	(-0.99)	(-0.99)	(-0.95)
2 bedrooms	-0.00505	-0.00505	-0.00503	-0.00535
	(-1.45)	(-1.45)	(-1.44)	(-1.53)
3 bedrooms	-0.00448	-0.00448	-0.00446	-0.00523
	(-1.27)	(-1.27)	(-1.27)	(-1.47)
4 bedrooms	-0.00330	-0.00330	-0.00325	-0.00325
	(-0.94)	(-0.94)	(-0.93)	(-0.92)
5 or more bedrooms	-0.00331	-0.00331	-0.00324	-0.00409
	(-0.81)	(-0.81)	(-0.79)	(-0.99)
Housing units with a mortgage contract to purchase or similar debt Both second m	0.00561	0.00561	0.00562	0.00542
	(1.54)	(1.54)	(1.55)	(1.49)
Housing units with a mortgage contract to purchase or similar debt No second mor	0.00268**	0.00268**	0.00263**	0.00240**
	(3.06)	(3.06)	(3.01)	(2.75)
Housing units without a mortgage	0.00391***	0.00391***	0.00388***	0.00257**
	(4.00)	(4.00)	(3.97)	(2.75)
Median WHP 2020=1				0.000139
				(0.45)
Median WHP 2020=2				0.00226***
				(3.50)
Median WHP 2020=3				0.00444***
				(4.37)
Median WHP 2020=4				0.00693***
				(4.31)
Median WHP 2020=5				0.00789
				(1.74)
Observations	129741	129741	129741	129492
r2	0.00542	0.00542	0.00544	0.00695

t statistics in parentheses
Models (1)-(4) use state and time fixed effects with robust standard errors.
Model (3) and (4) have pre-fire controls for wildfires within 4km from a block group in 2005-2009 and 2010-2014 periods.
Model (4) includes the 2020 Wildfire Hazard Potential (WHP) control.
$^{*}\ p < 0.05, ^{**}\ p < 0.01, ^{***}\ p < 0.001$

Table 21: Summary Statistics Single Family Homes Sonoma, Napa, and Solano County March 2021

	Mean	Standard Deviation	Min	Max
Price Sold	1613235	2426880	169000	32000000
Natural Log of Price Sold	14	1	12	17
Minimum Distance to Wildfire Perimeter Km	9	8	0	35
Number of Bathrooms	3	1	0	15
Number of Bedrooms	3	1	0	13
Lotsize Square Feet	209361	981170	0	13939200
Year Built	1978	30	1860	2021
Home Square Footage	2351	1486	212	14545
Observations	751			

Table 22: OLS Regressions Within 4km from a Wildfire Perimeter for Sonoma, Napa, and Solano County

	(1) Price Sold	(2) ln Price Sold	(3) Price Sold	(4) ln Price Sold
Within 4km from a Wildfire Perimeter	-139613.0	-0.0251		
	(-0.97)	(-0.51)		
Minimum Distance to Wildfire Perimeter (m)			-5.148	-0.00000455
			(-0.76)	(-1.70)
Observations	659	659	751	751
R^2	0.770	0.710	0.740	0.687

t statistics in parentheses

$^{*}\ p < 0.05, ^{**}\ p < 0.01, ^{***}\ p < 0.001$

Model (1) and (2) limit sample to within 20km from Wildfire Perimeter (i.e. comparison of inner and outer rings).

Robust standard errors are used.

Controls include number of bathrooms, number of bedrooms, year built, lotsize square feet, home square footage.

Model (1)-(2) distance base category is beyond 4km.

9 Figures

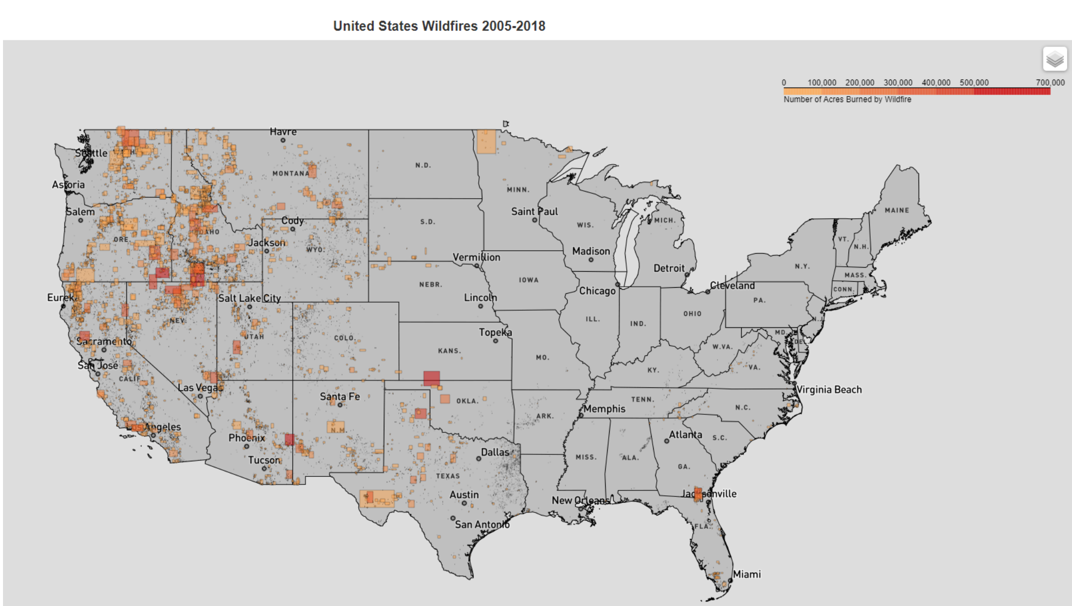

Figure 1: United States Bounding Boxes Wildfires 2005-2018

STATE	YEAR	
Arizona	2005-2009	1759.0
	2010-2014	178.0
	2015-2019	312.0
California	2005-2009	5802.0
	2010-2014	1120.0
	2015-2019	1675.0
Colorado	2005-2009	1079.0
	2010-2014	121.0
	2015-2019	179.0
Idaho	2005-2009	302.0
	2010-2014	10.0
	2015-2019	26.0
Kansas	2005-2009	700.0
	2010-2014	58.0
	2015-2019	99.0
Montana	2005-2009	312.0
	2010-2014	11.0
	2015-2019	28.0
Nebraska	2005-2009	484.0
	2010-2014	45.0
	2015-2019	70.0
Nevada	2005-2009	506.0
	2010-2014	136.0
	2015-2019	194.0
New Mexico	2005-2009	518.0
	2010-2014	35.0
	2015-2019	104.0
North Dakota	2005-2009	212.0
	2010-2014	19.0
	2015-2019	28.0
Oklahoma	2005-2009	1037.0
	2010-2014	58.0
	2015-2019	115.0
Oregon	2005-2009	486.0
	2010-2014	66.0
	2015-2019	119.0
South Dakota	2005-2009	300.0
	2010-2014	14.0
	2015-2019	28.0
Texas	2005-2009	4436.0
	2010-2014	853.0
	2015-2019	1419.0
Utah	2005-2009	501.0
	2010-2014	46.0
	2015-2019	65.0
Washington	2005-2009	1190.0
	2010-2014	120.0
	2015-2019	198.0
Wyoming	2005-2009	91.0
	2010-2014	6.0
	2015-2019	25.0

Figure 2: Dropped Block Groups Without Median Property Values or Location Data

STATE	YEAR	
Arizona	2005-2009	46.0
	2010-2014	2235.0
	2015-2019	2170.0
California	2005-2009	1347.0
	2010-2014	7108.0
	2015-2019	7049.0
Colorado	2005-2009	26.0
	2010-2014	1219.0
	2015-2019	1200.0
Idaho	2005-2009	9.0
	2010-2014	310.0
	2015-2019	305.0
Kansas	2005-2009	13.0
	2010-2014	707.0
	2015-2019	705.0
Montana	2010-2014	270.0
	2015-2019	264.0
Nebraska	2005-2009	9.0
	2010-2014	490.0
	2015-2019	486.0
Nevada	2005-2009	29.0
	2010-2014	990.0
	2015-2019	959.0
New Mexico	2005-2009	7.0
	2010-2014	526.0
	2015-2019	504.0
North Dakota	2005-2009	4.0
	2010-2014	139.0
	2015-2019	138.0
Oklahoma	2005-2009	15.0
	2010-2014	1058.0
	2015-2019	1042.0
Oregon	2005-2009	19.0
	2010-2014	583.0
	2015-2019	581.0
South Dakota	2005-2009	5.0
	2010-2014	257.0
	2015-2019	253.0
Texas	2005-2009	208.0
	2010-2014	5134.0
	2015-2019	5027.0
Utah	2005-2009	15.0
	2010-2014	679.0
	2015-2019	671.0
Washington	2005-2009	65.0
	2010-2014	1093.0
	2015-2019	1085.0
Wyoming	2010-2014	97.0
	2015-2019	94.0

Figure 3: Dropped Block Groups When Merged with Wildfires Across All Years 2005-2018

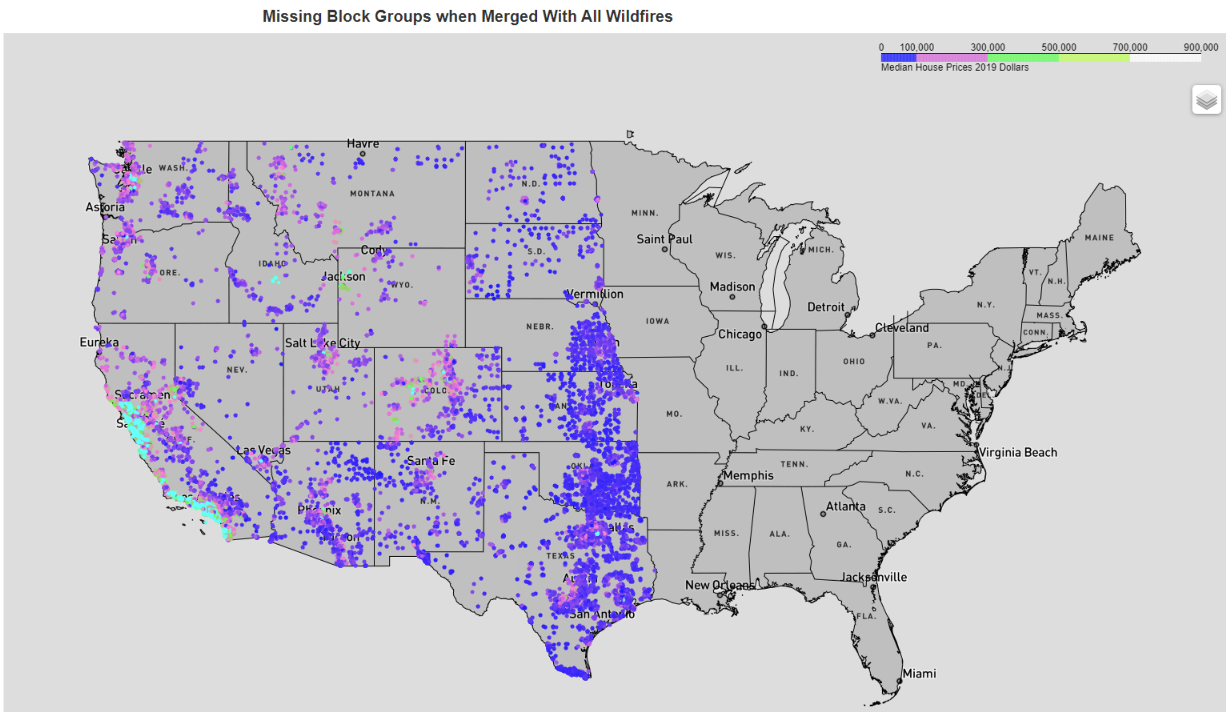

Figure 4: Map of Dropped Block Groups When Merged with Wildfires Across All Years 2005-2018

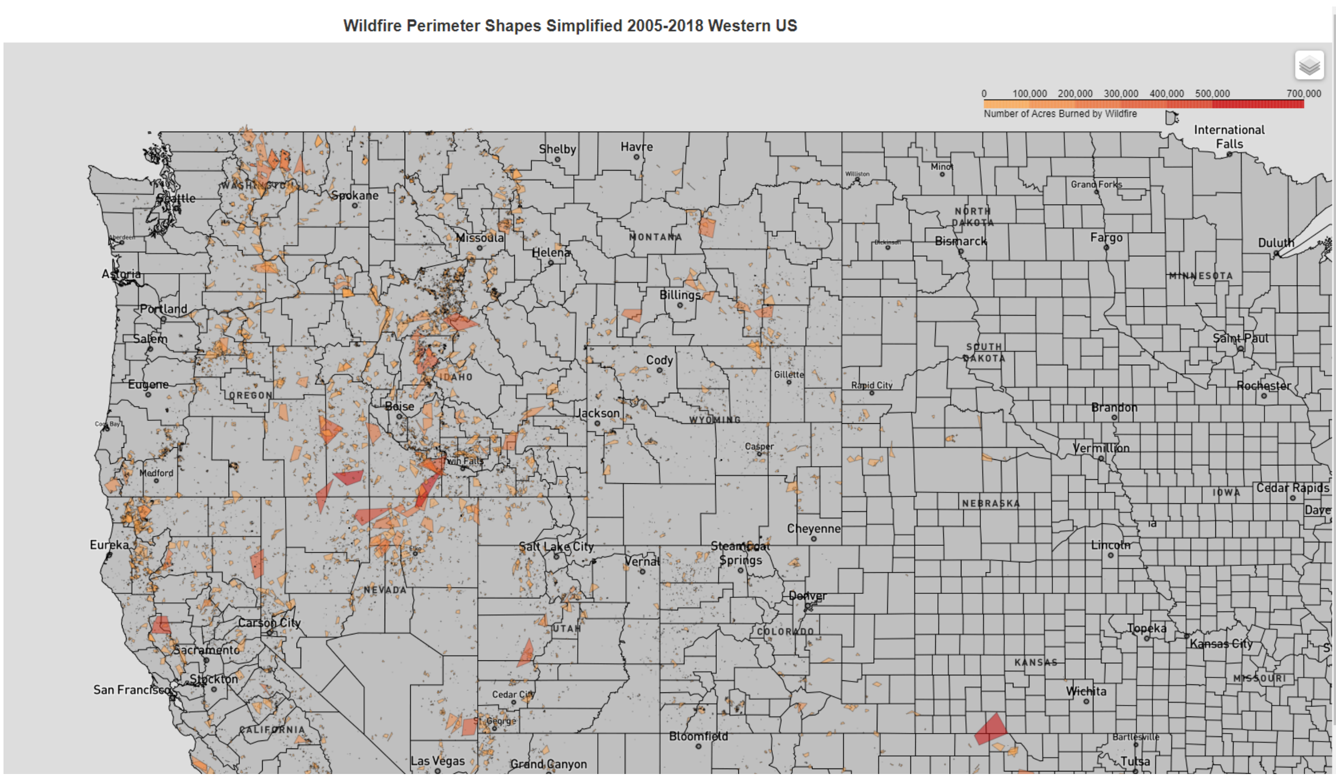

Figure 5: Map of Geopandas Simplified Polygons Topology Preserved Tolerance 5000 Wildfires Across All Years 2005-2018

Wildfire Perimeter Shapes Complex 2005-2018 Western US

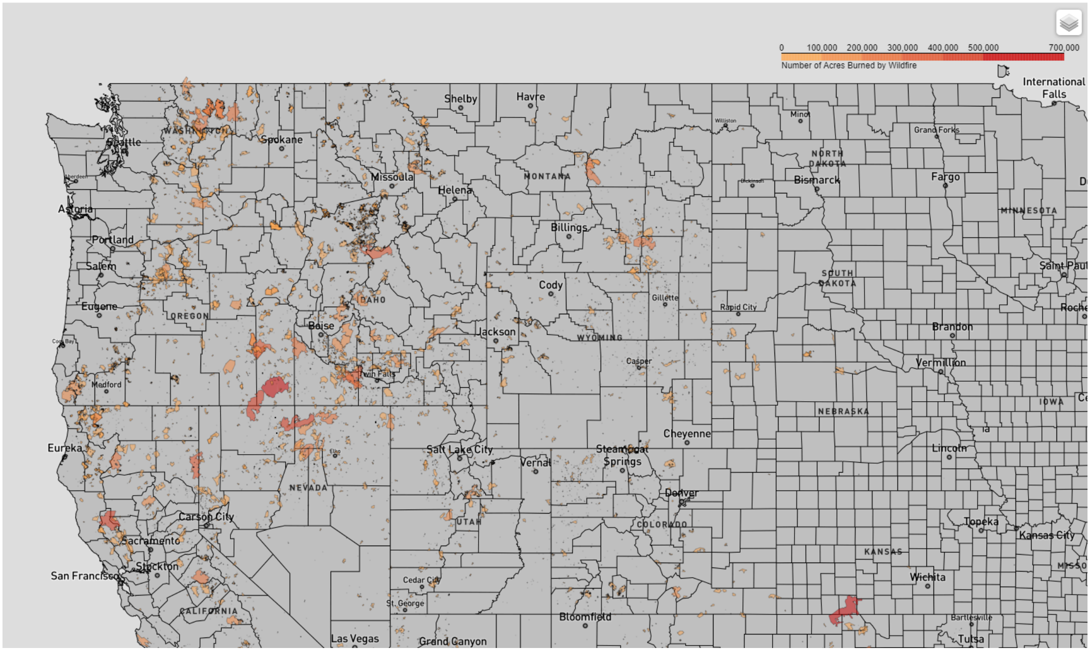

Figure 6: Map Non-Simplified Polygons Wildfires Across All Years 2010-2018

Example of Finding the Minimum Distance to a Wildfire Perimeter

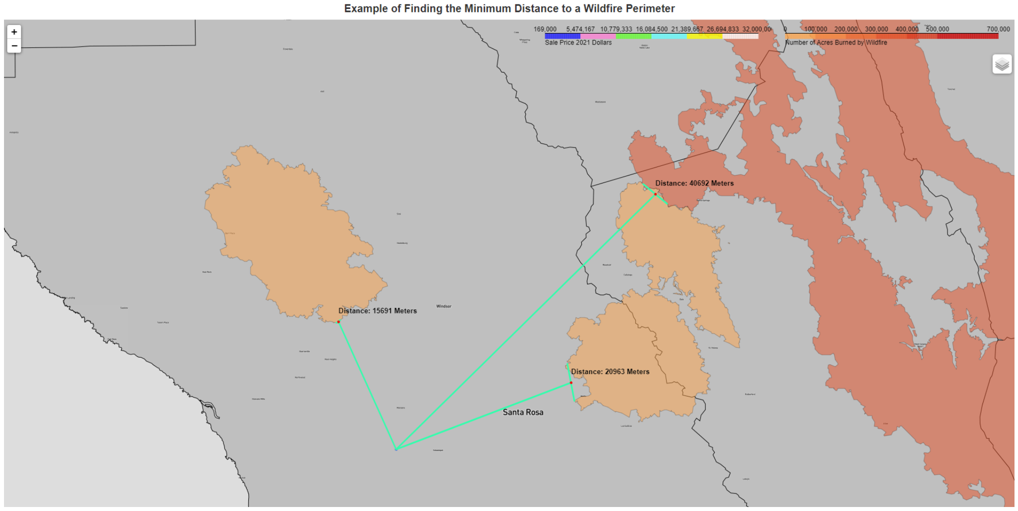

Figure 7: Example of Finding a Minimum Distance to a Wildfire Perimeter

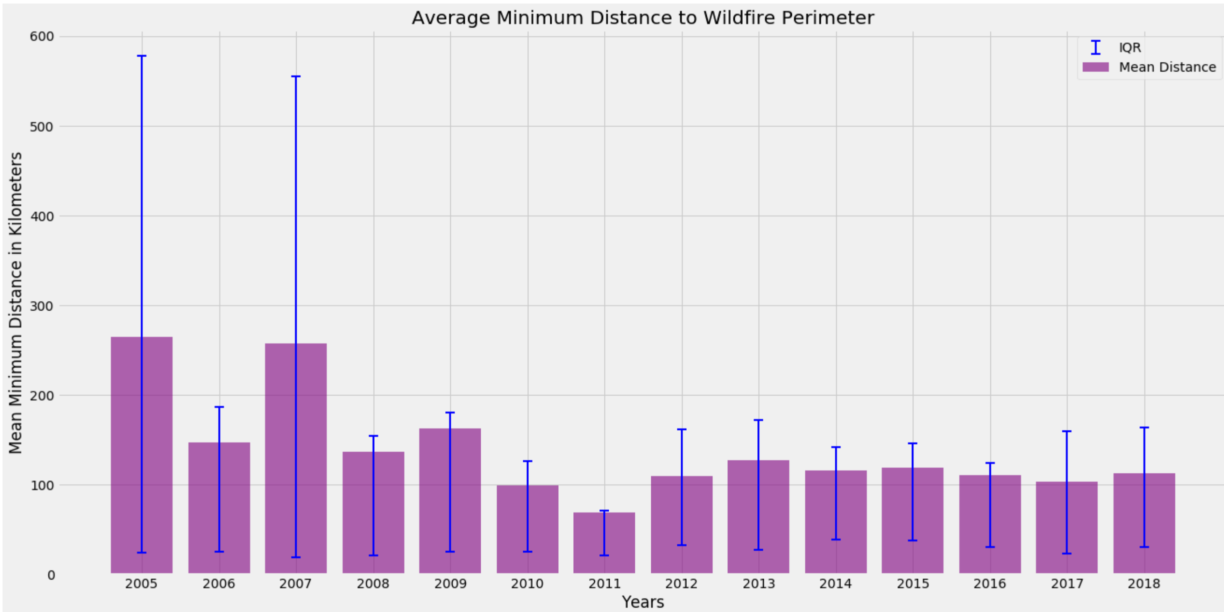

Figure 8: Average Minimum Distance to Wildfire Perimeter

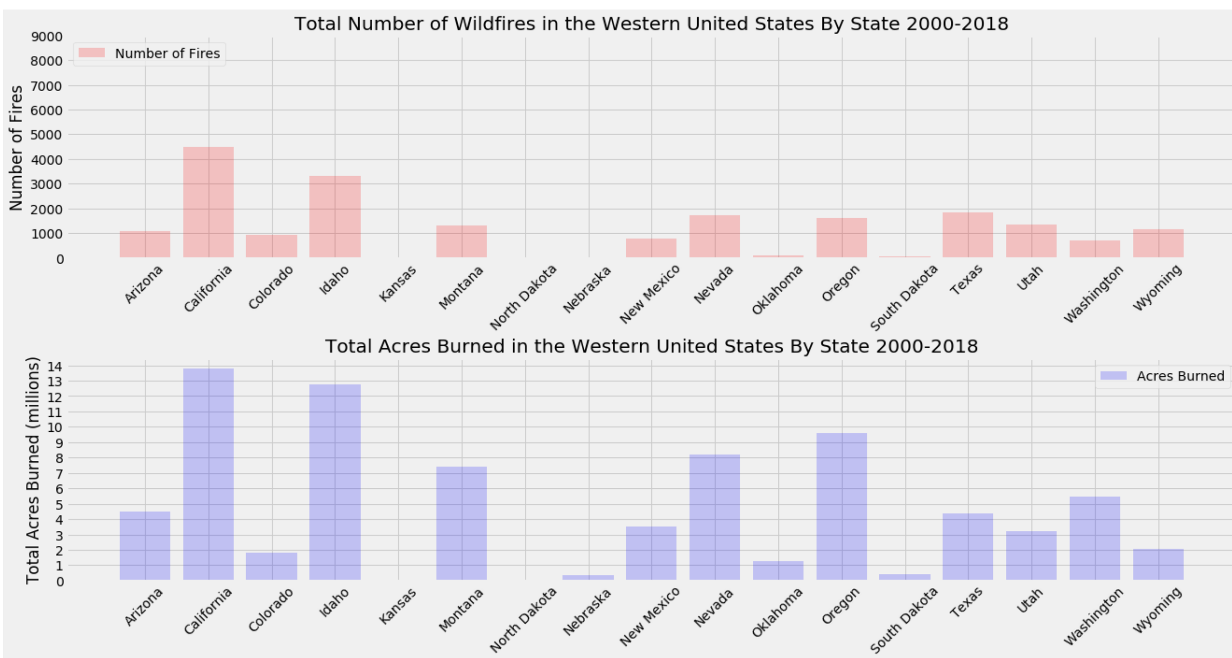

Figure 9: Total Number of Wildfires and Acres Burned in the Western United States By State

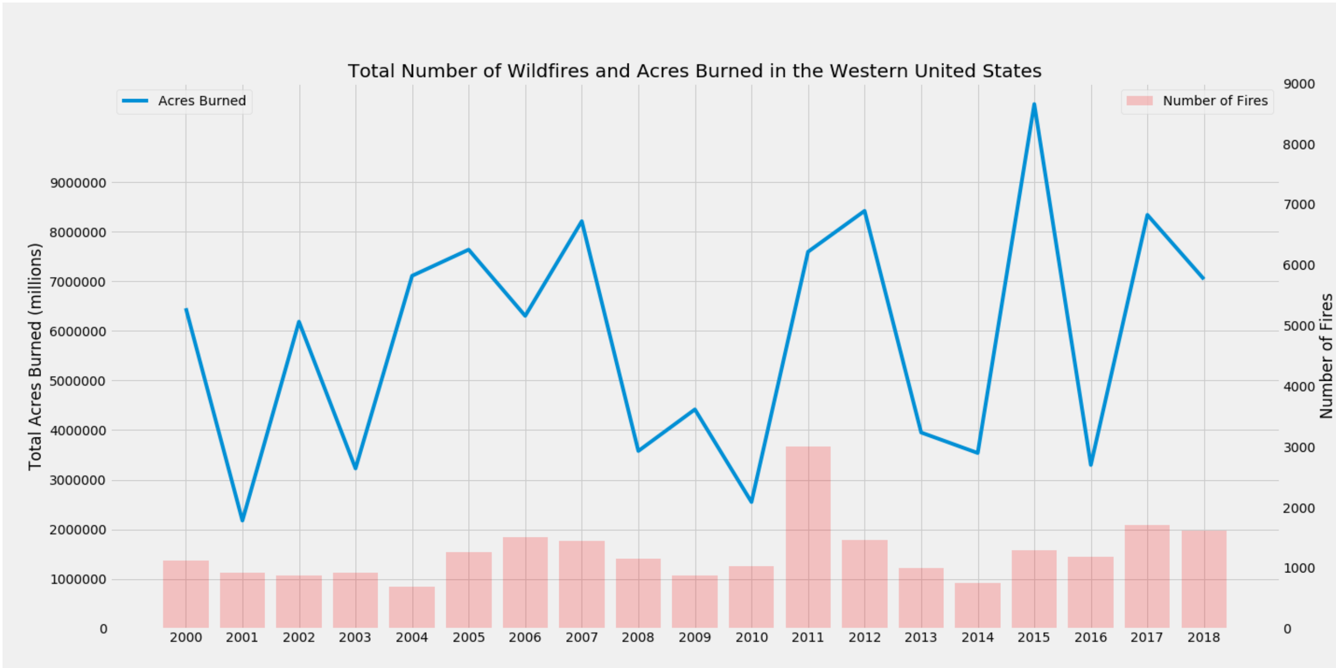

Figure 10: Total Number of Wildfires and Acres Burned in the Western United States

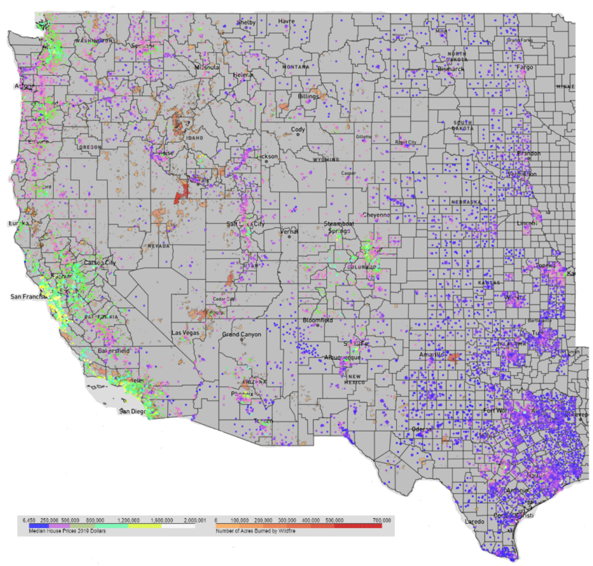

Figure 11: 2005-2009 Wildfires and Median Property Values

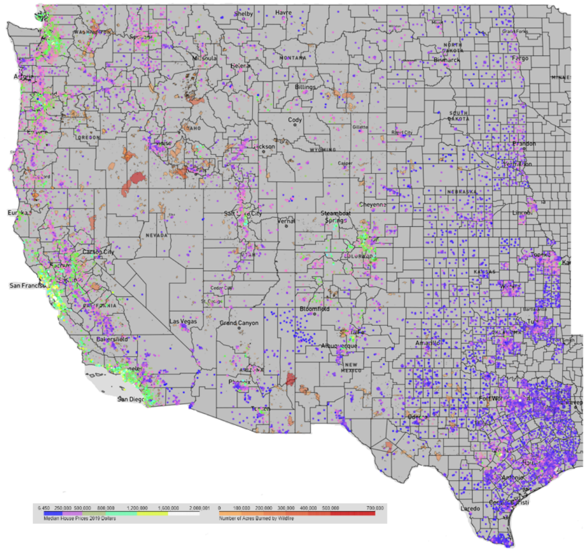

Figure 12: 2010-2014 Wildfires and Median Property Values

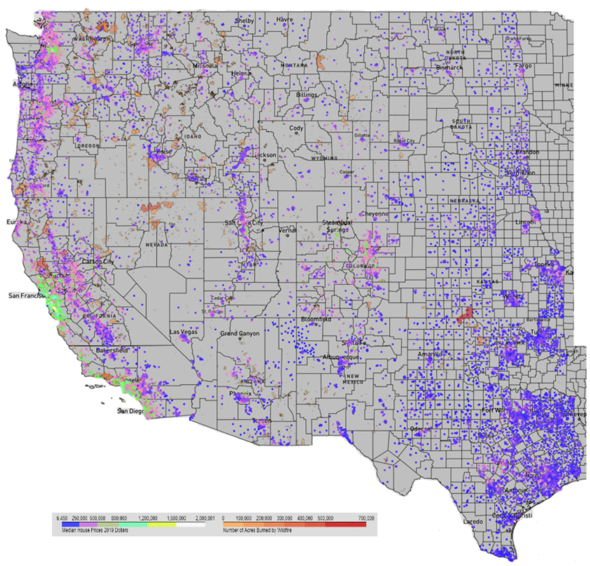

Figure 13: 2015-2018 Wildfires and Median Property Values

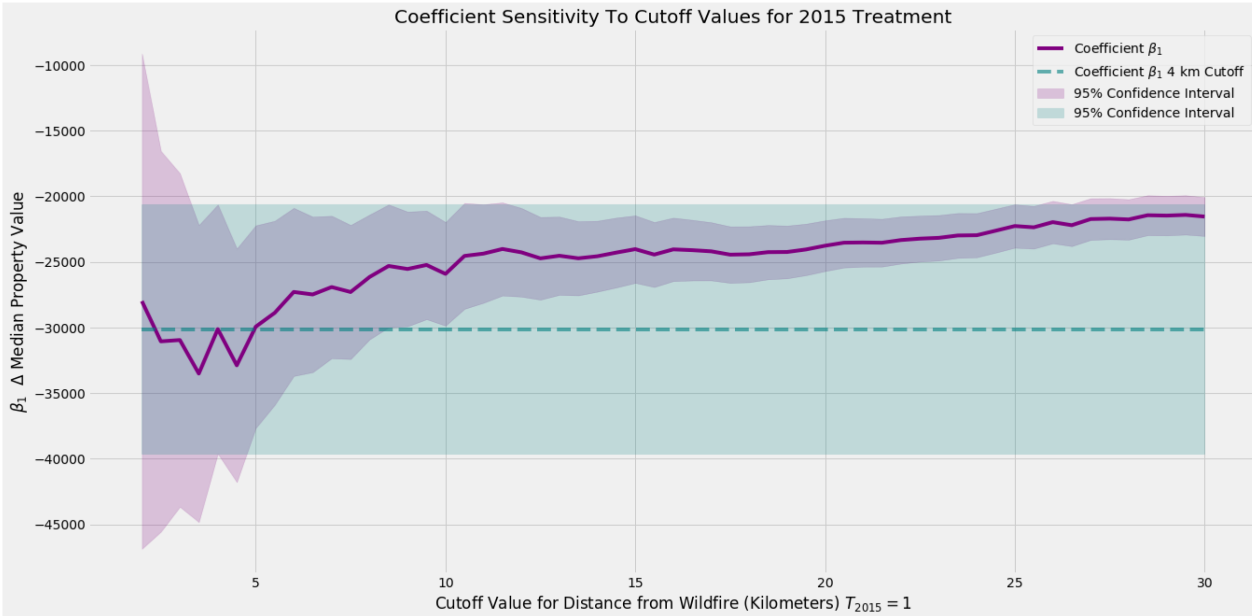

Figure 14: 30km Coefficient Sensitivity to Cutoff Values for the 2015 Treatment

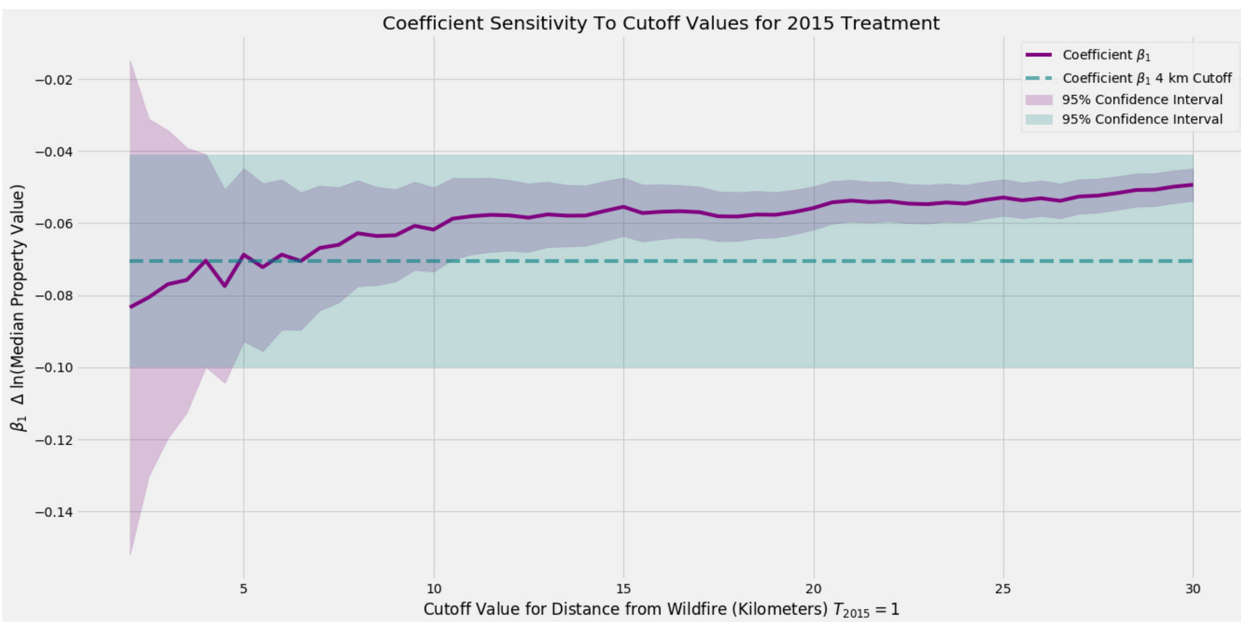

Figure 15: 30km Coefficient Sensitivity to Cutoff Values for the 2015 Treatment $\Delta \ln$(Median Value)

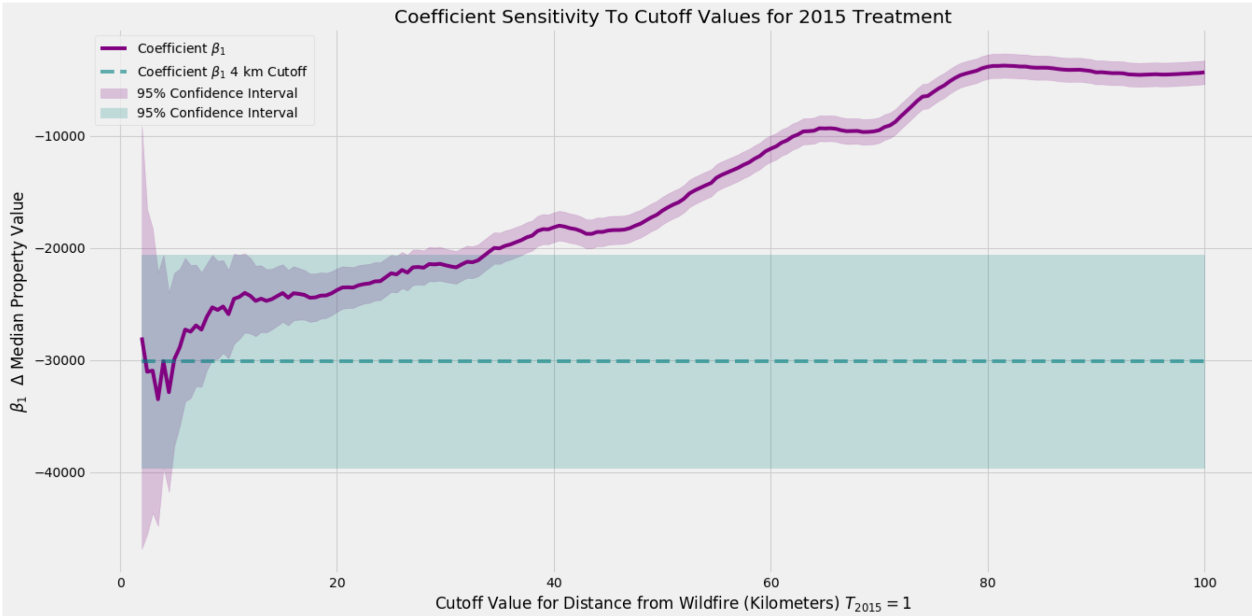

Figure 16: 100km Coefficient Sensitivity to Cutoff Values for the 2015 Treatment

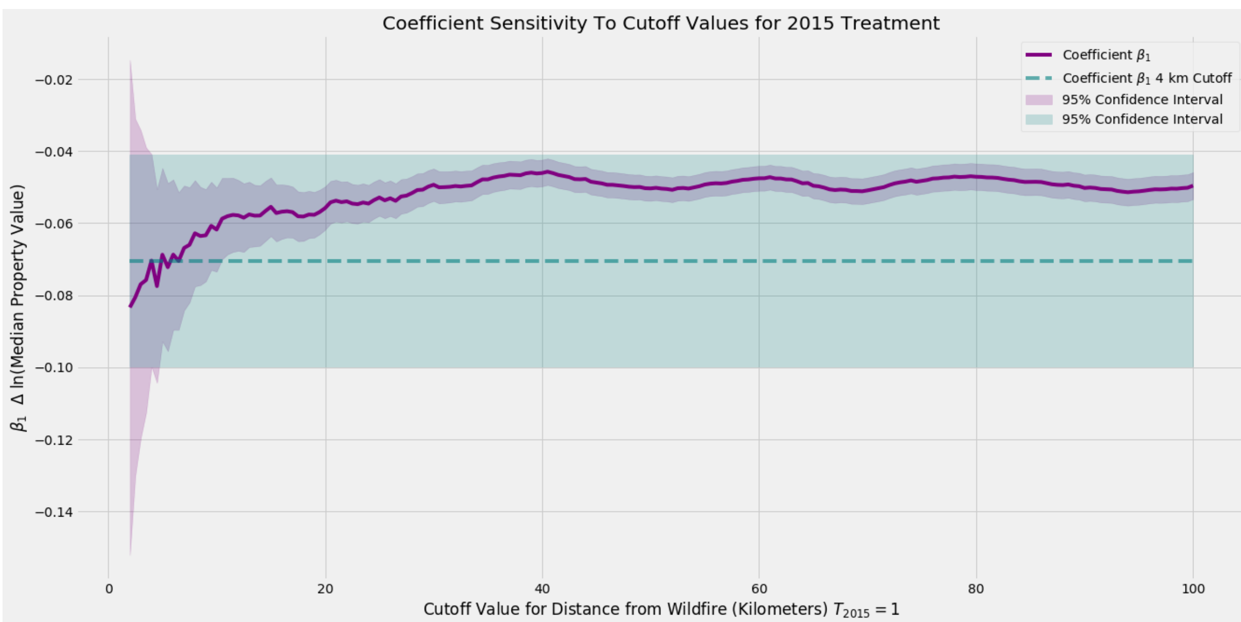

Figure 17: 100km Coefficient Sensitivity to Cutoff Values for the 2015 Treatment $\Delta \ln$(Median Value)

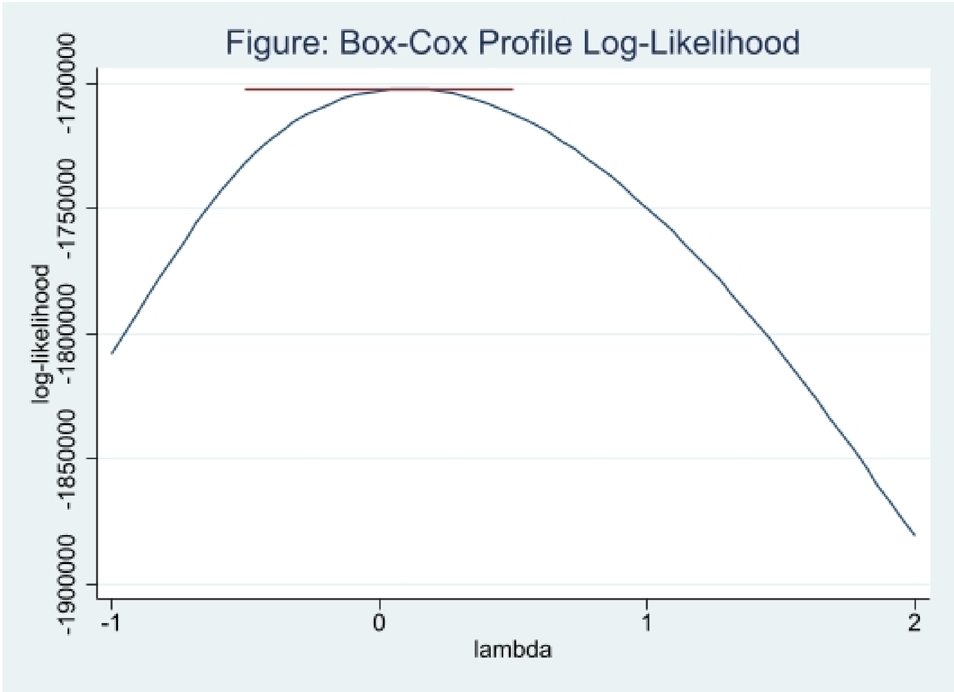

Figure 18: Box-Cox Profile Log-Likelihood

10 Appendix

Table 23: Sensitivity to Demographic and Neighbourhood Controls: First Difference Block Group Median Property Values on Within 4km from a 2015 Wildfire Perimeter

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Median Value	Δ Median Value	Δ Median Value	Δ Median Value	Δ Median Value	Δ Median Value	Δ Median Value
4km 2015 Ring	-28362.0***	-27892.4***	-27526.9***	-26726.0***	-28096.9***	-27237.7***	-26644.8***
	(-4.69)	(-4.59)	(-4.49)	(-4.40)	(-4.61)	(-4.59)	(-4.47)
Observations	86022	86022	86016	86016	86016	86016	86016
R^2	0.284	0.285	0.287	0.304	0.308	0.325	0.328

t statistics in parentheses

Model (1) to (7) use time fixed effects, and standard errors clustered at the census block group level.

Model (1) no controls.

Model (2) control for Percent Race.

Model (3) controls for Percent Race and Percent Travel Time to Work.

Model (4) controls for Percent Race, Percent Travel Time to Work, and Percent Educated

Model (5) controls for Percent Race, Percent Travel Time to Work, Percent Educated, and Percent Year Built.

Model (6) controls for Percent Race, Percent Travel Time to Work, Percent Educated, Percent Year Built, and Percent Number of Bedrooms.

Model (7) controls for Percent Race, Percent Travel Time to Work, Percent Educated, Percent Year Built, Percent Number of Bedrooms, and Percent with Mortgage.

Model (1)-(7) distance base category is beyond 4km.

$^{*}\ p < 0.05, ^{**}\ p < 0.01, ^{***}\ p < 0.001$

Figure 19: Pretrends Median Property Value by Within 4km from a 2015 Wildfire Perimeter

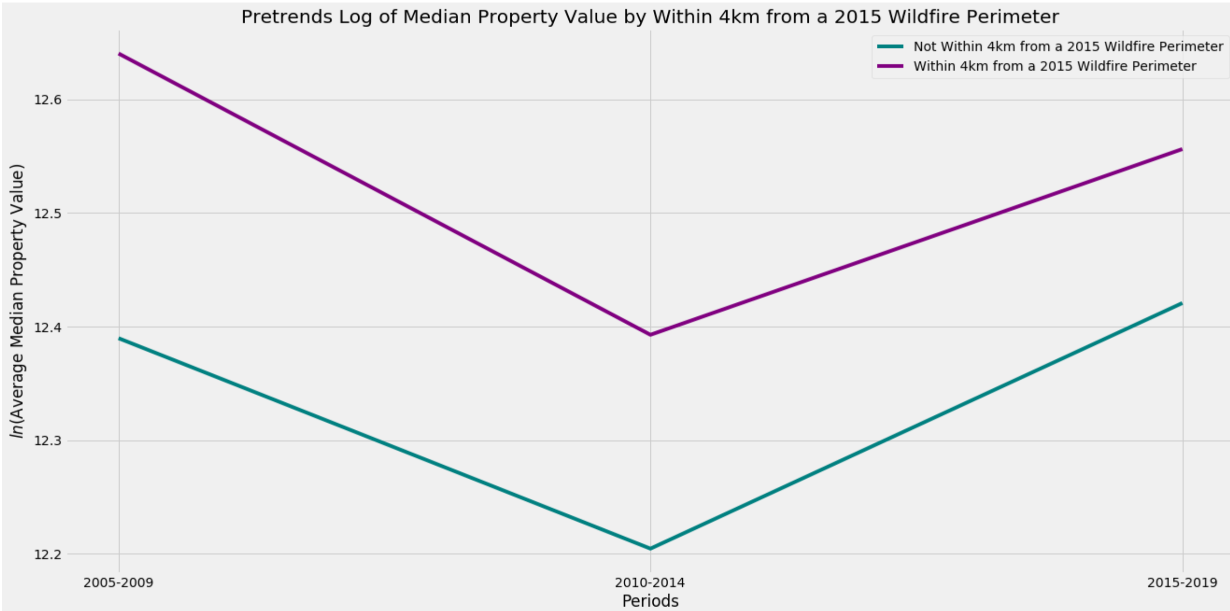

Figure 20: Pretrends $\ln$Median Property Value by Within 4km from a 2015 Wildfire Perimeter

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