THE COST OF WILDFIRES IN HEAVILY URBANIZED AREAS: MEASURING PROPERTY VALUE AND RECREATIONAL IMPACTS IN SOUTHERN CALIFORNIA

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food, and Resource Economics—Doctor of Philosophy
Environmental Science and Policy—Dual Major

2018

ABSTRACT

THE COST OF WILDFIRES IN HEAVILY URBANIZED AREAS: MEASURING PROPERTY VALUE AND RECREATIONAL IMPACTS IN SOUTHERN CALIFORNIA

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Wildfire frequency and severity are increasingly important issues in the western United States, as fires threaten lives, properties and outdoor amenities. This dissertation seeks to measure the impact of wildfires in Southern California using nonmarket valuation techniques. In the first essay we employ the hedonic property method to estimate how wildfires affect nearby property values. Using data from 15 years of property sales prices and 20 years of wildfire data, we find that the average impact of a wildfire on housing sales price depends on the market context and whether the event increases, decreases, or does not change prior risk perceptions. This suggests that public policy and availability of risk information can be effective tools in capitalizing wildfire risk in housing markets prior to events.

The second essay uses evidence from a choice experiment given to respondents who were intercepted at national forest sites to estimate preferences for environmental attributes of recreation sites. Specifically, the main attribute of interest is fire history, where fire history is given by distinct categories in relation to the dominant vegetation at the site. Using conditional logit, random parameters logit, and latent class models, we find that tree cover, compared to shrubs or barren areas, and water are highly desirable attributes, while evidence of past fires decreases the value of a site. Forest fires that reach the crowns of trees are least desirable, while older forest fires and shrub fires have less of a negative effect. We find evidence of significant preference heterogeneity over the vegetation and fire attributes.

The third essay combines revealed preference data from site intercepts and stated preference data from online surveys to estimate the welfare impacts of different fire scenarios at recreation sites. We estimate a multi-site zonal travel cost model of trips to hiking and day use sites in the Angeles

National Forest. Stated preference data on reduction in trips to recreation sites under different fire history scenarios are used to calibrate the zonal travel cost model and estimate the welfare impacts of fire. The greatest estimated welfare losses are from recent fires that burn all vegetation as opposed to less intense fires or older fires that have had time to recover. For popular recreation sites, these losses from intense fires can total over $1 million in one summer. Applying this method to a large fire that affected many sites in our study area, we illustrate how losses decrease over time, but can continue well after sites are re-opened due to lasting effects on the landscape.

ACKNOWLEDGEMENTS

I would like to thank Dr. Frank Lupi for putting his name on my whiteboard, for his impeccable sense of timing, and for his brilliant and insightful comments and commentary. Thank you for spending the time and effort it takes to be an advisor and mentor – you are a constant source of good advice. Thanks also to Dr. Cloé Garnache for her support, and Dr. Joe Herriges and Dr. John Hoehn for the helpful suggestions and feedback. Sincere thanks also to Dr. Scott Swinton for inviting me into the program, for his guidance during the transition to graduate school, and for his continued support throughout the years. I would also like to thank Dr. Robert Myers and Ashleigh Booth for their all-around heroism. Without you we would all be lost.

There are many people to whom I am grateful for assistance and support, but I would like to especially acknowledge the people whose friendship has been a constant through difficulties and celebrations. Thanks, Asa Watten, for being an incredible friend and teacher, for your generosity, and of course for the snacks. Thank you to Mary Doidge for your unshakably sensible perspective on life. It was very much necessary. Thanks to Stephen Morgan for your excellent advice and your ability to make all situations funny. Try to keep the chaos in check. Samantha Padilla, thank you for being always and aggressively on my side. Your encouragement, friendship, and willingness to advocate for me are incredible, and this is definitely your page.

Finally, thank you to my brother William for taking on the role of on-call programming tutor and best rubber duck in exchange for gifts of food. Nothing is possible without my parents, Harold Tanner and Yiyun Jiang-Tanner – thank you.

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INTRODUCTION

Throughout the western United States wildfires are increasing in size, number, and severity (Miller et al. 2009; Westerling et al. 2006). In a study of the past three millennia of wildfires in the west, Marlon and et al. (2012) conclude that historic wildfire frequency and severity are driven by large scale climate anomalies – anomalies of the kind we are currently creating with climate change. In particular, an increase in mean temperature, along with precipitation changes and earlier springs have lengthened and worsened the wildfire season in all western regions (Westerling et al. 2006). Compounding this issue, humans have contributed to large scale fire exclusion and suppression, which has driven a wedge between the expected number fires given climatic conditions alone and actual wildfire levels. This fire deficit is unsustainable, suggesting fire seasons will continue to worsen in the future (Marlon et al. 2012).

Southern California is home to four national forests that provide respite and recreation for millions of visitors and residents in the surrounding cities: the Los Padres, Angeles, San Bernardino, and Cleveland National Forests. They are unique among western forests; at higher altitudes, they are comprised of pine and oak, but the lower altitudes are dominated by chaparral, a dense shrubland characteristic of the region. High-intensity chaparral fires are subject to the same forces that drive earlier springs, and hence longer fire seasons, but large fires closely correspond to times when the Santa Ana wind is blowing (Moritz et al. 2010), a legendary dry wind that rushes from high pressure areas above the Great Basin towards the Pacific Ocean. Because of this, perhaps wildfires have always been a way of life southern California; as Didion writes in 1968: "The city burning is Los Angeles's deepest image of itself ... the violence and unpredictability of the Santa Ana affect the entire quality of life." However, even the wind is affected by recent climate change, as Miller and Schlegel find (2006). Models of air pressure predict consistent shifts in Santa Ana Occurrences (SAOs) from September -

October in the fall to November - December, suggesting an additional extension of the wildfire season in the opposing direction.

Clearly these wildfires have a significant impact on the lives of the 23.8 million people living in southern California (US Census Bureau). Besides fire making its way in to the local mythos, any individual blaze could cause loss of life, displace people from their homes, threaten or destroy structures, degrade air quality, close down roads and recreation sites in the national forests, and leave a lasting burn scar. In addition, the Forest Service is facing the rising financial cost of fire containment, which has started to shift resources away from non-fire related programs. For the first time, wildland fire management is a full 50% of its FY2017 budget ($2.45 billion out of $4.9 billion in discretionary funds) ("Fiscal Year 2017 Budget Overview" 2016).

In addition to the financial cost of fire suppression and damage, there is a need to estimate the indirect effects of wildfires on surrounding communities. Given how wildfire prone the four southern California national forests are, and the densely populated areas directly adjacent to them, there may be significant negative effects of fire. On the other hand, southern California is unusually disposed to natural disasters – fires, earthquakes, flooding, and landslides coincide in the region. If wildfire risk is common knowledge, or wildfires are commonplace, we may see a more muted impact of any individual event.

The objective of this dissertation is to measure the cost of wildfires to southern California in several different ways: first, we use the hedonic property method to estimate the impact of wildfires on nearby property values. The hedonic method allows us to capture impacts for those who live in the direct vicinity of wildfires. However, the four national forests of southern California attract millions of visitors each year, many of whom travel from coastal areas or out of state. To understand additional effects of wildfires, the second essay uses a choice experiment to estimate impacts of fire on different types of national forest visitors. In the third essay, using trip data combined with stated preference data, we take an alternate approach to estimating the effect of wildfire on patterns of recreation in the Angeles National Forest and welfare loss to recreationists caused by fire. We find evidence that the effects of wildfires are heterogeneous. They affect communities and groups of people differently depending on both the physical attributes of the environment and how fire burns and recovers, as well as individuals' perceived risk, knowledge of fire, and preferences. We also find evidence of heterogeneous impacts over time; recent wildfires cause greater welfare losses than older fires. However, intense forest fires can have lasting effects for many years.

The first essay uses a 16-year multi-county housing data set that spans from the border of the Los Padres National Forest in the north to the Cleveland National Forest in the south to estimate the impact of wildfires on the value of surrounding properties. Previous studies in the area use small data sets, identifying the impact of a few wildfires on the immediate surrounding neighborhood. By contrast, the housing data used here includes single-family residences within 30 km of a national forest boundary that sold between January 1, 2000 and December 31, 2015. The wildfire data set spans 21 years, from 1995 to 2015, and includes all wildfires in the area at least 500 acres in size. Tax records on sales were combined with data on the location and geographic features of the property to identify the effect of selling after a nearby large wildfire. Using a larger dataset allows us to better estimate the impacts of wildfires in general, rather than focusing on immediate effects of a single event. Results suggest that wildfires have an ambiguous effect on housing price; we argue that this ambiguity stems from housing market prior expectations of wildfire risk. If a wildfire causes a large increase in risk perception for buyers and sellers in the market, there should be a large negative impact of fire on nearby properties. However, if a wildfire does not change risk perceptions overall, there should be a smaller or insignificant impact.

After a major wildfire, damaged recreation sites may be closed for months or years, and many have visible wildfire burn scars that last until the forest regrows. The second essay uses stated preference data from a choice experiment to explore systematic heterogeneity in visitor preferences over wildfire burned areas. Data for the second essay comes from two rounds of onsite surveys administered June – August 2016 and June – August 2017 and two rounds of online survey conducted in the winters of 2016 and 2017 that followed up with onsite participants. Respondents made a series of choices between hypothetical national forest sites that differed in terms of vegetation and water near the site, fire history, and driving distance from home. We look for preference heterogeneity across respondents by comparing conditional logit, latent class, and random parameters logit models. Our results suggest that some environmental attributes – such as the presence of lakes or streams at a recreation site – are desirable and that preferences for these have little heterogeneity. Preferences for other attributes, including tree cover at sites and past fire history, do have heterogeneity; it may be of interest to forest managers that increased wildfire activity will impact some recreationists more than others – for some, it may be a curiosity to visit sites in fire recovery, while for others, it drives them towards other sites or activities.

The third essay uses contingent behavior questions from the same online recreation survey. In contrast to trip choice over hypothetical sites, we instead analyze a choice about the site at which respondents were intercepted and interviewed. Under eight different fire history scenarios which corresponded to the vegetation at the site they visited, respondents were asked to make a choice between the same trip as before, visiting a different national forest site, or doing something else altogether. Using real trip data, we first estimate a multi-site zonal repeated logit model of trip participation and site choices. The revealed preference model uses a full set of site-specific fixed effects to control for site differences. We then use the contingent behavior data and a contraction map to calibrate the demand model to the stated trip visitation changes under our fire history scenarios in order to derive the welfare impacts of different fires. We find that recent forest fires cause larger trip and welfare losses than less recent forest fires or shrub fires, with forest fires decreasing welfare by roughly $29 per lost trip.

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CHAPTER 1. Burning Down the House: The Effect of Wildfires on Housing Prices

1.1 Introduction

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

Wildfires have significant economic impact: federal agencies respond to tens of thousands of wildfires on roughly 7 million acres of land, spending a combined total of $1-2 billion each year on fire suppression (National Interagency Fire Center 2016). The US Forest Service expects its annual cost of fire suppression will reach an estimated $1.8 billion by 2025 (USDA Forest Service 2015) and has growing concerns that other management efforts suffer when funds are re-directed towards fire suppression. In addition to the direct costs of wildfire – suppression, damages, health, and loss of life - people living near areas affected by wildfire may experience indirect costs such as the aesthetic disamenity of the burn scar, loss of nearby recreation opportunities, and heightened perceived risk of wildfires.

The policy background is particularly relevant for Southern California. Its native shrubland, chaparral, has a natural high-intensity fire regime, and so the existence of large wildfires is not a recent phenomenon as it is in the Pacific Northwest or the Rocky Mountains. The largest wildfires in Southern California are driven by the Santa Ana winds, a phenomenon in which dry air from Nevada sweeps toward the Pacific Ocean (Moritz et al. 2010); however, dangers from these large wildfires only increase as the cities expand outward. In addition to this extensive experience with fire, the state passed a pivotal piece of legislation known as the Bates Bill in response to several severe fires affecting urban areas in the late 1980s and early 1990s. The Bates Bill mandates the state fire-fighting agency CAL FIRE develop and maintain maps of high wildfire hazard in wildland areas, where the state takes fiscal responsibility for fire containment costs, as well as in urban areas, where local governments have primary responsibility (California Govt. Code 51175-89). Homeowners are also required to disclose the wildfire hazard status of their property at the time of sale. These two features may mean that, distinct from other places, California residents may be exceptionally well informed about fire risks.

This essay estimates the cost of wildfires to residents of southern California using a hedonic price approach. Our study area has several distinguishing features that make it a key place of inquiry: Southern California faces very high levels of development and urbanization, with suburbs of Los Angeles and San Diego running straight into four fire-prone national forests: the Angeles, Cleveland, Los Padres, and San Bernardino National Forests. The ecosystems in these national forests are characterized predominantly by chaparral, a dense shrubland unique to this region with a natural high-intensity fire regime. At higher altitudes, they are comprised of pine, oak, and other mixed forest. The regulatory environment also sets California apart. State law requires the disclosure of potential risks, including location on a wildland fire zone, to home buyers at the time of purchase. Unlike some studies that use small data sets and individual fires, this essay uses a large dataset with 15 years of property sales prices and 20 years of wildfire data to exploit extensive spatial and temporal variation to identify fire effects. We employ difference-in-differences to identify the effects of proximity to a past wildfire and risk perceptions associated with wildfires. Using a model of subjective risk, we argue that risk perceptions can cause wildfires to have an ambiguous effect on welfare. The empirical results suggest significant heterogeneity in the impacts of wildfire, which may be explained by differences in the risk information communicated to buyers, as well as differences in the recovery and regrowth patterns of the two dominant vegetation types in Southern California.

The rest of this essay is organized as follows: a brief review of the existing literature on environmental risk and property values is followed by a conceptual model, a description of the data and sources, the results, and a discussion.

1.2 Literature Review

Wildfires have become an increasingly urgent environmental and public policy issue in the past decade, and literature on the effects of wildfires on housing prices has developed at pace. The hedonic literature attempts to disentangle the aesthetic disamenity caused by a large wildfire from the effects of increased risk perception among potential buyers. In one of the earliest studies, Loomis (2004) estimates the change in property values in a town near, but not directly affected by, a major wildfire in Colorado. He finds that housing prices dropped 10-15% in the unburned town after the fire and that the effects were still present five years later. Donovan, Champ, and Butry (2007) study changes to housing prices after wildfire risk ratings are made publicly available. They find that both spatial lag and spatial error dependence are statistically and economically significant; their preferred specification is the joint spatial lag-spatial error model. However, evidence on the economic significance of spatial dependence is mixed. Mueller and Loomis (2008) using Los Angeles county data on 2,520 transactions find that there is little of economic significance distinguishing estimates using spatial dependence and those that do not. With the same dataset Mueller, Loomis, and González-Cabán (2009) estimate the effects of repeated wildfires in a small part of Los Angeles county. Concentrating instead on the impact of successive fires that occurred within either 2 years or 4 years, the authors find a much steeper decrease in price after the second fire (23% as opposed to 10%).

Like other environmental risks such as hazardous waste sites, nuclear plants, and pipelines, the impact of a wildfire does not have a clearly demarcated boundary – properties located within a fire perimeter suffer damage, but people living outside the perimeter may also experience a loss of recreational opportunities, poorer view, or greater awareness of fire risk. Researchers have approached the issue of the appropriate distance to use in estimating impacts of wildfires in two different ways. Some studies impose an artificial boundary, outside of which they assume the wildfire has no impact (Loomis 2004; Mueller, Loomis, and González-Cabán 2009; Mueller and Loomis 2014). Mueller, Loomis, and Gonzalez-Caban look at the impact of fires on properties within a 1.75-mile radius of one or two large wildfires in a neighborhood outside of Los Angeles. They motivate the choice of a distance by appealing to Superfund studies (e.g. Gayer, Hamilton, and Viscusi 2000) which consider impacts on property values within a very short distance of a site, usually around one mile, as well as conversations with USFS officials about how far they expect an effect. However, they do not empirically test their assumption that fire effects are negligible outside 1.75 miles.

Others estimate the impact of fires allowing for a distance decay. Evidence on the distance at which wildfires have a significant impact on property prices is mixed. The relevant distance may depend on the context of the study area, severity of the fire, and geographic features of the area. In a study on an area of northwest Montana, Stetler et al. (2010) estimated several hedonic price models with a suite of environmental controls, including distances to many amenities – lakes, wilderness, and recreation areas – canopy cover, location on wildland-urban interface, and view of the burned area. They estimate a hedonic price model using housing data between 1996 and 2007, and information from more than 200 medium to large fires over the same time period. They include a property's distance from a fire and time since the nearest fire in the controls, as well as structural and environmental characteristics of the property. The results suggest importance of environmental amenities, and that there are significant differences for homes with a view of the burned area as opposed to without. They also find large and lasting effects of wildfires – home prices suffered at distances up to 10 km away from the nearest wildfire compared to homes at least 20 km from a fire. In addition, they do not find any significant attenuation in the effect for seven years after a wildfire, potentially because the time frame of covered by their data set is shorter than the long wildfire recovery time in the Rocky Mountain forests.

Using data from properties in the Colorado Front Range, McCoy and Walsh (2018) utilize a quasi-experimental approach looking at how a wildfire affects three distinct treatment groups: houses in close proximity to the burn perimeter, houses with a view of the burn scar, and those located in an area of high latent wildfire risk. High latent risk areas are defined by geographic characteristics such as slope, vegetation, and housing density that make some communities more susceptible to fire than others. To test the sensitivity of their proximity treatment to the cutoff, they start with a treatment group of 1 km from a fire and increase the treatment group size in 250 m increments. In contrast to Stetler et al. they find no significant effect of a wildfire more than 2 km from the property. Within 2 km of the burn perimeter, housing prices decrease by 8.7% in the first year after a fire, 7.7% the second year, and 6.7% the third year after a fire.

We use a quasi-experimental approach similar to that of McCoy and Walsh to examine impacts of fire on nearby houses, as well as impacts of fire on areas of latent risk, but adapt the model to the southern California context. While other California studies have used a cross-sectional hedonic function and smaller datasets (less than 3,000 transactions) and focus on the impacts of specific fires, we use a long-term data set with a large number of transactions in a region that experienced numerous spatially and temporally distinct fires to identify the effect of fire events on property values.

1.3 Conceptual Model

The hedonic model developed by Rosen (1974) treats houses as differentiated products, where price is a function of attributes including structural properties of the house, characteristics of the neighborhood, and environmental amenities, such as those provided by the national forests, and the observed market price is an equilibrium between buyers and sellers. In addition, a property's value will capture the subjective perception in the market of future wildfire risk. A wildfire's impact is at least two-fold: first, it will cause a change to the house's amenities, and second, it may change the market-wide subjective probability of risk. We argue that both these changes will have an ambiguous effect on the equilibrium housing price. Hansen and Naughton (2013), in a study of the impacts of natural disturbances to forests in Alaska, find that major disturbances such as pine beetle outbreaks and large wildfires increased assessed property values. They posit that for their study area the benefits of improved views after tree die-off outweigh the diminished forest amenities. The properties in our sample are located near a large national forest with recreation areas that wildfires diminish or destroy. However, a wildfire could also open up views or lead to a wildflower explosion the following spring. A wildfire also causes market agents to update their subjective probability of risk but will not necessarily cause them to expect a greater probability of fire in the future. If a fire heightens buyers' risk salience, we expect to find a significant decrease in property values nearby. However, in some areas years of fire suppression have caused an overgrowth of brush and fuel; after one fire occurs, the probability of a second fire decreases. In both cases the overall impact will depend on how prospective buyers' priors are affected and the relative magnitude of impacts.

More formally, we lay out a model of subjective risk in the housing market following the example of Beron et al. (1997) who incorporate risk of earthquake damage into the hedonic price function. The hedonic price function is given by Equation 1.

$$P = P\left(\boldsymbol{Z}, \boldsymbol{r}, \rho^f, \rho^d(\rho^f)\right) \tag{1}$$

In equation 1 $\boldsymbol{Z}$ is a set of structural, neighborhood and geographic characteristics that influence housing price; $\boldsymbol{r}$ is a vector of environmental and geographic characteristics of the neighborhood, including elevation, housing density, distance to the forest, and forest quality that are positive attributes in the market, but are also related to risk of wildfire; ρ^f is the buyer's subjective probability of a fire occurring; and ρ^d the buyer's subjective probability of property damage, which is an increasing function of the probability of fire. It is important to note that after a fire occurs changes in ρ^f could be due to increased risk salience – perhaps due to media attention, more accurate risk perceptions, or a change (either an increase or decrease) in the future risk of wildfire. For example, in the pre-fire state of the world, market actors could be either overestimating or underestimating objective wildfire risk (Beron et al. 1997). Another, perhaps unlikely, possibility is that buyers in the market are always correct about wildfire risk and any observed change in the marginal change in ρ^f can be attributed to actual changes in fire risk.

The risk term ρ^f can be written more fully as a function of the amenity variables $\boldsymbol{r}$ and market information about wildfire risk *I*.

$$\rho^f = \rho^f(\boldsymbol{r}, I) \tag{2}$$

We expect that the subjective risk of fire will depend on both environmental and geographic attributes that are correlated with risk of wildfire as well as market information *I* regarding fire risk, which may come from local governments, the media, or other market actors. A recent wildfire is one such source of information that we expect to have some impact on the market price. In California another source of information comes from hazard disclosure documents provided to buyers when a house is purchased regardless of whether a recent fire has occurred. Hazard disclosures inform buyers whether or not the property is located on a Fire Hazard Severity Zone (FHSZ). FHSZ status indicates that the land has a high probability of experiencing a fire given its physical characteristics and historical fire activity. Details on construction of FHSZ are provided in the Data section.

Since $\boldsymbol{r}$ represents characteristics positively correlated with fire risk, by construction the partial derivative of ρ^f with respect to $\boldsymbol{r}$ is nonnegative.

$$\frac{\partial \rho^f}{\partial r} \geq 0 \tag{3}$$

However, we cannot sign the partial derivative with respect to *I* as buyers' subjective risk perceptions could be either increasing or decreasing in the level of information they receive. If their priors are that wildfire risk is low, media coverage of wildfires in their area may increase subjective probability of fire. If their priors are that wildfire risk is higher than it actually is, receiving more accurate risk information may decrease subjective probability of fire.

The subjective probability of damage ρ^d is an increasing function of probability of fire and is given by the following equation,

$$\rho^d = \rho^d\left(\rho^f(\boldsymbol{r}, I)\right) \tag{4}$$

and its partial derivative is nonnegative.

$$\frac{\partial \rho^d}{\partial \rho^f} \geq 0 \tag{5}$$

Again, subjective risk perceptions cannot be signed with respect to information since the partial derivative of ρ^f with respect to *I* cannot be signed.

$$\frac{\partial \rho^d}{\partial I} = \frac{\partial \rho^d}{\partial \rho^f}\frac{\partial \rho^f}{\partial I} \gtrless 0 \tag{6}$$

In this framework, a wildfire acts as a shock to both information and forest quality. Much of the Southern California forests is chaparral, a dense shrubland at maturity. Though it burns with high intensity, it also has a quick regrowth rate: sometimes burn scars are difficult to detect one to two years after a fire (Barro and Conard 1991). However, if fires occur more quickly than the natural 30 to 150-year regime, chaparral may be replaced with non-native grasses, which are even quicker to burn (Barro and Conard 1991; Bell, Ditomaso, and Brooks 2009). In older forests, stand clearing fires have the effect of removing available fuel, making another fire less probable. Hence, the overall effect of fire on subjective risk is indeterminable.

A buyer on the market maximizes expected utility across three states of the world. In the first state of the world, a fire is not realized, and utility depends on housing characteristics and the level of site attributes r. In the second, which occurs with subjective probability ρ^f a fire occurs and may affect nearby amenities denoted r^f in the fire state but does not damage the property. In the third, which occurs with probability ρ^d, property damage is sustained, and structural characteristics $\boldsymbol{Z}$ change to $\boldsymbol{Z}^f$. In each state, the buyer faces a budget constraint that depends on a numeraire good X and the price of the home P.

$$Y = X + P(\cdot) \tag{7}$$

Recall that equation (1) defined the hedonic price function below, where ρ^f is a function of $\boldsymbol{r}$.

$$P = P\left(\boldsymbol{Z}, \boldsymbol{r}, \rho^f, \rho^d(\rho^f)\right) \tag{8}$$

Following the arguments laid out above, the effect of fire on P is now ambiguous and depends on the relative effects on amenities and subjective risk perceptions. The buyer's maximization problem over the three states is given by

$$\begin{aligned} \max_{Z,r} E[\![U]\!] = \rho^f \cdot (1-\rho^d) \cdot v\left(X, \boldsymbol{Z}, \boldsymbol{r^f}\right) + \rho^f \cdot \rho^d \cdot v\left(X, \boldsymbol{Z^f}, \boldsymbol{r^f}\right) \\ +(1-\rho^f) \cdot v(X, \boldsymbol{Z}, \boldsymbol{r}) \end{aligned} \tag{9}$$

subject to the budget constraint given by (7). In the model, a buyer maximizes utility from a home purchase by selecting characteristics $\boldsymbol{Z}$ and site amenities $\boldsymbol{r}$. This conceptual framework leads to four expectations:

1. If the disamenity effects of a fire outweigh changes in risk perception, the impact of a recent fire will be negative.
2. Assuming that the nearer a property is to a wildfire perimeter, the greater the level of information received by that fire, we expect that the impact of a fire should be greater at closer distances than at farther distances. Similarly, we expect that properties selling more recently after a fire receive more information from the fire.
3. The more accurate the buyer's information prior to purchasing a home, the less likely a recent wildfire will change risk perceptions. We expect that if FHSZ status is conveying accurate information, the impacts on price observed at closer distances from a fire should be mitigated if a property is on FHSZ. However, if FHSZ status leads to a general overestimation of market risk, this may not hold.
4. A fire may serve as either a positive or negative information shock, so the overall impact of a fire on housing value will be ambiguous.

We are able to test 2-4 by taking advantage of California's Fire Hazard Severity Zones (FHSZ). Properties sold on FHSZ have elevated fire hazard, and potential buyers are made aware of the increased risk on natural hazard disclosure forms as well as by their realtor prior to sale. Given elevated market information for buyers of properties on FHSZ, we expect that a recent fire will have a significantly smaller impact on sales price than on non-FHSZ properties. Second, we expect that larger or more destructive fires will serve as greater information shocks than smaller or less destructive fires. Finally, we expect that there may be some areas or times after which a fire when the impact on sales prices is ambiguous, which may depend on the market, physical characteristics of the area burned, or characteristics of the fire. If a large destructive fire decreases buyers' perception of future fire risk, sales prices may increase after a fire. If a fire serves to increase buyers' risk salience, prices may decrease after a fire.

1.4 Econometric Model

The hedonic price method is commonly used to value environmental amenities, from the benefits of open space to air quality to risks such as nuclear waste (Anderson & West 2006; Kim, Phipps, & Anselin 2003; Gawande & Jenkins-Smith 2001). However, a concern in the estimation of hedonic price functions is that coefficients will be biased if unobserved variables that influence price are correlated with observed variables. To address this, we turn to a difference-in-differences (DID) approach commonly used in in the risk literature to identify the effects of wildfires on a group of treated properties (Hallstrom and Smith 2005; Gawande, Jenkins-Smith, and Yuan 2013; McCoy and Walsh 2018). In our case, a unique feature of using wildfires as treatments over a large area is that our events are scattered through time and space. As opposed to a single before and after time period for the study area, two properties selling in the same year far away from each other will be nearest to two different wildfire perimeters; one may have sold before its nearest wildfire, while the other may have sold after its nearest wildfire.

To implement the DID approach, we first calculate the distance between each property and all wildfires within 15 km, measured as the distance from the property to the wildfire perimeter – because of the prevalence of wildfires in the area, many properties are within 15 km of multiple fires. We expect that excluding these properties from the dataset will bias estimates, so we keep them and add a control variable equal to the number of past fires. The past fires variable is defined by the number of fires 500 acres or more within 15 km prior to the transaction. The model takes this form:

$$\begin{aligned} lnP_{it} = \beta_0 + \beta_{dist}Dist_{it} + \beta_{post}Postfire_{it} + \beta_{distpost}(Dist \times\ Post)_{it} + \boldsymbol{\beta}_{house}\boldsymbol{X}_{it} \\ + \boldsymbol{\beta}_{geo}\boldsymbol{G}_i + \boldsymbol{\beta}_{neighbor}\boldsymbol{N}_{it} + \boldsymbol{\beta}_{county}\boldsymbol{C}_i + \boldsymbol{\beta}_{time}\boldsymbol{T}_{it} + \varepsilon_{it} \end{aligned} \tag{10}$$

where $\ln P_{it}$ is the natural log of the sale price for house *i* selling in year *t*. $Dist_{it}$ is the natural log of distance from the fire perimeter. We exclude properties within the fire perimeter if they sold after the fire, but in order to keep properties within the perimeter that sold before a fire occurred, we transform the distance variable by adding .01 (or 1 meter) before taking the natural log. Since the housing closing process takes 30 to 60 days, we define $Post_{it}=1$ if the property is sold between 60 days and three years after the nearest fire occurs.[1] The coefficient of interest is $\beta_{distpost}$, the difference-in-difference coefficient that measures the effect of selling after a fire for houses in each treatment group. The model also controls for housing characteristics $\boldsymbol{X}$, geographic characteristics $\boldsymbol{G}$, neighborhood demographics $\boldsymbol{N}$, and includes county fixed effects $\boldsymbol{C}$, and year by quarter dummies $\boldsymbol{T}$. Housing characteristics are drawn from tax assessor data and are accurate to the most recent tax assessment. For unbiasedness in difference-in-difference estimates, three assumptions must be met: correct specification of the model, error terms satisfy $E(\varepsilon_i|X) = 0$, and there must be parallel trends between treatment and control groups.

1.5 Study Area and Data

1.5.1 Study Area

There are several key features of Southern California that make it an interesting area to investigate potential for wildfire risk. First, in many areas of the country, areas at high wildfire risk are remote or undeveloped. By contrast, some of the largest cities in California including Los Angeles and San Diego are adjacent to forested or wilderness areas with extreme wildfire risk. In our selected study area of southern California in particular, these high-risk areas also benefit from amenities from national forests. Second, the physical characteristics of the study area are unique: the dominant vegetation in the region chaparral, which has a very different fire regime from forests in the Pacific Northwest or the Rocky Mountains. Finally, Californians are familiar with natural hazards and risks, and the housing market has many sources of fire risk information for potential home buyers. One major source of risk information is that the state natural hazard disclosure law requires buyers to be

[1] Models were also run defining postfire as 120 days to three years and there was little effect on results.

notified of homes on land that has been classified as at high wildland fire risk. These risk zones are defined by state and local governments; more on how they were developed in Section 1.5.4.

The study area is geographically large and covers several of California's biggest urban areas, including Santa Barbara, Los Angeles, Anaheim, Riverside, and San Diego. Because we expect heterogeneity between these major cities, and because it is unlikely that they share a housing market, in addition to running models with pooled data from all counties, where possible, we also run models with five smaller markets. The five markets consist of: (1) Santa Barbara and Ventura Counties; (2) Los Angeles County; (3) Orange County; (4) Riverside and San Bernardino Counties; and (5) San Diego County. Figure 1.1 depicts the entire study area, county boundaries (labeled), and national forests (shaded). The five markets are denoted by county fill. From north to south the markets are: Santa Barbara & Ventura; Los Angeles; Orange County; San Bernardino & Riverside; and San Diego.

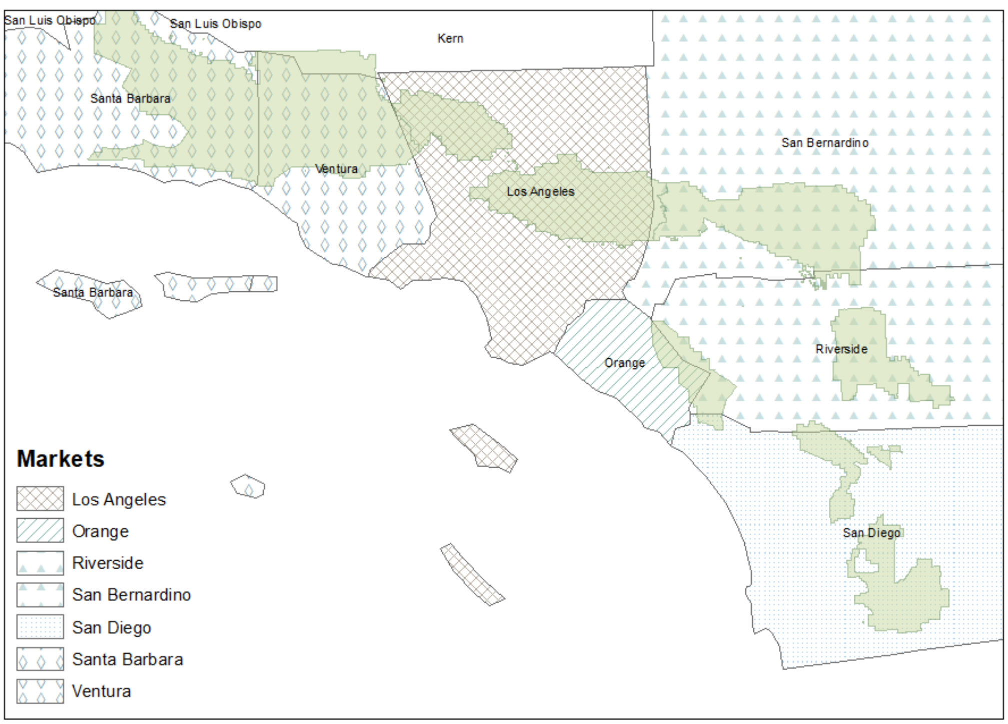

Figure 1.1 Study Area and Markets

1.5.2 Housing Data

We obtained property transactions data for homes sold between January 2000 and December 2015 near the Los Padres, Angeles, San Bernardino, and Cleveland National Forests, spanning seven counties: Santa Barbara, Ventura, Los Angeles, San Bernardino, Riverside, Orange, and San Diego. The study area was defined by selecting Zip Code Tabulation Areas (ZCTA) within 30 km of the National Forests on the coastal side. Figure 1.2 shows the study area with the selected ZCTA as well as the four National Forests. Housing data was purchased from CoreLogic, a company that provides real estate data obtained from public records to financial and research institutions. This data includes transactions data for residential properties, street address, a set of structural variables including bedrooms, bathrooms, square footage, lot size, and features such as parking, fireplace, and pool. For a subset of properties, we also observe information on one prior sale. Data quality for features of the properties – e.g. swimming pool, fireplace, view – is quite low so models include only structural variables such as the number of rooms and square footage. Data are limited to relevant transactions of owner-occupied residential single-family residences in a series of steps. To identify arms-length transactions as opposed to transfers between family members or built-to-order homes, we exclude properties built in the same year as they were sold, that sold twice in 12 months, properties transferred using quit claim or other unusual deeds, and those marked with a partial sale code.

After excluding properties with missing sales data, we drop houses in the top 1% of bedrooms, bathrooms, and total rooms, and the top 1% of square feet, to remove extreme values from the sample[2], and remove condos and duplexes. The cleaned dataset still contains extreme values in size and sales price: the HPI-adjusted sales price of remaining properties ranges from $3,500 to $191,000,000, including some properties with a price per square foot of $1, and the minimum square

[2] Muehlenbachs Spiller and Timmins (2015) and McCoy and Walsh (2018) use similar methods to trim extreme values

footage is under 50. For all models we then further exclude properties with fewer than 500 square feet[3], with a price per square foot of less than $40[4], a sales price of less than $10,000, or a sales price of greater than $10,000,000. After trimming, we have 1,346,132 observed transactions; some properties sold twice between 2000-2015, and information from both transactions are included in the total observations. A comparison of sales price summary statistics before and after trimming extreme values is in Table 1.1. The price distribution in the trimmed sample now shows a more realistic minimum of around $20,000 rather than $3,500, while the distribution in middle 90% of the sample has not changed drastically.

Table 1.1 Distribution of Sales Prices in the Full Sample Before and After Trimming

	Before Trimming	After Trimming
Minimum	$ 3,496	$ 19,379
1st Percentile	$ 139,598	$ 140,879
5th Percentile	$ 198,511	$ 198,882
Median	$ 447,159	$ 447,159
95th Percentile	$ 1,069,509	$ 1,063,000
99th Percentile	$ 1,750,977	$ 1,701,387
Maximum	$ 191,000,000	$ 9,984,551
N	1,348,336	1,346,132

Table 1.1 displays summary statistics on the HPI-adjusted sales price of transactions in the full sample before and after trimming by four criteria: (1) properties under 500 square feet; (2) transactions with a price per square foot of less than $40; (3) transactions with a sales price less than $10,000; and (4) transactions with a sales price greater than $10,000,000.

The focus of this paper is to identify the immediate impact of a recent fire, so to minimize the potential for confounding influences, models are limited to transactions which occur in the three years

[3] 500 square feet is the size cutoff to meet the definition of a micro-home
[4] Wolf and Klaiber (2017) remove properties with a price of less than $40/sqft

before or after the wildfire, and properties within 10 km of a wildfire 500 acres or more. Table 1.2 shows summary statistics for the fully cleaned dataset and the dataset used in most of the models presented (transactions within three years before or after a fire, and within 10 km of a wildfire 500 acres or more – the estimation sample). Transactions in the estimation sample have more wildfires prior to the sale (2.4 compared to 1.5) and are on average closer to a fire perimeter (3.5 km compared to 4.3 km) than the full sample. The structural characteristics of the properties, including square footage, price, and age, as well as year of sale, are very similar to those in the full sample of properties.

Table 1.2 Summary Statistics on Transactions in the Full Sample and Estimation Sample

	Full sample of properties (N= 1,346,132)				**Properties in Estimation Sample (N= 223,323)**			
Variable	Mean	Std dev	Min	Max	Mean	Std dev	Min	Max
Sales price ($)	520,349	346,689	19,379	9,984,551	525,494	341,233	44,039	9,637,375
Price per square foot ($)	281	145	40	8,022	284	137	40	4,516
Bedrooms	3.4	0.8	1	5	3.4	0.8	1	5
Bathrooms	2.4	0.8	1	5	2.4	0.8	1	5
Square feet	1,909	757	500	4,981	1,903	750	500	4,981
Age	36	23	1	214	35	23	1	208
Sale year	2007	5	2000	2015	2006	4	2000	2015
Distance from USFS land (km)	14.7	8.2	3.0E-4	30.0	11.5	7.4	3.0E-4	30.0
Distance to other open space (km)	0.6	0.5	0.0	6.1	0.6	0.5	0.0	5.9
Number of fires prior to sale (over 500 acres and within 15 km)	1.5	1.7	0	16	2.4	1.9	0	16
Distance to fire perimeter (km)	4.3	3.1	0.0	15.0	3.5	2.5	0	10.0
FHSZ (0/1)	0.1	0.3	0	1	0.1	0.3	0	1
Sold after a fire (0/1)	0.5	0.5	0	1	0.5	0.5	0	1

Table 1.2 summarizes structural and relevant geographic characteristics of properties; statistics for the full sample of properties are displayed on the left, and statistics for the Estimation Sample (transactions that occur in the three years before or after a wildfire) are on the right. Property characteristics, including sales price, size, number of rooms, and age are similar between the two samples. In addition, there is no evidence for significantly different transaction times between the two samples. There are some differences in terms of distance to fire perimeter and number of fires prior to sale.

1.5.3 Wildfire and Geographic Data

Using wildfire perimeter data available from California's Fire Resource and Assessment Program (FRAP), we select wildfires that occur between 1995-2015, and only fires at least 500 acres in size; earlier models suggest fires older than ten years or smaller than 500 acres have a negligible effect on sales. The FRAP data set obtained from the state of California includes all footprints of fires 10 acres or greater that local agencies reported to the state. After matching each property with all fire perimeters within 15 km, there are 1116 individual footprints 10 acres or more – summary statistics for fires by year are in Table 1.3. The 25th percentile in size is 40 acres, the 50th is 131, and the 75th percentile in fire size is 521 acres. Thus, limiting to fire perimeters 500 acres or more allowed us to concentrate on a subset of significantly large fires. A total of 288 wildfires are within 15 km of a property in the data set and 500 acres or more. Figure 1.2 shows the selected study area and spatial distribution of wildfires in the greater Los Angeles area.

Conditional on being more than 500 acres, these fires burned on average 10,900 acres and lasted roughly a week. Robustness checks include models with only these extra-large fires 10,000 acres or more. The study period spans some of California's worst wildfire incidents, including the "California Fire Sieges" of 2003, in which 14 fires blazed through southern California over the course of two weeks, and 2007, which charred nearly one million acres between Santa Barbara and the US-Mexico border (Blackwell and Tuttle 2003; CAL FIRE, USFS, and OES).

Addresses were geocoded with Texas A&M Geoservices. Fifty percent of properties matched with a parcel latitude and longitude, 46% matched with a street segment, and 4% were matched with a zip code centroid. Next, geographic data for properties was obtained, including distance to the nearest wildfire perimeter, distance to the closest National Forest boundary, and distances to other amenities for each individual property. Distance to primary and secondary roads was calculated using road data from the US Census Bureau's TigerLine road shapefiles. Distances to city centers were calculated using metropolitan boundaries from the San Diego Association of Governments and the city of Los Angeles – each property was matched with either Los Angeles or San Diego as the nearest major city – and distance to the nearest park or open space used data from the California Protected Area Database.

Table 1.3 Descriptive Statistics for Wildfires > 500 ac and within 15 km of a Property by Year

Year	Number of Fires	Smallest (Acres)	Median (Acres)	Largest (Acres)
1995	23	531	1,680	21,444
1996	24	502	1,084	19,861
1997	19	522	1,326	24,797
1998	11	580	2,056	28,136
1999	16	502	3,298	63,508
2000	4	798	1,199	11,734
2001	8	531	1,599	10,438
2002	20	555	3,432	61,691
2003	21	806	8,474	270,686
2004	17	513	3,693	16,447
2005	12	618	1,630	23,396
2006	12	500	6,549	161,816
2007	27	602	3,839	240,359
2008	8	500	7,059	30,305
2009	8	839	4,824	160,833
2010	7	522	717	12,582
2011	5	508	1,027	2,134
2012	9	519	2,637	11,667
2013	14	510	2,505	30,268
2014	7	959	1,952	15,186
2015	5	1,049	1,462	31,284

Table 1.3 shows summary statistics for the sample of wildfires 500 acres or more, and within 15km of a property in the sample, by year. An average year had 14 wildfires, and a median fire size of around 2,000 acres. Some exceptional years (2003, 2007) had wildfires more than 200,000 acres.

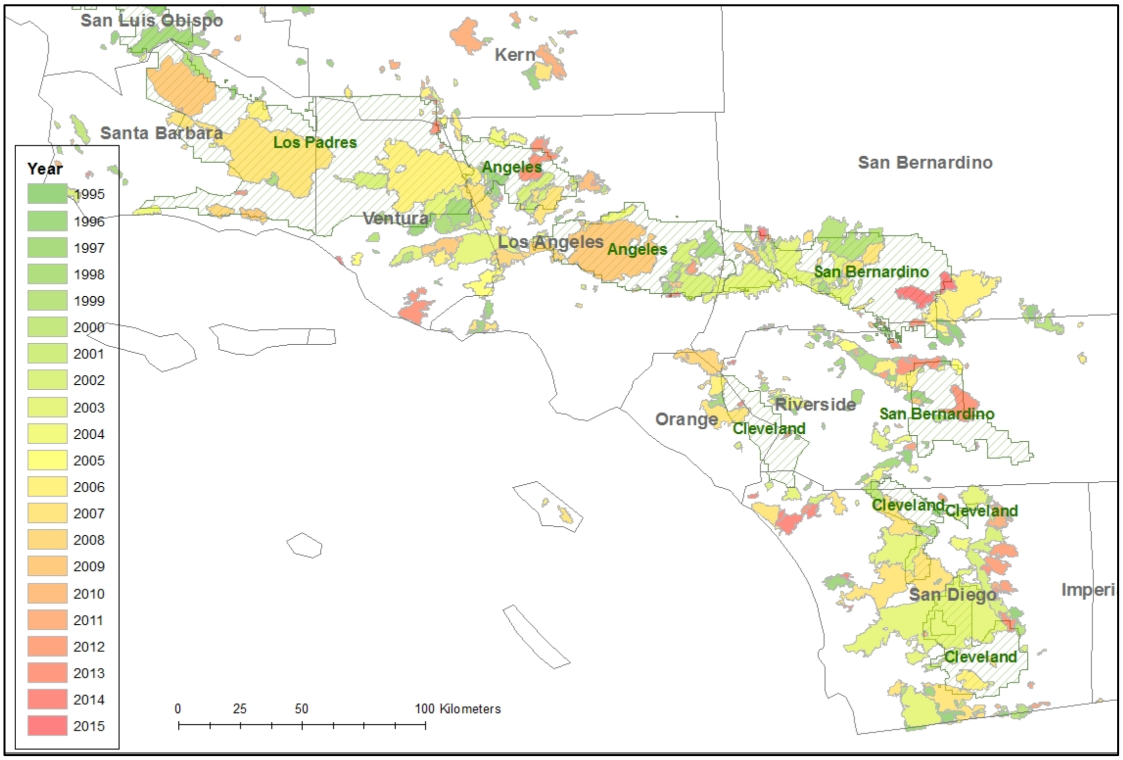

Figure 1.2 Study Area with National Forests and Wildfires Perimeters from 1995-2015[5]

1.5.4 Fire Hazard Data

Previous research suggests that risk of wildfire is generally not salient to potential home buyers except shortly after an information shock such as publicly available risk ratings, or an actual fire. A household survey of Colorado Springs residents found that homeowners had not been aware of fire risk when they purchased their homes (Champ, Donovan, and Barth 2009), and a related study on the impact of making available parcel-level risk ratings in the same town found that before the program amenities associated with risk were positively related to price, while after ratings were posted online the amenities were insignificant (Donovan, Champ, and Butry 2007). We therefore identify effects of

[5] Figure 1.2 shows county boundaries (labeled), USFS boundaries (labeled and denoted by a striped pattern), and fire perimeters in the study area. Each fire perimeter is at least 10 acres in size, within 15 km of a property in our study area and occurred between 1995 and 2015. Many of the fire perimeters overlap with USFS land, but several wildfires affect other areas.

wildfires along two main dimensions: the effect of being close to a recent fire for properties located on and off areas of high risk as defined by the state.

California Department of Forestry and Fire Protection (CAL FIRE) produces statewide maps of areas with significant fire hazards, called Fire Hazard Severity Zones (FHSZ). Hazard zones are developed using information about the physical attributes of the area and fire history, including fuel availability, topography, typical weather, and models of ember production and movement. FHSZs do not take into consideration private actions to reduce fire risk on a given property, such as fuel reduction and defensible space. Hazard zones are divided into two main categories defined by the level of government responsible for firefighting costs: state responsibility areas (SRAs) and local responsibility areas (LRAs). For SRAs, hazard severity is rated as one of three categories: moderate, high, or very high. For LRAs, there is only data on areas rated "very high".

Maps of FHSZ have existed since the 1980s, however, early geographic records are incomplete. Mapping efforts were greatly expanded in the early 2000s; the current version of maps for SRA were proposed in 2007 and adopted by January 2008. Current hazard zones for LRAs were proposed between 2007 and 2008 and were adopted by local jurisdictions on an individual basis afterwards[6]. Our main models define FHSZ to be a binary variable equal to one if the property is on any of the above zones and use the hazard zone designation that is most accurate to the sale year; properties that sell prior to 2008 are coded using older FHSZ maps that date back to 1985 and properties selling in 2008 or later are coded using the more recent maps.

FHSZ may be used in the development of building standards and defensible space requirements, but more importantly since 1998 California's Civil Code has required natural hazard disclosures at the time of property sale, including both location on areas of wildland fire risk (any SRA rating) and

[6] The state of California advised the city of San Diego that LRA maps would be updated roughly every five years but as of 2018 there are no additional updates from after the 2007-2008 remapping effort

whether the property is in a "Very High" wildfire hazard zone (anywhere with a "very high" hazard rating). Location of FHSZ according to maps adopted in 2008 is shown in Figure 1.3.

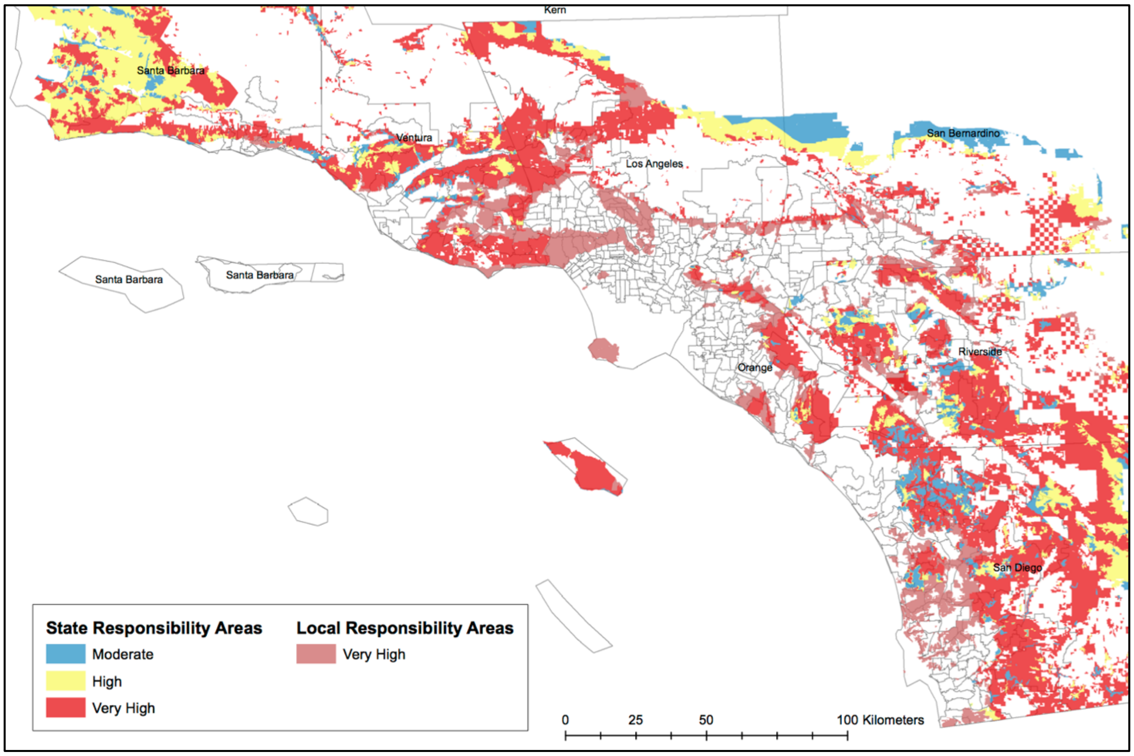

Figure 1.3 Fire Hazard Severity Zone (FHSZ) Maps Adopted in 2008: Both SRA and LRA[7]

1.5.5 Data on Major Highways as Barriers

For a robustness check presented in the appendix we use an additional treatment that uses highways, which often act as a physical barrier for wildfires, as an information treatment. Because it is rare that fires jump barriers with little fuel (e.g. a large road or river), we expect that properties in the interior of a highway – between a major highway and USFS land – will be more impacted by a recent fire than those directly on the other side.

[7] Figure 1.3 shows county boundaries (labeled), ZCTA boundaries in a light gray, and boundaries of FHSZ in the study area. There are two categories of FHSZ: SRA are areas where the state is responsible for fire-fighting costs, and LRA are areas where the local governments are responsible for fire-fighting costs. In addition, all land is either unclassified or classified into three hazard categories: moderate, high, or very high.

To develop a model that uses major highways as barriers we use Highway I-210 as a reference point for major road on Google Maps. Highway 210 runs almost parallel to the boundary of the Angeles National Forest from Santa Clarita to San Bernardino and is often used as a reference point for wildfire news. With 210 as a reference point, we select similar major roads from the TigerLine shapefile in GIS and individually select the portions of road that run parallel to all four forest boundaries. We calculate both the distance and angle to the selected roads for each property in the sample. Then, by selecting groups of properties based on latitude, longitude, and angle to the nearest of the roads, we are able to identify the properties in each county that are between the highway and forest ("between") and on the other side of the highway.

1.6 Empirical Model and Results

1.6.1 Cross-Sectional Difference-in-Differences Model

Our empirical approach uses the hedonic pricing model in a difference-in-differences framework where selling near a recent wildfire is the treatment and properties that sold prior to the wildfire or farther away are controls. In this specification, treatment estimates the effect of a recent fire but cannot separately identify amenity and risk effects. Prior studies testing the effect of wildfire proximity on housing prices have used a range of values from 2 km (McCoy Walsh 2018) to roughly 3.2 km (Loomis 2004). Rather than assuming a strict distance cutoff after which proximity to a recent fire has no effect, we allow impacts farther away from a fire by using continuous distance as our treatment variable. In all models we allow for heterogeneous effects according to FHSZ classification by interacting an indicator variable for FHSZ with postfire and distance variables.

The econometric specification takes the form

$$lnP_{it} = \beta_0 + \beta_{dist}\ln(Dist)_{it} + \beta_{post}Postfire_{it} + \beta_{fhsz}FHSZ$$
$$+ \beta_{distpost}[\ln(Dist) \times Post]_{it} + \beta_{distfhsz}[\ln(Dist) \times FHSZ]_{it}$$
$$+ \beta_{postfhsz}[Post \times FHSZ]_{it} + \beta_{postfhszdist}[\ln(Dist) \times Post \times FHSZ]_{it} \quad (11)$$
$$+ \boldsymbol{\beta}_{house}\boldsymbol{X}_{it} + \boldsymbol{\beta}_{geo}\boldsymbol{G}_i + \boldsymbol{\beta}_{neighbor}\boldsymbol{N}_{it} + \boldsymbol{\beta}_{county}\boldsymbol{C}_i + \boldsymbol{\beta}_{time}\boldsymbol{T}_{it} + \varepsilon_{it}$$

The dependent variable is log of an HPI-adjusted sales price[8]. We control for distance from the fire perimeter, selling after a fire, and FHSZ (0/1 dummy variable). The coefficient $\beta_{distpost}$ on the interaction term is the difference-in-difference coefficient which describes the effect of distance from a wildfire after the fire occurs; $\beta_{postfhsz}$ describes the impact of selling on FHSZ after a wildfire; and $\beta_{postfhszdist}$ shows the additional impact of selling on FHSZ after a nearby wildfire. In all models we control for a set of structural, geographic, and demographic characteristics; Table 1.4 is a list of all controls used in the cross-sectional difference-in-differences estimation.

[8] The dependent variable is actual sales price rather than assessed property value.

Table 1.4 Structural, Geographic, and Demographic Controls used in Cross-Sectional Models

Category	Variable Name	Description
Structural Variables	Bedrooms	Number of bedrooms
	Bathrooms	Number of bathrooms
	Ln(Square feet)	Logged square footage
	Ln(Acres)	Logged parcel acreage
	Age	Age of the house
Geographic Variables	Development density	Indicator variables for housing development density (4 categories)
	National forest (NF)	Indicator variables for the closest national forest (4 variables)
	Distance from NF	Logged distance from NF land in km
	Slope	Slope of property
	Elevation	Elevation of property
	WUI	Indicator variable for located on Wildland-Urban Interface
	Urban	Indicator variable for located on land classified as urban
	Distance to city	Logged distance from the nearest major city center, either Los Angeles or San Diego
	Distance to open space	Logged distance to land in the California Protected Area Database
	Distance to highway	Logged distance to major road
	Number of past fires	Number of fires (500 acres or more) within 15 km prior to the transaction
Census Tract Characteristics	Percent Bachelor's degree	Percent of the population 25 years and older with at least a Bachelor's degree
	Median income	Median household income
	Percent Hispanic	Percent of the population that is Hispanic
	Percent black	Percent of the population that is black
	Unemployment rate	Percent of the population unemployed

In the pooled model with all counties the sign of the coefficient on Ln(Distance) is positive and significant, indicating that before a fire occurs, prices are higher farther away from the area that eventually buns. Given that distances from various amenities – Los Angeles or San Diego city centers, major highways, USFS and other wild land – are controls, we would have expected an insignificant sign on this variable, and its significance suggests some omitted variable correlated with fire. One possible explanation is that property price differentials are in part driven by insurance rates. Insurance companies are increasingly using sophisticated modeling techniques to estimate fire risk at a parcel level and may use variables beyond the controls in our model. After major fires, they update insurance rates not only for affected properties but also properties in other areas determined to have a high risk of fire.

Closer examination of the by-county models provides evidence for a mixed impact of distance from fire perimeter across the sample. The positive significant coefficient on FHSZ indicates that in general, properties on risky areas have a premium (being on FHSZ is associated with a 7.3% higher sales price). In general, FHSZ areas are less developed and adjacent to areas with nice views and recreational opportunities and prior to a fire, the benefit from these amenities may outweigh any sources of risk information. The coefficient on Ln(Distance) x FHSZ describes the impact of distance from a fire perimeter on FHSZ before the fire happens. Similar to Ln(Distance), we expected this value to be insignificant. It is in the pooled county model, while in the models by market there are mixed impacts.

Recall hypotheses (3) the greater the buyer's information prior to purchasing a home, the less likely a recent wildfire will change risk perceptions; and (4) a fire may serve as either a positive or negative information shock, so the overall impact of a fire on housing value will be ambiguous. The Postfire x FHSZ coefficient is negative and significant in the pooled county model – on average there is a 1.7% decrease in sales price on FHSZ after a fire. This is consistent with our hypothesis that potential buyers and sellers of properties on FHSZ will experience either an increase in fire risk salience or an increase in insurance market rates that will decrease the sales price on these zones compared to properties that are not rated as at greater wildfire risk. However, by looking at the models by market, we can see that this effect only holds for part of the sample. It may be the case that in those areas where we see the opposite effect, after a fire subjective risk decreases for the future.

On average after a fire, sales price decreases as distance from the fire increases, meaning after a fire happens, houses are selling for higher prices near the fire perimeter. This contradicts prevailing results in the literature. Our study does have some significant differences from prior studies, the most major being that we allow for effects over a much wider distance (10 km compared to a norm of 2-5 km or even less). Robustness checks include models that use 5 and 15 km distance cutoffs as well as an alternate model specification that interacts Postfire with 1-km bins from the fire perimeter (these results are summarized in the appendix). For models in smaller markets we are not able to detect the effect of distance from a recent fire on property sales prices. The Los Angeles County market model has an estimated parameter that is positive and significant, indicating as you get farther away from a recent fire, price increases. The overall effect seems to be driven mostly by Orange County.

The coefficient on the triple interaction of Distance x Postfire x FHSZ in both the All Counties and Orange County models is the opposite sign than the main DID estimate Distance x Postfire. Considering expectation (3) above, this suggests that no matter the overall impact of a fire on risk expectations, being on FHSZ has a mitigating impact. In areas that do not get this extra risk information when houses are on the market, distance to open space or other sources of information are used to form priors on fire risk. However, for buyers and sellers of properties on FHSZ, each receive a more accurate information signal about fire risk, and so after a fire, beliefs are updated to a lesser amount.

Table 1.5 Results of Cross-Sectional DID Models; All Counties and Five Markets

	(1) All Counties	(2) Santa Barbara & Ventura	(3) Los Angeles	(4) Riverside & San Bernardino	(5) Orange County	(6) San Diego
Ln(Distance)	0.013***	0.021***	-0.006***	-0.009***	0.012***	-0.057***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Postfire	0.040***	0.010	-0.007***	0.030***	0.066***	0.010***
	(0.000)	(0.418)	(0.009)	(0.000)	(0.000)	(0.000)
FHSZ	0.073***	0.045*	0.044***	0.040***	0.038***	0.015***
	(0.000)	(0.068)	(0.000)	(0.000)	(0.000)	(0.004)
Ln(Distance) x FHSZ	-0.007	0.029	0.020***	0.023***	-0.007*	-0.006**
	(0.000)	(0.143)	(0.000)	(0.000)	(0.092)	(0.024)
Postfire x FSHZ	-0.017***	0.055*	0.015*	-0.011	-0.066***	0.053***
	(0.000)	(0.051)	(0.067)	(0.191)	(0.000)	(0.000)
Ln(Distance) x Postfire	-0.010***	-0.006	0.014***	0.001	-0.061***	0.002
	(0.000)	(0.436)	(0.000)	(0.343)	(0.000)	(0.257)
Ln(Distance) x Postfire x FHSZ	0.019***	-0.008	-0.008	-0.001	0.043***	-0.032**
	(0.000)	(0.723)	(0.184)	(0.895)	(0.000)	(0.048)
Constant	9.565***	9.350***	9.653***	12.075***	9.051***	9.313***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	206,841	6,351	61,438	67,791	31,636	39,625
R-squared	0.830	0.793	0.777	0.838	0.804	0.782

Table 1.5 describes the controls used in the cross-sectional DID model, including structural controls, geographic variables, and census tract characteristics. All logged variables have been transformed by adding one so that properties with distance=0 from open space, city center, or fire perimeter remain in the models.

1.6.2 Repeat Sales Model

A concern of the cross-sectional DID approach is that there are unobservables that bias the treatment effect estimate. We take advantage of observing repeated sales from a subsample of properties to create a two time-period panel and run property fixed effects models. The repeat sales model should better control for time-invariant unobservables that are correlated with both distance to fire and price. The model takes the form:

$$\begin{aligned} lnP_{it} &= \beta_0 + \beta_{post}Postfire_{it} + \beta_{fhsz}FHSZ_{it} \\ &+ \beta_{distpost}[\ln(Dist) \times Post]_{it} + \beta_{distfhsz}[\ln(Dist) \times FHSZ]_{it} \\ &+ \beta_{postfhsz}[post \times FHSZ]_{it} + \beta_{postfhszdist}[\ln(Dist) \times Post \times FHSZ]_{it} \\ &+ \beta_{age}Age_{it} + \boldsymbol{\beta}_{neighbor}\boldsymbol{N}_{it} + \boldsymbol{\beta}_{time}\boldsymbol{T}_{it} + FE + \varepsilon_{it} \end{aligned} \tag{12}$$

Like Equation 15, the coefficient $\beta_{distpost}$ describes the effect of proximity to a wildfire after the fire; $\beta_{postfhsz}$ describes the impact of selling on FHSZ after a wildfire; and $\beta_{postfhszdist}$ shows the additional impact of selling on FHSZ nearby a wildfire. The model still includes all covariates that change over time. FHSZ is included in the model because of the hazard zone update in 2008; each property's FHSZ rating corresponds to the map in use during the year of sale. Census tract characteristics also vary over time. For sales in 2010-2015, demographic variables are from the American Community Survey (ACS) 5-Year Estimates. For sales in 2009 or earlier, we use the 2009 estimates.

Another difference of note: in the cross-sectional DID dataset the primary unit of observation is the transaction. Each *transaction* was matched to the nearest fire; if the closest fire was more than 10 years ago, we matched the transaction in question with the next nearest fire, expanding the dataset. Hence, the same house could be matched with two different relevant fires if the sales were for example in 2000 and then again in 2012, and standard errors were clustered at the property level to account for correlation in the sales. In the repeat sales models, we match each property with the nearest wildfire, which could have occurred in the three years prior to the first sale, between the two sales, or in the three years after the second sale.

The subset of 47,842 houses for which we observe a true repeat sale – meaning each transaction was arms-length, involved the whole property parcel, with reasonable sales price – is much smaller than the Estimation Sample. Table 1.6 shows the breakdown of the Repeat Sales Sample by Postfire and FHSZ.

Table 1.6 Summary of Postfire and FHSZ Observations in the Repeat Sales Sample

	Postfire		
FHSZ	0	1	Total
0	23,475	21,029	44,504
1	1,111	2,227	3,338
Total	24,586	23,256	47,842

Table 1.6 shows the cross-tabulation of Postfire and FHSZ to illustrate that the number of treated houses decreases significantly in the repeat sales model compared to the cross-sectional DID model. The count includes all counties and only properties that were already included in the Estimation Sample.

In Table 1.7 we present results from a repeat sales model on the pooled county data. The sign and magnitude of the coefficients of interest are fairly similar to the cross-sectional model. In the repeat sales model we see a price premium for selling on FHSZ before a fire (13.2%), but there is no significant effect of selling on FHSZ after a fire. The coefficient on the Distance x Postfire coefficient is insignificant. However, the coefficient of Distance x Postfire x FHSZ is negative and significant. In this model distance from a recent fire seems to only matter for properties on FHSZ and not for other properties.

Table 1.7 Fixed Effects Model with Repeat Sales Only

	(7) All Counties
Postfire	-0.017***
	(0.000)
FHSZ	0.132***
	(0.000)
Postfire x FSHZ	-0.008
	(0.389)
Ln(Distance) x Postfire	-0.003
	(0.624)
Ln(Distance) x Postfire x FHSZ	-0.017***
	(0.000)
Constant	0.022***
	(0.002)
Observations	47,842
Number of Houses	23,921
R-squared	0.449

Table 1.7 shows estimates from a Fixed Effects model on the Repeat Sale Sample. Pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

1.6.3 Effects of Fire Over Time

So far, we have focused on the impacts of fire over space, but it may be of interest to look at effects over time. Prior studies have shown evidence of a decrease in risk salience over time. In the wildfire literature, McCoy & Walsh (2018) estimate effects by year since a fire by interacting treatments with dummy variables for year. They find evidence that properties on high risk land, but which are far enough away not to receive visual disamenities see a short-term decrease in price, followed by a recovery by the third year after a fire. On the other hand, they find that properties with a view of a burn scar see a decrease in price that remains for at least three years. We adapt their approach to look for evidence of diminishing effects over time and expand the original model to include interactions with year variables.

$$lnP_{it} = \beta_0 \sum_{j=1}^{3} \beta_{postj} Postj_{it} + \beta_{fhsz} FHSZ_{it} + \sum_{j=1}^{3} \beta_{distpostj} [\ln (Dist) \times Postj]_{it}$$
$$+\beta_{distfhsz} [\ln(Dist) \times FHSZ]_{it} + \sum_{j=1}^{3} \beta_{postjfhsz} [Postj \times FHSZ]_{it} \tag{13}$$
$$+ \sum_{j=1}^{3} \beta_{postjfhszdist} [\ln (Dist) \times Postj \times FHSZ]_{it}$$
$$+ \beta_{age} Age_{it} + \boldsymbol{\beta}_{neighbor} \boldsymbol{N}_{it} + \boldsymbol{\beta}_{time} \boldsymbol{T}_{it} + FE + \varepsilon_{it}$$

Table 1.8 presents results from a pooled model with yearly effects as well as the five market models. On average we do not find any evidence that the impact of distance from a fire decreases year by year - the coefficient on the interaction term Distance x Postfire is significant up to three years after a fire. We do see a diminishing effect on FHSZ only; in the first year after a fire, there is a 2.5% decrease in price on FHSZ, in the second year, a 1.9% decrease, and in the third year no discernible decrease after a fire. An F-test for significant differences in coefficients is unable to reject the null hypothesis that the first and second year coefficients are equal, but the second and third year are significantly different from each other, as well as the first and third years. This is consistent with the McCoy and Walsh finding, and suggests that risk salience from a recent event is greater in the year after it than as time passes. However, in the sub-market models we can see that this trend is being driven by negative and significant estimates for Orange County, while some estimates in other counties are either insignificant or positive.

Table 1.8 Effects of Fire Over Time

	(8) All Counties	(9) Santa Barbara & Ventura	(10) Los Angeles Market	(11) Riverside & San Bernardino	(12) Orange County	(13) San Diego
Post Year 1	0.036***	-0.002	-0.009**	0.018***	0.061***	-0.037***
	(0.000)	(0.906)	(0.014)	(0.000)	(0.000)	(0.000)
Post Year 2	0.045***	0.031**	-0.007*	0.025***	0.072***	-0.046***
	(0.000)	(0.034)	(0.053)	(0.000)	(0.000)	(0.000)
Post Year 3	0.039***	-0.006	-0.005	0.040***	0.073***	-0.079***
	(0.000)	(0.669)	(0.259)	(0.000)	(0.000)	(0.000)
Ln(Distance)	0.013***	0.021***	-0.006***	-0.009***	0.011***	0.010***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
FHSZ	0.073***	0.043*	0.043***	0.040***	0.037***	0.015***
	(0.000)	(0.077)	(0.000)	(0.000)	(0.000)	(0.003)
Post 1 x FHSZ	-0.025***	0.055	0.009	-0.022*	-0.058***	0.034***
	(0.000)	(0.148)	(0.406)	(0.068)	(0.000)	(0.002)
Post 2 x FHSZ	-0.019***	0.061*	0.015	-0.009	-0.067***	0.057***
	(0.000)	(0.070)	(0.116)	(0.461)	(0.000)	(0.000)
Post 3 x FHSZ	-0.006	0.052	0.024**	0.003	-0.076***	0.073***
	(0.262)	(0.148)	(0.018)	(0.811)	(0.000)	(0.000)
Ln(Distance) x FHSZ	-0.007***	0.030	0.020***	0.023***	-0.006	-0.006**
	(0.000)	(0.129)	(0.000)	(0.000)	(0.117)	(0.027)

Table 1.8 (cont'd)

Ln(Distance) x Post 1	-0.010***	0.004	0.008***	0.000	-0.059***	0.005*
	(0.000)	(0.699)	(0.002)	(0.828)	(0.000)	(0.077)
Ln(Distance) x Post 2	-0.011***	-0.013	0.019***	0.003*	-0.067***	-0.005*
	(0.000)	(0.267)	(0.000)	(0.069)	(0.000)	(0.093)
Ln(Distance) x Post 3	-0.010***	-0.008	0.014***	0.001	-0.057***	0.008***
	(0.000)	(0.415)	(0.000)	(0.779)	(0.000)	(0.005)
Ln(Distance) x Post 1 x FHSZ	0.005	-0.012	0.000	0.015	0.033***	-0.037***
	(0.190)	(0.682)	(0.981)	(0.168)	(0.000)	(0.000)
Ln(Distance) x Post 2 x FHSZ	0.021***	0.005	-0.006	-0.020**	0.046***	-0.021***
	(0.000)	(0.834)	(0.381)	(0.032)	(0.000)	(0.001)
Ln(Distance) x Post 3 x FHSZ	0.030***	-0.019	-0.016**	0.001	0.048***	-0.035***
	(0.000)	(0.507)	(0.019)	(0.918)	(0.000)	(0.000)
Constant	9.555***	9.312***	9.656***	12.078***	9.087***	9.315***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	206,841	6,351	61,438	67,791	31,636	39,625
R-squared	0.830	0.793	0.777	0.838	0.804	0.783

Table 1.8 shows estimates from an expanded model with interactions with each year since a fire. Overall the results suggest that there is no diminishing effect of a fire over time in terms of how it affects distance, but there is some evidence that properties on FHSZ see an immediate decrease in sales price and recovery over three years. However, there is a lot of heterogeneity in the results by market. Robust pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

1.6.4 Heterogeneous Effects by Fire Size

Most previous literature has focused on estimating impacts of specific fire events (all papers prior to 2010 here). With a larger dataset and a wide range of wildfires in the study period, it is possible to investigate the potentially different impacts by fire size in acres, which here acts as a proxy for severity. A dummy variable for fires greater than 405 hectares (or 1,000 acres) in the Stetler et al. Montana study is negative and statistically significant, indicating that larger fires are less desirable than more moderately sized ones. In our study area many properties are nearby wildfires much larger than 1,000 acres; conditional on being 500 acres or more, the average fire size in the sample is 10,000 acres. We run additional models splitting the data by properties closest to fires 500-10,000 acres (Medium Fires) and properties closest to fires 10,000 acres or more (Large Fires). These results are presented in Table 1.9 and Table 1.10. If fires with greater severity serve as larger information shocks, we should expect to see a larger impact in the Large Fire model compared to the Medium Fire model.

In the Medium Fire model with all counties the sign of the coefficient on Ln(Distance) is negative and significant; as a house gets farther from an (eventual) fire perimeter, sales price decreases. This is the opposite effect than in the model that uses fires 500 acres and above, as well as the large fire model that includes fire 10,000 acres and above. The coefficient on FHSZ is positive and significant, as before, and suggests that there are amenities associated with being on otherwise risky land (2.6% in the Medium Fire model and 10.5% in the Large Fire model).

The next two coefficients of interest have opposite signs in the two models. Postfire x FHSZ is positive in the Medium Fire model – after a fire, price increases by 1.9% on FHSZ – and negative in the Large Fire model – after a fire, price decreases by 6.1% on average. In the Medium Fire model Distance x Postfire has a positive coefficient, meaning increased distance from the fire perimeter increases sales price while in the Large Fire model, it is negative and significant, meaning sales price decreases as you move farther from the perimeter.

Table 1.9 Medium Fire Size (500-10,000 Acres)

	(1) All Counties	(2) Santa Barbara & Ventura	(3) Los Angeles	(4) Riverside & San Bernardino	(5) Orange County	(6) San Diego
Postfire	0.012***	-0.073***	0.014***	-0.012***	-0.007	0.054***
	(0.000)	(0.000)	(0.010)	(0.000)	(0.535)	(0.001)
Ln(Fire Dist)	-0.009***	0.035***	-0.038***	-0.026***	-0.010***	0.018**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.018)
FHSZ	0.026***	0.049*	0.039*	0.012	0.017*	0.038***
	(0.000)	(0.079)	(0.057)	(0.101)	(0.055)	(0.000)
Postfire x FSHZ	0.019***	0.030	0.017	0.026***	0.003	-0.053***
	(0.001)	(0.330)	(0.452)	(0.003)	(0.803)	(0.000)
Ln(Distance) x FHSZ	0.024***	0.034	0.077***	0.039***	0.013**	-0.022***
	(0.000)	(0.160)	(0.000)	(0.000)	(0.027)	(0.004)
Ln(Distance) x Postfire	0.004*	-0.023**	0.020***	-0.000	-0.008	-0.038***
	(0.062)	(0.043)	(0.000)	(0.931)	(0.105)	(0.000)
Ln(Distance) x Postfire x FHSZ	-0.013***	-0.015	-0.079***	-0.003	-0.003	0.037***
	(0.002)	(0.578)	(0.000)	(0.714)	(0.679)	(0.001)
Constant	10.267***	10.752***	9.653***	10.372***	8.346***	9.505***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	80,506	3,975	28,978	33,191	12,155	4,418
R-squared	0.858	0.725	0.791	0.830	0.796	0.840

Table 1.9 shows estimates from a model with medium-sized fires (500-10,000 acres) only. Robust pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 1.10 Large Fires (>10,000 Acres)

	(1) All Counties	(2) Northern Market	(3) Los Angeles Market	(4) Inland Empire Market	(5) Orange County Market	(6) San Diego Market
Postfire	0.030***	0.053***	-0.003	0.043***	0.083***	-0.060***
	(0.000)	(0.000)	(0.257)	(0.000)	(0.000)	(0.000)
Ln(Fire Dist)	0.017***	0.054***	-0.008***	-0.009***	0.017***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)
FHSZ	0.105***	0.053**	0.062***	0.036***	-0.003	-0.010
	(0.000)	(0.026)	(0.000)	(0.000)	(0.891)	(0.206)
Postfire x FSHZ	-0.061***	0.059**	-0.031***	-0.025**	-0.033	0.072***
	(0.000)	(0.033)	(0.001)	(0.013)	(0.186)	(0.000)
Ln(Distance) x FHSZ	-0.011***	0.028	0.021***	0.026***	-0.026***	0.000
	(0.000)	(0.176)	(0.000)	(0.000)	(0.000)	(0.952)
Ln(Distance) x Postfire	-0.015***	-0.016*	0.011***	-0.003**	-0.067***	0.003
	(0.000)	(0.080)	(0.000)	(0.039)	(0.000)	(0.176)
Ln(Distance) x Postfire x FHSZ	0.027***	-0.002	0.007	-0.003	0.066***	-0.045***
	(0.000)	(0.921)	(0.230)	(0.736)	(0.000)	(0.000)
Constant	9.735***	11.616***	9.977***	12.229***	9.423***	9.273***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	126,335	4,969	32,460	58,635	19,481	35,207
R-squared	0.815	0.822	0.790	0.838	0.824	0.780

Table 1.10 shows estimates from a model with large-sized fires (10,000 acres or more) only. Robust pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

1.7 Discussion and Conclusions

Previous hedonic literature on the impacts of wildfires finds a consistently negative effect of fire on nearby properties, ranging from 7-15% decrease after a fire (Loomis 2004; Stetler et al. 2010; McCoy and Walsh 2018). These effects are attributed to both a decrease in amenities – the presence of a burn scar or loss of forest recreation opportunity – and an increase in risk perception. Some argue that the majority of the effect is a risk salience increase rather than the impact of amenity loss (Stetler et al. 2010). However, the literature has tended to focus on regions with low population density and infrequent wildfires. Using a richer dataset and longer time frame, our analysis suggests that there is no reason to presuppose that all wildfire activity must result in a decrease in housing sales prices nearby whether due to risk salience or disamenity. Our conceptual model shows that the effect of a fire should depend on the way beliefs about future fire risk are updated after the fire. In contrast to floods or hurricanes where an event likely increases perception of future risk, a wildfire does not always indicate that future risk of fire will increase if available fuel was burned off. If a wildfire causes a market-wide increase in belief that fires will occur in the future, we expect to see a drop in nearby housing prices. However, in areas with fire risk priors that are very high, a wildfire may not change or even decrease beliefs about future risk. Prior information can come from a variety of sources including fire hazard severity zone (FHSZ) status (a public disclosure of risk classification unique to California) or distance from some physical barrier such as a major highway. There is evidence that wildfires provide information to the market: on average, over the full sample of properties, there is a large pre-fire premium for properties on land with high physical risk of wildfire which decreases by 2% after a fire.

Results on the treatment effect of distance to a recent wildfire diverges from the majority of the hedonic literature: in most of the estimated models, properties sell for higher prices nearer the fire perimeter than farther away. However, this effect varies depending on the sample of properties used. We find heterogeneous effects of fire by geographic area – frequently, treatment effects have opposite signs in Los Angeles and Orange counties – as well as according to the size of the wildfire. We find that for the average medium-sized fire (500 – 10,000 acres) proximity to a recent wildfire decreases sales price, while for the average larger ones (10,000 acres or more) proximity to a recent wildfire increases sales price. This is consistent with the result from Hansen and Naughton (2013) who hypothesize that larger fires in Alaska opened up views which increased property assessment values and that large fires reduce future risk. Finally, we find some evidence that more complete information prior to a wildfire has a mitigating impact on the effect, no matter the direction of the effect. The interaction of Distance x Postfire x FHSZ is on average in opposite direction of Distance x Postfire, suggesting that while proximity to a wildfire changes subjective risk of future fire, for properties located on FHSZ, subjective risk does not change as much as for properties not on FHSZ. This result is consistent with the hypothesis that FHSZ areas provide information signals that mitigate how property markets will react to information signals from new fires.

The results presented here suggest several directions for future research. With the frequency of wildfires increasing, there is a greater need for more comprehensive multi-fire studies with spatial and temporal variation in treatment effects. Case studies of small areas or few fires may not provide an accurate picture of the average treatment effect of wildfires. Further investigation into the impact that fire size, prevalence in the news, and proximity to urban areas have on the treatment effect will allow for better inference about how future impacts of wildfires relate to these other factors and offer potential solutions to better match actual future risk with perceptions of future risk – e.g. public information campaigns, more reliable news coverage, and other avenues of public engagement. More studies with larger variation in wildfire size and impacts will also provide better insight into the pattern of impacts across fire sizes and specifically whether the result that smaller fires reduce property prices while larger ones can increase them holds generally. Future research in California should also consider that burns scars of large fires may reduce future fire risk but increase risk of other natural disasters such as flooding and mudslides.

Second, there may be potential local policy nuances that could lead to the differing results across the markets. Fighting wildland fires requires coordination from state, federal, and local agencies, however, it is possible that wildfires indirectly increase local fire department funding. If that is the case and residents are aware of funding levels, this dynamic could explain an increase in sales prices after a wildfire. It is also possible that areas newly classified as having wildland fire hazard similarly see changes to local funding or support for fire departments. For these reasons, future research into the effect that wildfires have on local or state-level mitigation strategies such as fire department funding or new fire prevention strategies (e.g., defensible space requirements) would shed more light on geographic differences in the effects of fire.

Finally, an important direction for future studies is to account for not only heterogeneity in wildland fire characteristics but also heterogeneity in indirect preferences of market actors. In southern California there are large differences in wealth, demographics, and political views that might affect the indirect preferences across the region. Differences in income may affect the hedonic value of amenities and risk, and future work in regions with major urban areas that include both extremely wealthy residents and less-affluent residents should consider whether people are sorting into many smaller hedonic markets. There may also be significant differences in risk perceptions for other reasons – studies on the effect of flooding on housing price has found evidence of significant heterogeneity in risk perceptions of future flooding (Bakkensen and Barrage 2018). Future research into wildfire risk perceptions should account for heterogeneity in preferences by developing models of sorting behavior which may help explain differences in effects of fires across regions.

APPENDICES

Appendix 1A. Additional Descriptive Tables

Table 1.11 Correlation between Geographic Variables

	Fire Dist	Forest Dist	Park Dist	Slope	Elev	FHSZ
Fire Dist	1					
Forest Dist	0.4016	1				
Park Dist	0.0108	-0.1248	1			
Slope	-0.2152	-0.0263	-0.0295	1		
Elevation	-0.3349	-0.4358	0.2633	0.0124	1	
FHSZ	-0.2078	-0.0647	0.1451	0.2490	0.0664	1

Table 1.12 Breakdown of Sample Sizes for Moderate, High, & Very High FHSZ Properties

	Moderate			High			Very High		
Post	0	1	Total	0	1	Total	0	1	Total
0	102,745	1,667	104,412	113,886	1,693	115,579	112,182	3,397	115,579
1	99,674	1,228	100,902	106,651	1,093	107,744	99,789	7,955	107,744
Total	202,419	2,895	205,314	220,537	2,786	223,323	211,971	11,352	223,323

Table 1.13 Distribution of Distances (in km) to a Barrier Highway

	All Observations	Between Barrier Highway and Forest
Minimum	2.2E-4	2.2E-4
1st Percentile	0.15	0.13
5th Percentile	0.47	0.34
Median	5.80	3.33
95th Percentile	18.87	19.48
99th Percentile	24.58	29.93
Maximum	41.14	41.14
N	223,323	44,461

Appendix 1B: Robustness Checks for Essay 1

Table 1.14 Small Fires (10-500 Acres)

	All Counties	Santa Barbara & Ventura	Los Angeles	Riverside & San Bernardino	Orange County	San Diego
Postfire	0.012***	-0.017*	0.015***	-0.007***	0.010	0.024***
	(0.000)	(0.078)	(0.000)	(0.003)	(0.148)	(0.000)
Ln(Distance)	0.006***	0.021***	0.008***	-0.025***	0.001	0.013***
	(0.000)	(0.004)	(0.000)	(0.000)	(0.883)	(0.000)
FHSZ	0.021***	-0.004	0.067***	-0.027***	0.043***	-0.027***
	(0.000)	(0.819)	(0.000)	(0.000)	(0.000)	(0.001)
Postfire x FSHZ	-0.025***	0.024	-0.036***	-0.013**	-0.070***	0.009
	(0.000)	(0.210)	(0.000)	(0.026)	(0.000)	(0.421)
Ln(Distance) x FHSZ	0.036***	0.012	0.026***	0.030***	0.019**	0.004
	(0.000)	(0.535)	(0.000)	(0.000)	(0.042)	(0.505)
Ln(Distance) x Postfire	0.001	-0.002	-0.011***	0.009***	-0.003	0.003
	(0.482)	(0.766)	(0.000)	(0.000)	(0.531)	(0.469)
Ln(Distance) x Postfire x FHSZ	-0.015***	-0.023	0.019**	-0.005	-0.000	-0.009
	(0.000)	(0.258)	(0.014)	(0.329)	(0.986)	(0.235)
Constant	9.780***	10.756***	10.061***	10.204***	6.049***	9.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	182,172	9,467	60,691	100,286	22,877	15,479
R-squared	0.845	0.821	0.822	0.795	0.772	0.748

Note: this table shows estimates from a model with small-sized fires (less than 500) only using the Estimation Sample of properties that sell within three years of a fire. Robust pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 1.15 Model using Transactions Five Years Before or After a Fire

	All Counties	Santa Barbara & Ventura	Los Angeles	Riverside & San Bernardino	Orange County	San Diego
Postfire	0.030***	0.026***	-0.010***	0.019***	0.024***	-0.069***
	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Distance)	0.010***	0.008	-0.011***	-0.008***	0.009***	0.010***
	(0.000)	(0.129)	(0.000)	(0.000)	(0.000)	(0.000)
FHSZ	0.075***	0.044**	0.062***	0.037***	0.027***	0.031***
	(0.000)	(0.040)	(0.000)	(0.000)	(0.000)	(0.000)
Postfire x FSHZ	-0.032***	0.043*	-0.012	-0.017**	-0.053***	0.028***
	(0.000)	(0.070)	(0.102)	(0.028)	(0.000)	(0.000)
Ln(Distance) x FHSZ	-0.004**	0.030*	0.022***	0.024***	-0.004	-0.002
	(0.014)	(0.098)	(0.000)	(0.000)	(0.305)	(0.342)
Ln(Distance) x Postfire	-0.012***	0.000	0.019***	-0.010***	-0.044***	-0.003**
	(0.000)	(0.979)	(0.000)	(0.000)	(0.000)	(0.024)
Ln(Distance) x Postfire x FHSZ	0.022***	-0.016	-0.010**	-0.001	0.031***	-0.019***
	(0.000)	(0.432)	(0.036)	(0.862)	(0.000)	(0.000)
	9.482***	9.480***	9.616***	11.837***	8.562***	9.255***
Constant	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	331,796	10,585	103,661	103,518	54,237	59,795
R-squared	0.826	0.787	0.772	0.821	0.799	0.776

Note: This dataset was constructed in the same way as the Estimation Sample but includes all transactions within five years of a fire rather than three. Robust pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 1.16 Effects by FHSZ Rating

	All Counties
Postfire	0.041***
	(0.000)
Ln(Distance)	0.013***
	(0.000)
Moderate	0.065***
	(0.000)
High	0.015**
	(0.017)
Very High	0.088***
	(0.000)
Postfire x Moderate	-0.042***
	(0.000)
Postfire x High	-0.014
	(0.133)
Postfire x Very High	-0.021***
	(0.000)
Ln(Distance) x Moderate	-0.045***
	(0.000)
Ln(Distance) x High	-0.026***
	(0.000)
Ln(Distance) x Very High	0.004*
	(0.063)
Ln(Distance) x Postfire	-0.011***
	(0.000)
Ln(Distance) x Postfire x Moderate	-0.013*
	(0.063)
Ln(Distance) x Postfire x High	0.020***
	(0.008)
Ln(Distance) x Postfire x Very High	0.012***
	(0.000)
Constant	9.551***
	(0.000)
Observations	206,841
R-squared	0.830

Robust pval in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 1.17 Barrier Highway Treatment

	No Interactions	Interactions
Postfire	0.055***	0.056***
	(0.000)	(0.000)
Ln(Distance)	0.012***	0.003
	(0.000)	(0.151)
FHSZ	0.033***	0.032***
	(0.000)	(0.922)
Between	0.008***	0.00
	(0.003)	(0.028)
Distance to Highway	-4.27e-6***	-4.06e-6***
	(0.000)	(0.000)
Postfire x Between	-0.030***	-0.028***
	(0.000)	(0.000)
Ln(Distance) x Between		0.016***
		(0.000)
Ln(Distance) x Between x Postfire		-0.011***
		(0.000)
Constant	9.785***	9.783***
	(0.000)	(0.000)
Observations	75,302	74,830
R-squared	0.853	0.853

Note: this table shows results from an alternate model using "Between", meaning between a highway and the forest, as an indicator of risk rather than FHSZ. The positive coefficient on Distance x Between implies that price increases as you get farther away. Robust pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 1.18 Models with Properties up to 5 km

	All Counties	Santa Barbara & Ventura	Los Angeles	Riverside & San Bernardino	Orange County	San Diego
Postfire	0.039***	0.007	-0.011***	0.026***	0.006	-0.064***
	(0.000)	(0.545)	(0.000)	(0.000)	(0.267)	(0.000)
Ln(Distance)	0.008***	0.028***	-0.008***	-0.007***	0.011***	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FHSZ	0.070***	0.064**	0.057***	0.029***	-0.023**	0.005
	(0.000)	(0.012)	(0.000)	(0.000)	(0.013)	(0.341)
Postfire x FSHZ	-0.017***	0.052*	0.022**	-0.012	-0.014	0.038***
	(0.000)	(0.069)	(0.010)	(0.145)	(0.192)	(0.000)
Ln(Distance) x FHSZ	0.001	0.023	0.027***	0.021***	-0.011**	-0.002
	(0.487)	(0.267)	(0.000)	(0.000)	(0.018)	(0.419)
Ln(Distance) x Postfire	-0.007***	-0.020**	0.010***	-0.007***	-0.027***	-0.008***
	(0.000)	(0.030)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Distance) x Postfire x FHSZ	0.019***	0.014	0.008	0.001	0.012*	-0.019***
	(0.000)	(0.559)	(0.175)	(0.850)	(0.055)	(0.000)
Constant	9.615***	8.659***	9.757***	11.948***	8.479***	9.258***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	150,523	5,635	42,241	54,482	21,901	26,264
R-squared	0.843	0.786	0.784	0.846	0.807	0.788

Note: this table shows results using a dataset constructed in the same way as the Estimation Sample but includes properties up to 5 km from a fire only. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.19 Models with Properties up to 15 km

	All Counties	Santa Barbara & Ventura	Los Angeles	Riverside & San Bernardino	Orange County	San Diego
Postfire	0.041***	0.013	-0.005*	0.030***	0.092***	-0.057***
	(0.000)	(0.257)	(0.058)	(0.000)	(0.000)	(0.000)
Ln(Distance)	0.014***	0.023***	-0.004***	-0.009***	0.016***	0.010***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
FHSZ	0.070***	0.045*	0.038***	0.040***	0.046***	0.013***
	(0.000)	(0.066)	(0.000)	(0.000)	(0.000)	(0.008)
Postfire x FSHZ	-0.015***	0.056**	0.014*	-0.011	-0.082***	0.053***
	(0.000)	(0.047)	(0.085)	(0.196)	(0.000)	(0.000)
Ln(Distance) x FHSZ	-0.008***	0.025	0.020***	0.023***	-0.014***	-0.006**
	(0.000)	(0.207)	(0.000)	(0.000)	(0.000)	(0.020)
Ln(Distance) x Postfire	-0.012***	-0.007	0.011***	0.001	-0.074***	0.001
	(0.000)	(0.303)	(0.000)	(0.318)	(0.000)	(0.440)
Ln(Distance) x Postfire x FHSZ	0.021***	-0.006	-0.004	-0.001	0.059***	-0.031***
	(0.000)	(0.790)	(0.524)	(0.891)	(0.000)	(0.000)
Constant	9.654***	9.423***	9.906***	12.088***	8.991***	9.344***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	221,870	6,729	66,878	67,898	39,926	40,439
R-squared	0.823	0.793	0.778	0.838	0.816	0.785

Note: this table shows results using a dataset constructed in the same way as the Estimation Sample but includes properties up to 15 km from a fire. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.20 Model with Postfire Interacted with 1-km Bins that Measure Distance from Fire

	All Counties	P-value
Postfire	-0.037***	(0.000)
0-1 km	-0.108***	(0.000)
1-2 km	-0.092***	(0.000)
2-3 km	-0.090***	(0.000)
3-4 km	-0.091***	(0.000)
4-5 km	-0.102***	(0.000)
5-6 km	-0.104***	(0.000)
6-7 km	-0.073***	(0.000)
7-8 km	-0.042***	(0.000)
8-9 km	-0.025***	(0.000)
Postfire x 0-1 km	-0.024***	(0.002)
Postfire x 1-2 km	-0.024***	(0.000)
Postfire x 2-3 km	-0.012**	(0.037)
Postfire x 3-4 km4	-0.021***	(0.000)
Postfire x 4-5 km	-0.027***	(0.000)
Postfire x 5-6 km	-0.021***	(0.000)
Postfire x 6-7 km	-0.017***	(0.001)
Postfire x 7-8 km	-0.004	(0.487)
Postfire x 8-9 km	-0.016***	(0.008)
FHSZ	0.070***	(0.000)
Ln(Distance) x FHSZ	0.002	(0.342)
Post x FHSZ	-0.015***	(0.000)
Ln(Distance) x Post	0.000	(0.926)
Ln(Distance) x Post x FHSZ	0.011***	(0.000)
Constant	9.691***	(0.000)
Observations	206,841	
R-squared	0.830	

Note: this table presents estimation results from a model where distance from a fire is measured in 1-km bins. We use all counties and include both FHSZ and non-FHSZ properties. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 1C: Previous Robustness Checks

Robustness Check	Note
Exclude years affected by the housing crisis (2007-2009)	This was tested in a previous iteration with data on transactions within five years of the nearest fire and results were not significantly different
Exclude properties that experience multiple fires in the past five years	This was tested in a previous iteration with data on transactions within five years of the nearest fire and results were not significantly different

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CHAPTER 2. Heterogeneous Preferences Over Recreation Sites in Wildfire Prone Areas

2.1 Introduction

Residents and visitors to southern California benefit from ecosystem services provided by four major National Forests that surround the Los Angeles Basin – Angeles, Cleveland, Los Padres, and San Bernardino National Forests. These forests cover the San Gabriel, San Emigdio, San Jacinto, and San Bernardino mountains, that shield the cities from the Mojave Desert. Areas adjacent to national forests are pleasant to live in, offering views and solace from the busier urban area. In addition, there are many recreation opportunities – trails, picnic areas, fishing, visitor centers, and other attractions located in the national forests. This essay examines visitor preferences for the environmental attributes of national forest sites, including vegetation, water, and wildfire history.

Preferences regarding wildfire history are especially relevant for this area, as these forests are frequently affected by fire. The four national forests are largely covered by chaparral, a vegetation characterized by dense, dry shrubs and grasses, found primarily in southern California and northern Mexico, though oak and pine dominate in higher elevations. Chaparral in southern California burns every 30 years or more in high-intensity stand-replacing fires that play an important part in regeneration (Moritz et al. 2014; Rundel 2018). However, this unique environment is home to millions of people in the Los Angeles and San Diego metro areas, whose presence changes the natural fire regime. Humans not only suppress or contain natural wildfires, potentially leaving dry fuel to spark another, but also cause as many as 84% of all wildfires through negligence or intentional actions (Balch et al. 2017). Smaller, less severe forest wildfires may shut down a road for a few days; larger fires can cause mass devastation. In 2002, the Curve Fire destroyed 20,000 acres of forest, and affected campsites were closed for nearly a decade afterward. The 2009 Station Fire burned for over a month along the entire Angeles Crest Highway, a major road that cuts from one side of the Angeles National

Forest to the other. Charred trees left in its wake are still visible today in many campgrounds, trails, and picnic areas along the highway.

We use evidence from choice experiments to explore how the visible effects of past wildfires might affect recreation decisions by visitors to National Forests, and, given the diverse user groups in Southern California, we also test for systematic differences in preferences for recreation sites in wildfire prone areas. The simplest way to estimate preference heterogeneity with discrete choice data is to interact demographic variables with choice attributes in a conditional logit model. However, the conditional logit model has fairly rigid assumptions about choice behavior, specifically it suffers from independence of irrelevant alternatives (IIA). In addition to conditional logit models, we turn to random parameters logit and latent class logit models to relax the IIA assumption and explore heterogeneity.

2.2 Literature on Effects of Wildfire on Recreation Demand

The earliest studies to consider the impact of wildfire on recreation tend to use direct approaches such as contingent valuation. Vaux, Gardner, and Mills (1984) use contingent valuation to estimate willingness to pay for entry to recreation sites recovering from wildfires of varying intensity with a group of 69 university students in California. They find that less intense fires have beneficial effects, whereas more severe fires decrease willingness to pay for recreation. This result suggests that there may be some groups of visitors who prefer sites affected by moderate fires – these visitors could be interested in the new growth that occurs after a fire or may be attracted by clearer hiking paths. Most of the wildfire valuation literature of the past two decades uses revealed preferences methods to estimate recreational welfare impacts of fire and suggests the effects vary significantly over time and across recreational groups.

There is evidence of time-varying impacts of wildfire – in some cases, there are per-trip welfare benefits directly after a fire, which then decline quickly before recovering. Englin, Loomis, and

González-Cabán (2001) estimate an initial sharply positive trip response lasting two years after fires in the western US (forests in Colorado, Wyoming, and Idaho), followed by a decline in visitation before a final slow recovery in trip numbers. Hilger and Englin (2009) as well as Englin, Holmes, and Lutz (2008) affirm this result – a short term increase in trips – using hiking trip data from the Cascade Mountains in Washington. However, Boxall and Englin (2008) present conflicting evidence. Using pooled RP-SP models, they incorporate correlation between the respondents' series of choices by using dummy variables for lagged choices. In models allowing for state dependence they observe initial decreases in visitation, while those without state dependence mimic the short-term increase pattern found in other papers.

Potential differences across user groups creates another potential source of heterogeneity. Loomis, González-Cabán, and Englin (2001) use a count data travel cost model and find that fires do not affect recreational values equally across hikers and mountain bikers in Colorado. Trips by mountain bikers are adversely affected by a crown fire in terms of both quantity of trips and the value of each trip, while for hikers the number of trips remains steady after a crown fire and per-trip welfare increases. Hesseln et al. (2003) use a Poisson count model and combined RP-SP data and find that while demand by mountain bikers is nearly nonexistent after a wildfire, fire is associated with a decrease in the number of hiking trips but also an increase in per trip net benefits.

Forest recreation studies have focused primarily on preference heterogeneity across management attributes. Applying this framework to wilderness and forest areas, Boxall and Adamowicz (2002) develop a latent class model to explore preferences for wilderness parks in Manitoba, allowing underlying motivations for wilderness trips as well as sociodemographic factors to predict preferences. Their results support significant heterogeneity over preferences for site attributes among the park visitors including management attributes. A study of forest users in Great Britain found significant heterogeneity both between and within user groups (Christie et al. 2007). More specialized user groups within each recreation category (mountain bikers are more specialized than general bikers) had greater willingness to pay for facilities than general forest users. Nordén et al. (2017) also analyze preferences for forest landscapes and facilities across stakeholder groups using random parameters models and latent class models, finding significant differences in their preferences over forest management practices.

Comparing separate models for classes of people is informative when there are distinct groups of recreational users but ignores other potential sources of heterogeneity and is not ideal in a setting where people could participate in many activities on a single trip. At day-use sites in the Angeles National Forest, most visitors are hiking, but a large portion of them also participate in other activities such as relaxing, picnicking, or swimming. An alternate way of modeling heterogeneity across individuals is to use a choice experiment to examine the trade-offs between attributes. In this essay we employ a RUM modeling framework that has been frequently used to examine preferences for water quality and beach attributes (Beharry-Borg and Scarpa 2010; Kosenius 2010; Schaafsma et al. 2014; Peng and Oleson 2017). Given the evidence of heterogeneous preferences over site attributes in the recreation literature (Beharry-Borg and Scarpa 2010; Kosenius 2010; Scarpa and Thiene 2005; Zhang and Sohngen 2018) and in forest management (Christie et al. 2007; Nordén et al 2017; Japelj et al. 2016), our discrete choice experiment examines the role of individual preferences over wildfire-burned areas in forest sites.

This essay has three main contributions: first, efforts to value the effects of wildfire on recreation have concentrated on forest areas. Chaparral has a significantly different wildfire regime and recovery pattern than conifer or hardwood forests, distinguished by intense crown fires which burn everything, but recover quickly. Hence, a fire's impacts on recreation in a chaparral dominated area could look significantly different than in a forested area. Second, the majority of wildfire studies occur in sparsely populated areas, whereas our data comes from one of the largest metropolitan areas in the world. Third, there is little information about systematic heterogeneity within recreationist categories with respect to preference over past wildfires.

2.3 Survey Data and Design

2.3.1 Study Area and Onsite Sampling

The Angeles National Forest spans 700,000 acres of open space only an hour's drive from downtown Los Angeles and receives more than 3 million visits per year (US Forest Service 2001). In addition to visitor's centers and developed recreation areas, it contains all or part of five different designated wilderness areas and manages most of the recently established San Gabriel Mountains National Monument. Data for this study comes from two onsite intercept surveys with follow-up surveys conducted in the Angeles National Forest during consecutive summers. The first onsite intercept survey was conducted June 17 – August 14, 2016 with a follow-up survey conducted November 2016 – February 2017. The second onsite intercept survey conducted June 16 – August 20, 2017 with a follow-up survey conducted December 2017 – February 2018.

For the two intercept surveys we used a random sampling plan which stratified sites according to the day of the week and expected use level. Work shifts were drawn throughout the week where Friday afternoons and weekends had a higher probability of sampling compared to weekday mornings and afternoons, and for each shift two sites were drawn for sampling. Site visitation data from the USFS National Visitor Use Monitoring survey (NVUM) was used to classify sites as high or low use according to number of visits they generally receive on a weekend. Sites classified as high use were over-sampled compared to low-use sites. In 2016 the Angeles National Forest was also being sampled by NVUM, so the sites in our sample were also grouped into three geographic clusters. On any given day, sampling was only conducted in the geographic clusters without active NVUM enumerators. In summer 2017 we sampled at the same set of 39 sites as in 2016, using a similar stratified sampling strategy.

National forest visitors were intercepted as they exited the recreation site. At low-traffic sites, or where the parking lot was easily monitored, enumerators intercepted people as they approached their vehicle for a short questionnaire, while at high-traffic trailheads where that was not possible, visitors were intercepted as they existed the trailhead for their vehicles. To ensure a random selection of people, for each vehicle or group of visitors the person with the most recent birthday was interviewed. For each shift we recorded all exiting vehicle or foot traffic.

Onsite participants answered a short questionnaire that asked respondents for information about their current trip: the length of the visit, what activities they participated in, the number of people in the vehicle, and some information about who they were – gender, age, and racial identity. In addition, all onsite survey respondents were asked to provide an email or mailing address for the online survey. Of 2260 completed onsite surveys in 2016, 1755 (77.7%) provided contact information – 1685 email addresses and 70 mailing addresses. In 2017, 1726 individuals completed an onsite survey, with 1245 (72.1%) providing either an email or mailing address.

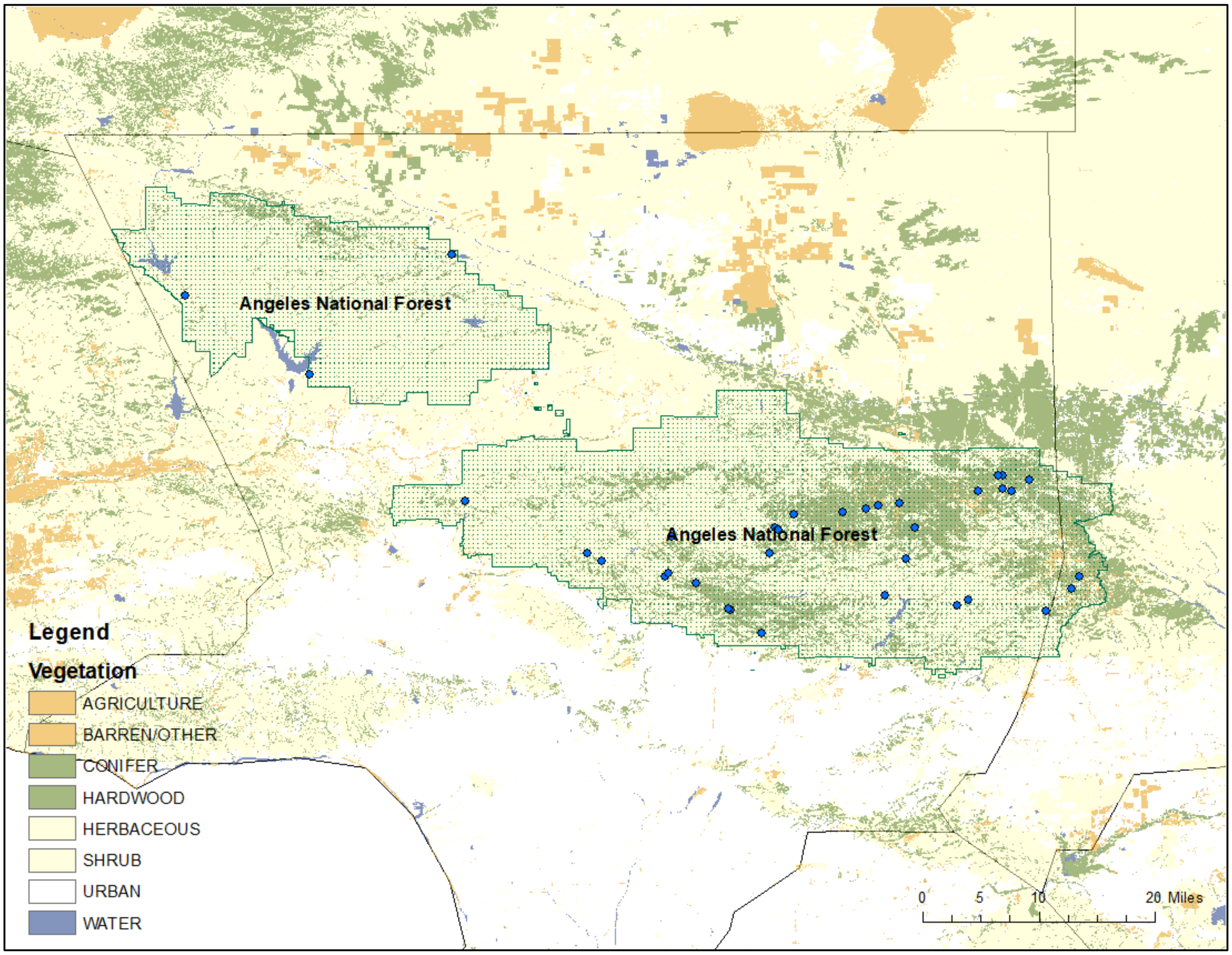

Figure 2.1 Map of Recreation Survey Sites

2.3.2 Online Survey and Choice Experiment Design

The survey was designed in three stages. Forty-nine in-person semi-structured interviews were conducted at recreation sites in July 2015, some of which test our intercept instrument and some of which probed people on their recreation habits and what they might do if a fire occurred nearby. Choice experiment questions were further tested in-person using paper survey instruments followed by cognitive interviews with 15-20 people at several sites in the Angeles National Forest (ANF) in May 2016. In October and November of 2016, the instrument was tested online in a webinar setting in a series of four individual cognitive interviews with people who had been intercepted at a site in the ANF previously and provided an email address. The four major sections of the survey are as follows:

Section 1 primes respondents on the attributes they faced choices over in the choice experiment. Attributes and levels are in Table 2.1. Respondents were also asked to think about attributes located "nearby" and "farther away" from the parking area: nearby is within a 5-minute walk from the parking area, and farther away is between 5 and 60 minutes away from the parking area. Figure 2.2 was used to illustrate the nearby and farther away areas. This allows us to capture differences in preferences for attributes by distance for people who may engage in different activities, e.g. picnicking vs. hiking. **Section 2** consists of information designed to introduce the choice attributes including vegetation types and fire effects followed by the stated preference questions. **Section 3** asks about respondents' habits regarding national forest visits as well as how they receive information about fires and site closures, and additional demographic information was collected in **Section 4**.

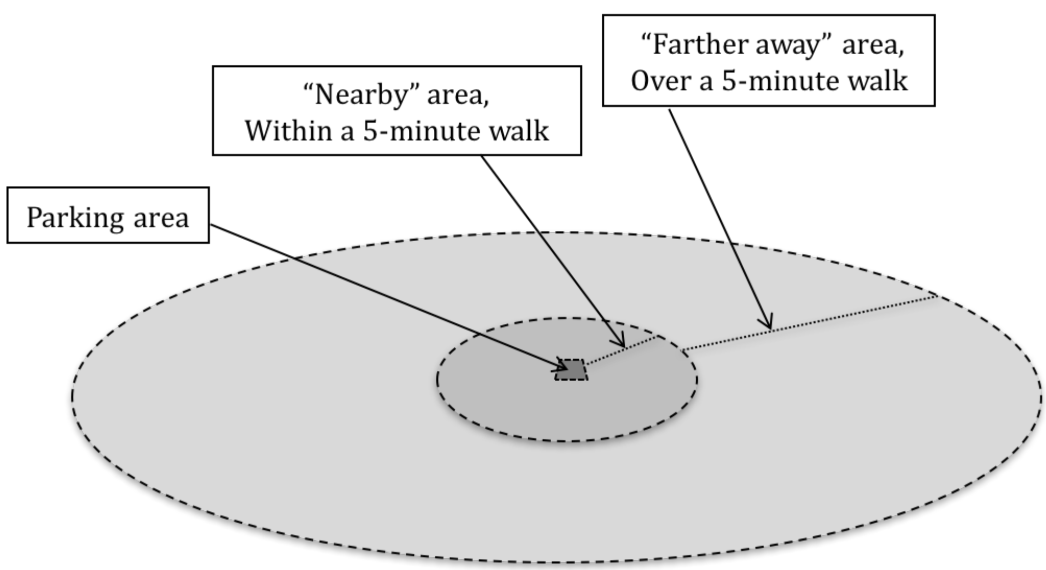

Figure 2.2 Illustration Depicting "Nearby" and "Farther Away" from Parking Area

Respondents from the onsite survey ranged from people living in nearby communities to international visitors. To ensure that they saw realistic choices in the online survey, the choice experiment section was tailored to respondents according to the distance between their home zip code and a mid-point in the Angeles National Forest. The survey attribute levels and combinations were altered between 2016 and 2017 to allow for a greater spread in the distance variable and to increase the D-efficiency of the design. All other attribute levels and elements of the survey were the same.

In 2016 (Round 1) respondents were categorized into four origin distance zones, (1) less than 60 miles, (2) 60-150 miles, (3) 150-300 miles, and (4) over 300 miles. Respondents in zones 1, 2, and 3 saw different distances from home in their options, tailored to their distance from ANF. Those in bin 4, living more than 300 miles away from the Angeles National Forest, received a version of the survey without choice experiment questions.

Three choice sets were shown to each respondent, and the overall design was grouped into 12 blocks of 3 questions each. In each of three scenarios they faced, respondents were asked to choose between two unlabeled National Forest sites to visit. These sites varied according to a) vegetation nearby and farther away from the parking area, b) presence of lakes or streams nearby and farther away from the parking area, c) fire history farther away,[9] and d) driving distance from home. Choice experiment attributes and levels are in Table 2.1, and an example of a question format is found in Figure 2.3. As shown in Table 2.1, driving distance from home is equal to baseline miles (ranging from 0 to 60) plus 20 if the respondent was in **zone 1**, plus 60 if in **zone 2**, and plus 120 if in **zone 3**.

The relevant choice experiment elements that vary by survey version are: choice set block and distance bin. There are 36 combinations of block and bin. In 2016, each survey version was also

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[9] The survey stated that the sites we were asking about "are safe" and "have no history of fire near the parking area." This was done to alleviate safety concerns that arose during pre-testing.

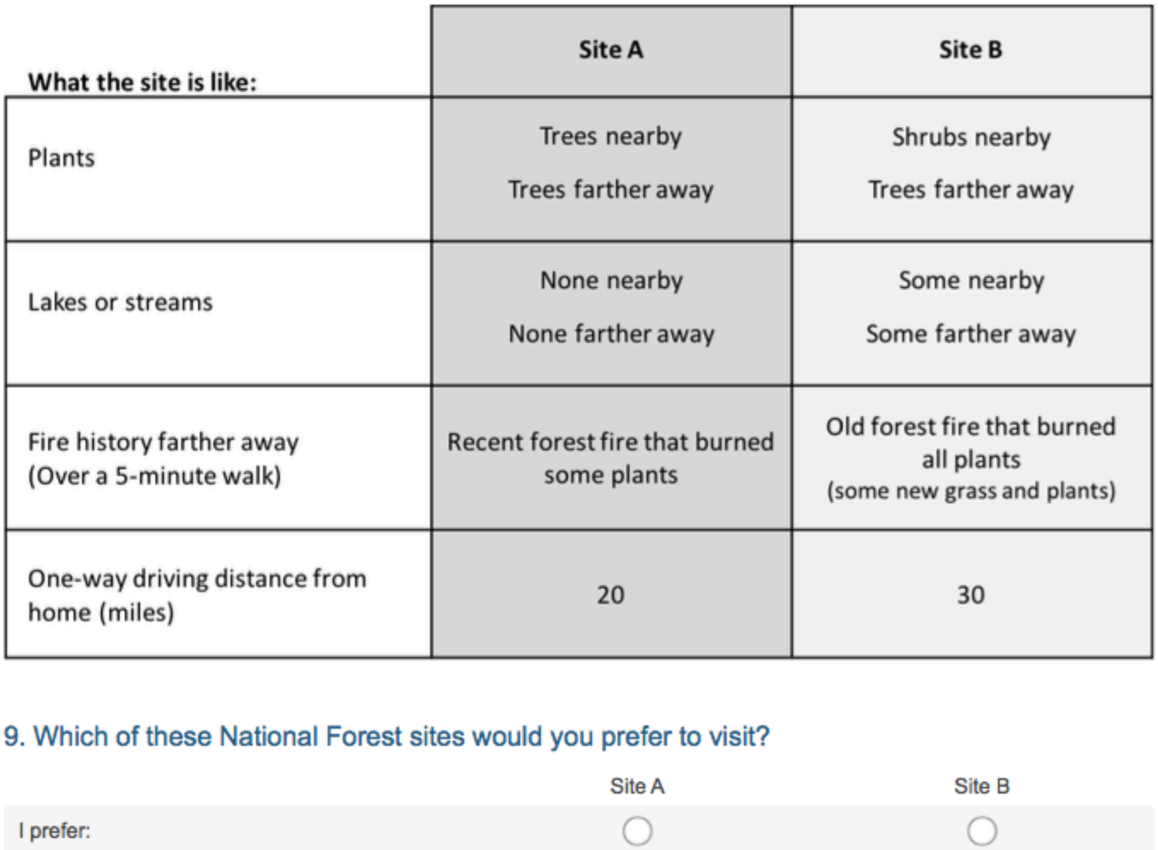
available in Spanish. **Respondents in 2017 (Round 2)** were also categorized into four distance zones, (1) less than 50 miles, (2) 50-100 miles, (3) 100-300 miles, and (4) over 300 miles. Again, those in the first three zones see site choices with different distances, while those in zone 4, living more than 300 miles away from the Angeles National Forest, received a version of the survey without the choice experiment. In 2017 the Spanish version of the questions were not offered because only 14 people opted to complete the 2016 survey in Spanish. As shown in Table 2.1, for 2017 the baseline miles used for the driving distance attribute was given a greater spread, ranging from 0 to 100, plus 10 if the respondent was in **zone 1**, plus 50 if in **zone 2**, and plus 100 if in **zone 3**. Round 2 choice sets were grouped into 14 blocks of three questions each, resulting in 42 survey versions for the combinations of choice set blocks and distance zones.

In both 2016 and 2017, NGene software (ChoiceMetrics 2014) was used to develop the attribute combinations using a design to minimize D-error subject to constraints on the feasible combinations of attributes. The feasibility constraints ensured the types of fire were consistent with the types of vegetation. For example, since shrubs recover quickly and effects of a fire that burned some vegetation would be hard to see, we ruled out an "old" fire if the vegetation was shrubs. Likewise, the fire type could not be a recent shrub fire if the vegetation near and far was trees.

Table 2.1 Attributes and their Levels in 2016 and 2017

Attributes	Levels
Plants	Trees nearby, trees farther away Trees nearby, shrubs farther away Shrubs nearby, trees farther away Shrubs nearby, shrubs farther away
Lakes or streams	Some nearby, some farther away Some nearby, none farther away None nearby, some farther away None nearby, none farther away
Fire history farther away (over a 5-minute walk)	Old forest fire that burned all plants (some new grass and plants) Recent forest fire that burned some plants Recent forest fire that burned all plants Recent shrub fire (some new grass and plants) None visible
One-way driving distance from home (miles) 2016 survey	Zone 1: 20, 30, 40, 60 , 80 Zone 2: 60, 70, 80 , 100, 120 Zone 3: 120, 130, 140, 160, 180
One-way driving distance from home (miles) 2017 survey	Zone 1: 10, 30, 50, 80, 110 Zone 2: 50, 70, 90, 120, 160 Zone 3: 100, 120, 140, 170, 200

Table 2.1 displays choice experiment attributes and levels for 2016 and 2017. The only difference between the two rounds of the survey were in the driving distance levels.



What the site is like:	Site A	Site B
Plants	Trees nearby Trees farther away	Shrubs nearby Trees farther away
Lakes or streams	None nearby None farther away	Some nearby Some farther away
Fire history farther away (Over a 5-minute walk)	Recent forest fire that burned some plants	Old forest fire that burned all plants (some new grass and plants)
One-way driving distance from home (miles)	20	30

9. Which of these National Forest sites would you prefer to visit?

	Site A	Site B
I prefer:	○	○

Figure 2.3 Choice Experiment Question Format

For the online survey, 1755 people total were contacted by email or by mail in Round 1, which ran November 2016 to January 2017: of those, 1685 were email addresses, and 70 were mailing addresses. In Round 2, running from November 2017 to February 2018, 1244 individuals, 1220 by email and 24 by mail. Overall 1054 (35%) responded to both rounds of the survey, 662 (38%) in Round 1 and 392 (32%) in Round 2; 607 of whom saw the choice experiment.

2.4 Econometric Models

The standard framework for analyzing choice experiment data is based on random utility theory (McFadden 1973). We assume that the utility for an individual facing a choice is made of a deterministic component and a random component. The utility function for individual *i* with option *j* is:

$$U_{ij} = \beta X_{ij} + \varepsilon_{ij} \tag{1}$$

Where the observable component βX_{ij} depends on preference parameters β and a vector of attributes X_{ij}, and ε_{ij} is the random or unobservable component. Therefore, the probability that we observe individual *i* select site *j* is the probability that the utility from site *j* was the greatest in the available choice set C:

$$P(j) = P(\beta X_{ij} + \varepsilon_{ij} > \beta X_{ik} + \varepsilon_{ik})\ \forall k \epsilon C \tag{2}$$

When the random error follows a type I extreme value distribution, the probability of observing choice *j* is:

$$P(j) = \frac{exp(\beta X)}{\sum_k exp(\beta X_k)} \tag{3}$$

Estimating this model with a common parameter vector β for the population leads to the conditional logit model. However, given results from prior studies showing that groups of visitors have differing responses to fire damage, we expect to find evidence of preference heterogeneity, and turn to more flexible forms. Three ways of modeling heterogeneity in preferences are explored: introducing demographic interaction terms with the preference parameters within conditional logit; random parameters logit models, which assume a continuous distribution of preference parameters β_i throughout the population; and latent class models, also called finite mixing models, which assume there are discrete groups of preference parameters within the population.

The probability of observing choice *j* in a random parameters set-up is:

$$P(j) = \frac{exp\left(\beta_i X_j\right)}{\sum_k exp(\beta_i X_k)} \tag{4}$$

Here, the β_i is distributed across the population. The difference in estimation between the random parameters logit and conditional logit is that the conditional logit model estimates a population average $\hat{\beta}$ while random parameters logit estimates a mean and standard deviation for $\hat{\beta}_i$ where i = 1, …, I. Although these models allow for preference heterogeneity, they do not lend themselves to explaining the types of people with different preferences (Boxall & Adamowicz 2002). To address this, we also consider latent class models, which assume that preferences systematically vary across classes that, to the researcher, are unobservable. The probability that an individual belongs to a certain class depends on demographics and other respondent characteristics such as attitudes towards the good being evaluated. The choice probability is then defined as the joint probability of observing a choice and the probability of belonging to a class. Suppose individual i belongs to class s in the set of classes S. Then the probability of observing choice j is dependent on class membership:

$$P(\text{site } j \,|\, \text{class } s) = \frac{exp(\beta_s X_j)}{\sum_k exp(\beta_s X_k)} \tag{5}$$

Within class s, the choice probability typically follows a conditional logit. Following Swait (1994) and Boxall and Adamowicz (2002), we assume there is an unobservable class-membership function, where sociodemographic characteristics predict class membership,

$$M_{is}^* = \lambda_s Z_i + \zeta_{is} \tag{6}$$

where M_{is}^* is the class membership latent variable for individual i in class s, Z_i are demographic characteristics, λ_s are parameters to be estimated, and ζ_{is} is a random error term. Assuming the random error follows a type-I extreme value distribution and is independent across individuals and classes, the probability of class membership is

$$P(s) = \frac{exp(\lambda_s Z_i)}{\sum_s exp(\lambda_s Z_i)} \tag{7}$$

Since the choice experiment asked respondents to make tradeoffs between site attributes and distance, marginal rates of substitution estimates are presented as willingness to drive and estimated as the negative of the ratio between the driving distance parameter, β_d, and the site attribute parameter, β_k. For the conditional logit where the average coefficient is estimated, the willingness to drive for attribute *k* estimate is:

$$WTD_i = -\frac{\beta_k}{\beta_d} \tag{8}$$

2.5 Results

Results use data collected from the onsite surveys conducted in 2016 and 2017 and the online surveys conducted winter 2016-2017 and winter 2017-2018. This section describes the demographics of the choice experiment respondents used in the analyses, and results from conditional logit, random parameters logit, and latent class models.

2.5.1 Sample Characteristics

Summary statistics for respondents who received a choice experiment are in Table 2.2 below. Respondents were around forty years old on average. One third of respondents were female, and two-thirds male. They tended to be well off, with more than half of respondents having annual household incomes of $75,000 or more. The largest minority group to respond were Hispanics or Latinos (24% in Round 1 and 30% in Round 2) followed by Asians (16%). Most respondents cited their main activity as hiking or walking – roughly 75% – while another 8-9% were picnicking or relaxing. Many of them are regular forest visitors: 23% visited 11-25 times in the past two years, and 33% visited more than 25 times in the past two years.

The respondents were asked to rate how important certain site attributes are to their site choice prior to completing the choice experiment. Results from these attitudinal questions show that most people agreed that the presence of water and plant type at recreation sites affects their decision to visit. However, they were split on whether the presence of burned vegetation affects their decision; 32% strongly disagreed or somewhat disagreed, 34% were neutral, and the last 34% somewhat agreed or strongly agreed—evidence of substantial heterogeneity. A majority were neutral or not concerned about safety or air quality at sites with visible fire damage. The majority also did not have experience with wildfires affecting their planned forest visits; 58% had never cancelled a forest visit because of an ongoing wildfire. In the extended models we explore whether experience with fire significantly affects preferences for fire history attributes.

Table 2.2 Summary Statistics for Choice Experiment Respondents

		Choice Experiment Sample			
	Variable	Mean	Std dev	Min	Max
Demographics	Age	41	15	18	87
	Has children	0.30	0.46	0	1
	College degree	0.67	0.47	0	1
	Employed full time	0.63	0.48	0	1
	Gender	0.67	0.47	0	1
	Hispanic	0.27	0.45	0	1
	Asian	0.16	0.37	0	1
	White	0.57	0.49	0	1
	Income ($1000s)	101	67.5	12.5	250
Experience with site closure	Experience	0.83	0.38	0	1
Likert (1/5)	Air quality affects decision-making	2.7	1.3	1	5
	Presence of burned plants affects decision-making	2.9	1.1	1	5
	Vegetation type affects decision-making	3.2	1.1	1	5
	Safety concerns affect decision-making	2.4	1.3	1	5
	Water affects decision-making	3.6	1.1	1	5
	Wildfires are natural	4.3	1.0	1	5
Main activity	Hiking	0.72	0.45	0	1
	Relaxing / Picnicking	0.08	0.27	0	1

Table 2.2 describes the sample of respondents used in the choice experiment analysis. Annual household income is converted to a continuous measure using midpoints of the following categories: Less than $25,000; $25,000-49,999; $50,000-74,999; $75,000-99,999; $100,000-149,999; $150,000-199,999; Over $200,000 (coded as $250,000). Experience means they indicated that they had altered or cancelled a trip due to concerns about site closure or health, or that they experienced actual site closure due to fire.

2.5.2 Conditional Logit Models

Table 2.3 shows the results of the conditional logit model. The conditional logit model correctly predicts the preferred alternative about 70% of the time using the option with the largest probability as the prediction criteria. The conditional logit coefficients for all the site attributes have the expected sign, with trees being preferred vegetation over shrubs, water is a positive attribute, and fire damage a negative attribute in general. The omitted vegetation attribute level is "shrubs nearby and shrubs farther away" – the results clearly show a strong preference for tree cover, especially locations with trees both nearby and farther away. Similarly, compared to sites with no water nearby, sites with lakes or streams were preferred, with the largest coefficient on the attribute for water both nearby and farther away. The fire history attributes are more mixed. Though all the coefficients are negative and significant at the 10% level, there is less strong evidence for the parameters on types of fires where some vegetation may be recovering (old forest fires and recent shrub fires). There is much stronger evidence that recent forest fires are undesirable.

Three additional models introduce heterogeneity in the conditional logit by interacting individual characteristics with site attributes. Conditional logit models with interaction terms are presented in Table 2.4. Model 2 includes the interaction of income[10] with distance; Model 3 interacts all fire attributes with a dummy variable for experience with fire; and Model 4 interacts all fire attributes with a dummy variable for Hispanic. Estimates indicate neither income nor experience with decision-making over fire-affected sites contributes to heterogeneity. Although the interaction was insignificant, the model fit criteria AIC and BIC as well as the log likelihood suggest that Model 2 which included an interaction between driving distance and income is a better fit for the data than the conditional logit with no interactions. However, there is evidence that on average Hispanic respondents have a lower preference for sites where water is only available farther away, and that they have a higher preference for trees nearby. In net, recent shrub fires at recreation sites do not matter as much to Hispanic respondents; a linear test of the hypothesis that the sum of the coefficients on recent shrub fire and the interaction are equal to zero is insignificant. Forest managers in Southern California are

[10] In the interaction term, income was re-scaled to $100,000s

interested in expanding outdoor access to underserved minority populations. Our results suggest minority populations could recreate in a significantly different way than other forest users.

Table 2.3 Conditional Logit Model Parameter Estimates

Attribute	Level	Model 1
Vegetation	Shrubs near, trees far	0.670***
		(0.000)
	Trees near, shrubs far	0.646***
		(0.000)
	Trees near, trees far	1.149***
		(0.000)
Water	None near, some far	1.032***
		(0.000)
	Some near, none far	1.014***
		(0.000)
	Some near, some far	1.405***
		(0.000)
Fire History (farther away)	Old forest fire that burned all plants	-0.194*
		(0.057)
	Recent forest fire that burned all plants	-1.054***
		(0.000)
	Recent forest fire that burned some plants	-0.341***
		(0.001)
	Recent shrub fire	-0.178*
		(0.055)
Driving Distance (one-way)	Distance	-0.014***
		(0.000)
Observations		4,968
AIC		3069.75
BIC		3141.37
Log Likelihood		-1523.88

P-values in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.4 Conditional Logit Model with Interactions

Attribute	Level	Model 2	Model 3	Model 4
Vegetation	Shrubs near, trees far	0.726***	0.672***	0.612***
		(0.000)	(0.000)	(0.000)
	Trees near, shrubs far	0.682***	0.653***	0.555***
		(0.000)	(0.000)	(0.000)
	Trees near, trees far	1.209***	1.152***	1.089***
		(0.000)	(0.000)	(0.000)
Water	None near, some far	1.048***	1.035***	1.126***
		(0.000)	(0.000)	(0.000)
	Some near, none far	1.046***	1.021***	1.025***
		(0.000)	(0.000)	(0.000)
	Some near, some far	1.510***	1.414***	1.437***
		(0.000)	(0.000)	(0.000)
Fire History (farther away)	Old forest fire that burned all plants	-0.173	-0.091	-0.112
		(0.120)	(0.650)	(0.346)
	Recent forest fire that burned all plants	-1.104***	-0.848***	-1.146***
		(0.000)	(0.000)	(0.000)
	Recent forest fire that burned some plants	-0.344***	-0.283	-0.367***
		(0.002)	(0.146)	(0.002)
	Recent shrub fire	-0.167*	-0.393*	-0.281***
		(0.095)	(0.064)	(0.009)
Driving distance (one-way)	Distance	-0.013***	-0.015***	-0.015***
		(0.000)	(0.000)	(0.000)
Income x Distance	Income by distance	-0.003		
		(0.176)		
Experience x Fire	Old forest fire that burned all plants		-0.132	
			(0.540)	
	Recent forest fire that burned all plants		-0.256	
			(0.240)	
	Recent forest fire that burned some plants		-0.078	
			(0.707)	
	Recent shrub fire		0.263	
			(0.248)	

Table 2.4 (cont'd)

Attribute	Level	Model 2	Model 3	Model 4
Hispanic x Veg	Shrubs near, trees far			0.262
				(0.383)
	Trees near, shrubs far			0.412*
				(0.087)
	Trees near, trees far			0.259
				(0.427)
Hispanic x Water	None near, some far			-0.398**
				(0.041)
	Some near, none far			0.097
				(0.671)
	Some near, some far			-0.033
				(0.892)
Hispanic x Fire	Old forest fire that burned all plants			-0.313
				(0.182)
	Recent forest fire that burned all plants			0.325
				(0.214)
	Recent forest fire that burned some plants			0.161
				(0.538)
	Recent shrub fire			0.393*
				(0.070)
Hispanic x Distance	Distance			0.001
				(0.802)
Observations		4,290	4,968	4,938
AIC		2623.00	3073.86	3044.89
BIC		2699.36	3171.52	3187.99
Log Likelihood		-1299.50	-1521.93	-1500.44

Table 2.4 shows parameter estimates from conditional logit models with interactions. Model 2 includes an interaction between distance and income; Model 3 includes interactions between dummy variables for experience with fire-affected sites and fire attributes; and Model 4 includes interactions of all attributes with an indicator variable for whether the respondent is Hispanic. where site choice is determined by the attributes of the sites. Standard errors are clustered at the individual level. P-values in parentheses: *** p<0.01, ** p<0.05, * p<0.1

2.5.3 Random Parameters Logit Model

The random parameters logit model allows for taste heterogeneity by assuming a continuous distribution of parameters across the population. In the specification used, vegetation, water, and fire attributes are assumed to have a normal distribution. Use of a normal distribution allows for the fact that any attribute could be positive or negative to different people. We expect that for the vegetation and water attributes, there may be some people who care more strongly about tree cover or bodies of water nearby and others who care more strongly about having those attributes farther away. In addition, in pre-testing, some respondents indicated an interest in recreation sites with visible fire effects, suggesting there could be heterogeneity in preferences for sites with fire history.

Model 5 assumes that all site attributes (vegetation, water, and fire history) are randomly distributed in the population and independent from each other, while preferences for driving distance are fixed. Table 2.5 reports coefficients and standard errors for the random parameters. Because we observe repeated choices by individuals, the model was estimated as a panel. In Model 6, we assume preferences for water are also fixed in the population but allow preferences for vegetation and fire history to be randomly distributed and correlated with each other. Table 2.5 also reports coefficient estimates for the correlated model, and the covariance matrix between correlated random attributes is found in the appendix. Although a joint significance test of the off-diagonal elements is significant at the 1% level, only two attributes have significant covariance variation between their preference distributions at the 10% level. Preferences for trees nearby and trees farther away are significantly positively correlated with preferences for trees nearby and shrubs farther away. Preferences for recent shrub fire and recent forest fire that burned some plants are also significantly positively correlated with each other – these two fires are likely both thought of as less severe than a forest fire that burns all plants, but because they are recent, still have some significant impact on the landscape. Overall the random parameters logit models suggest that not only are preferences over fire history heterogeneous, but the standard deviations are large compared to the coefficient, which indicates that there are visitors for whom signs of a previous fire are a positive attribute.

Table 2.5 Random Parameters Logit Models with and without Correlation between Attributes

		Model 5		Model 6	
Attribute	Level	Coef.	Std. Dev.	Coef.	Std. Dev.
Vegetation	Shrubs near, trees far	0.879***	0.378	1.020***	0.267
		(0.000)	(0.362)	(0.000)	(0.483)
	Trees near, shrubs far	0.891***	1.047***	1.018***	1.527***
		(0. 000)	(0.290)	(0.000)	(0.000)
	Trees near, trees far	1.559***	0.865***	1.816***	1.324***
		(0. 000)	(0.227)	(0.000)	(0.000)
Water	None near, some far	1.425***	-0.213	1.609***	
		(0. 000)	(0.365)	(0.000)	
	Some near, none far	1.396***	0.397	1.603***	
		(0. 000)	(0.365)	(0.737)	
	Some near, some far	1.959***	0.541	2.219***	
		(0. 000)	(0.381)	(0.000)	
Fire History (farther away)	Old forest fire that burned all plants	-0.248*	0.825***	-0.321**	0.574*
		(0. 074)	(0.277)	(0.034)	(0.050)
	Recent forest fire that burned all plants	-1.432***	-1.044***	-1.702***	1.581***
		(0. 000)	(0.303)	(0.000)	(0.000)
	Recent forest fire that burned some plants	-0.465***	1.013***	-0.617***	1.592***
		(0. 000)	(0.331)	(0.001)	(0.000)
	Recent shrub fire	-0.280**	0.863**	-0.289*	1.494***
		(0. 033)	(0.370)	(0.073)	(0.000)
Driving Distance (one-way)	Distance	-0.020***		-0.022***	
		(0.000)		(0.010)	
Observations		4,968		4,968	
AIC		3060.11		3073.86	
BIC		3196.83		3327.78	
Log Likelihood		-1509.05		-1497.93	
Correlation		No		Yes	

Note: Model 5 allows vegetation, water, and fire history parameters to be randomly distributed in the population. Model 6 only allows vegetation and fire history to be randomly distributed, and also allows the random parameters to be correlated with each other. Coefficient and p-values are shown here, and variance-covariance matrix estimates for the random parameters shown in the appendix. *** p<0.01, ** p<0.05, * p<0.1

2.5.4 Latent Class Models

If preferences are not continuously distributed across individuals but characterized by discrete classes of people with similar average preferences within classes, latent class models may be a better fit. An advantage of latent class models is that they allow class membership to be determined by demographic variables, which can help with understanding drivers of preferences among forest users. The specification in Model 7 allows children (binary), income (continuous), and Hispanic (binary) to determine class membership. The log-likelihood of the children, income, and Hispanic model improved significantly compared to a model with no demographics. However, models with more demographic variables such as gender and age performed poorly (singular variance matrix) or offered little improvement to the selected model. All latent class models are estimated using the expectation maximization algorithm (Pacifico and Yoo 2013).

When estimating latent class models, it is also necessary to determine the number of classes estimated. Because likelihood ratio tests are not possible with non-nested models, information criteria such as the AIC, CAIC, and BIC are frequently used in model selection (Dimitropoulos et al. 2016; Kermagoret et al. 2016; Von Haefen and Domanski 2018). Simulation studies have found that more parsimonious criteria such as CAIC, BIC, and bootstrapped LR test outperform AIC in selecting the true model (Tein et al. 2013). Using both the CAIC and BIC as model selection criteria, we prefer two-class models after testing the performance of 2, 3, 4, and 5-class models. Both information criteria also suggest an improvement over the conditional logit model. Table 2.6 shows a comparison of results for different numbers of classes in the latent class model.

Table 2.6 Comparison of results for different number of latent classes

Number of classes	Log-likelihood (LL)	Number of parameters	CAIC	BIC
2	-1250.385	26	2697.576	2671.576
3	-1237.862	41	2786.073	2745.073
4	-1208.098	56	2840.087	2784.087
5	-1189.758	71	2916.948	2845.948
6	-1179.217	86	3009.409	2923.409
7	-1174.698	101	3113.913	3012.913

Table 2.7 shows results from the 2-class latent class model that uses children, income, and Hispanic in the class membership equations. The prior probabilities of class membership predict that 90% of respondents are in Class 1, while 10% of respondents are in Class 2. Parameter estimates for respondents in Class 1 are similar to those in the conditional logit and random parameters models with positive preferences for trees and water and recreation sites, and negative preferences for recent forest fires. The two fire attributes significant at the 10% level are a recent forest fire that burned some plants and a recent forest fire that burned all plants. The coefficients on the socio-demographic variables are standardized to zero in a reference class (Class 2), indicating that those with a higher annual household income are less likely to be in Class 1 compared to Class 2, and those with children are more likely to be in Class 1 than Class 2.

In the second class of respondents they also have a significant, negative probability of choosing a recreation site with a recent forest fire that burned all plants. However, of all the environmental attributes, vegetation, water, and past fires, that was the only significant attribute level. In both Class 1 and Class 2 the driving distance attribute is negative and significant. Those without children and with a higher annual household income are more likely to be in Class 2 than in Class 1, where the only characteristics influencing decisions are distance and a severe recent fire. This subset of visitors might be driving the large amounts of heterogeneity seen in the RPL results.

Two groups of people are likely to be of interest to forest managers in the national forests around southern California: the Angeles National Forest is one of the most important outdoor recreation areas for the city of Los Angeles, whose population is half Hispanic. However, minorities are traditionally underrepresented among outdoor recreation visitors (Flores et al. 2018). In keeping with other literature which examines heterogeneity by activity group, we also include a dummy variable for hiking equal to one if the visitor cited hiking as their main activity. The two-class latent class model with Hispanic and Hiker determining class membership is reported in Table 2.8. The model results show that Hispanic respondents are significantly more likely to be in Class 2 than Class 1. The preferences in Class 2 are fairly consistent with results from Model 4 (conditional logit with Hispanic interacted with site attributes). In general, individuals in Class 2 are less sensitive to driving distance than those in Class 1, although it is still negative and significant. They have stronger preferences for trees as opposed to shrubs, and for water at the site. Compared to people in Class 1, for whom all recent fires have negative and significant coefficients, people in Class 2 are less sensitive to fire. The only fire type with a significant coefficient is for a recent forest fire that burned all plants farther away from the parking area. Note however, in models (not shown) where the income and children variables are also included, the Hispanic and hiker variables become insignificant at predicting class membership and class attribute preferences are similar to model 7.

Table 2.7 Latent Class Model with Children, Income, and Hispanic

		Model 7	
		Class 1	Class 2
Driving Distance (one-way)	Distance	-0.015***	-0.023***
		(0.000)	(0.010)
Vegetation	Shrubs near, trees far	1.491***	0.109
		(0.001)	(0.827)
	Trees near, shrubs far	1.408***	-0.091
		(0.004)	(0.824)
	Trees near, trees far	2.336***	0.098
		(0.000)	(0.892)
Water	None near, some far	1.946***	0.272
		(0.000)	(0.607)
	Some near, none far	2.322***	-0.093
		(0.002)	(0.874)
	Some near, some far	2.812***	0.465
		(0.000)	(0.439)
Fire History (farther away)	Old fire that burned all plants	-0.298	-0.086
		(0.216)	(0.750)
	Recent fire that burned all plants	-1.117***	-1.488***
		(0.000)	(0.000)
	Recent fire that burned some plants	-0.587*	-0.443
		(0.071)	(0.214)
	Recent shrub fire	-0.156	-0.458*
		(0.569)	(0.095)
Class Membership	Has children under 18	0.738**	
		(0.020)	
	Income	-0.005**	
		(0.049)	
	Hispanic	0.154	
		(0.651)	
	Constant	0.589	
		(0.552)	
Membership Share		0.90	0.10
Observations	2,115		
CAIC	2697.58		
BIC	2671.58		
Log Likelihood	-1250.38		

Table 2.8 Two-Class Latent Class Model with Hispanic and Hiking

		Model 8	
		Class 1	Class 2
Driving Distance (one-way)	Distance	-0.019***	-0.010*
		(0.000)	(0.061)
Vegetation	Shrubs near, trees far	0.322	2.031
		(0.138)	(0.194)
	Trees near, shrubs far	0.196	2.086
		(0.400)	(0.130)
	Trees near, trees far	0.591*	3.102*
		(0.086)	(0.091)
Water	None near, some far	0.763***	2.112***
		(0.002)	(0.004)
	Some near, none far	0.465	3.188*
		(0.133)	(0.072)
	Some near, some far	0.910***	3.450**
		(0.001)	(0.045)
Fire History (farther away)	Old fire that burned all plants	-0.053	-0.687
		(0.789)	(0.108)
	Recent fire that burned all plants	-1.222***	-1.062**
		(0.000)	(0.012)
	Recent fire that burned some plants	-0.329*	-0.612
		(0.078)	(0.344)
	Recent shrub fire	-0.381**	0.011
		(0.022)	(0.982)
Class Membership	Hispanic	-0.712**	
		(0.034)	
	Hiker	0.145	
		(0.608)	
	Constant	2.090***	
		(0.000)	
Membership share		0.92	0.08
Observations	2,086		
AIC	2515.69		
BIC	2656.76		
Log Likelihood	-1212.80		

2.6 Willingness to Drive for Attributes

In choice experiments, a common way to compare the strength of preferences across models to express them in terms of people's willingness to trade off one attribute to obtain another. In this section, the estimated preference parameters are used to compute the additional distance an individual would drive one way for a change in a site attribute, the willingness to drive (WTD)[11]. For the conditional logit and random parameters models we estimated average willingness to drive for a change in attributes, and this was computed using the full sample. Model 1 is conditional logit with no interactions, Model 2 is conditional logit with distance x income, Model 3 is conditional logit with experience x fire history, and Model 4 is conditional logit with Hispanic x all attribute interactions. Models 5 and 6 are random parameters logit with and without correlation, respectively. Model 7 is the two-class latent class model with children, annual household income, and Hispanic determining class membership and Model 8 is a two-class latent class model with Hispanic and hiking determining class membership.

In all the models presented, willingness to drive for vegetation and water attributes is positive, while willingness to drive for fire attributes is negative. Comparing the Model 7 estimates for vegetation and water for latent classes 1 and 2, we see that the WTD are much larger in magnitude for Class 1 respondents than Class 2 respondents or in the conditional logit or random parameters models. For Class 1, WTD for all the plant and water levels are significant at the 5% level. The only WTD estimate for fire that is significant at the 5% level is a recent fire that burned all plants farther away. For Class 2, only WTD for recent fire that burned all plants farther away is significant. Model 8

[11] In Appendix G, this willingness to drive (WTD) is also converted to a monetary measure using travel costs to estimate the willingness to pay (WTP) for an attribute change (see Table 2.21).

similarly identifies one latent class with extremely high WTD and one with WTD that are smaller in magnitude but none of the WTD in Class 2 are significant at the 5% level.

From the conditional and random parameters logit WTD results in Table 2.9 we see that on average respondents will drive about 45 miles more to visit a site with trees either nearby or farther away compared to sites with shrubs nearby and shrubs farther away. Sites with tree cover both nearby and farther away from the parking lot are valued even more, with average willingness to drive being at least 70 miles one-way. Sites with a water feature – in the Angeles National Forest these tend to be sites with rivers or streams, but sometimes lakes – are highly valued, with average willingness to drive ranging between around 70 miles for sites with water at a distance from the parking area, to around 100 for sites with water nearby and farther away. These results are consistent with observed recreation patterns, as those sites with streams and large shaded picnic areas were among the most heavily visited in our sample.

As expected, sites with fire history are less desirable than those with no visible effects of past fires, but there is a wide variation in WTD estimates between four categories of fire history. If a site has been affected by an older forest fire that is in recovery on average respondents would drive 12 fewer miles one-way to visit that site. However, if a site was affected by a recent forest fire that burned all vegetation, they would drive on average 79 fewer miles for that site. Recent forest fires that only affected some plants (like shallow ground fires as opposed to crown fires) and older shrub fires that are in recovery lie in between those two extremes.

Estimates of WTD for attributes across the four specifications of the conditional logit model and the two random parameters logit models are very similar. WTD to sites with mixed tree and shrub vegetation is roughly 45 miles one-way in Model 1, which estimated average preferences in the population. Both the random parameters logit models also show that visitors would be willing to drive about 45 more miles to those sites compared to sites with only shrubs. Similarly, WTD for trees nearby and farther away, water attributes, and fire history attributes are nearly the same for three of the conditional logit model specifications and the two random parameters logit models. Model 2, in which income was interacted with the distance attribute, consistently estimates greater WTD for trees and water, and less WTD for sites with fire history. The first latent class where children, income, and Hispanic determined class membership, the model identifies a group of respondents whose preferences are very strong and would be willing to drive 100 or more miles for sites with desirable attributes, and a second group with little WTD for any of the attributes presented. Although not shown in the table, the weighted average WTD for attributes for Model 7 is much higher than the conditional logit estimate. Model 8 identifies a group of people less with similar preferences to the average estimated by the conditional logit and a second group with no significant WTD for attributes.

Table 2.9 Willingness to Drive

Model	**Conditional Logit**				**Random Parameters**		**Latent Class**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)		(8)	
							Class 1	Class 2	Class 1	Class 2
Vegetation										
Shrubs near, trees far	**46**	**45**	**46**	**46**	**44**	**46**	**103**	5	17	204
Trees near, shrubs far	**45**	**43**	**45**	**45**	**44**	**46**	**97**	-4	10	210
Trees near, trees far	**79**	**76**	**79**	**78**	**77**	**82**	**161**	4	31	312
Water										
None near, some far	**71**	**66**	**71**	**70**	**71**	**73**	**134**	12	**40**	212
Some near, none far	**70**	**65**	**70**	**71**	**69**	**73**	**160**	-4	24	320
Some near, some far	**97**	**94**	**97**	**97**	**97**	**101**	**194**	20	**47**	347
Fire History (farther away)										
Old fire that burned all plants	-13	-11	-14	-13	-12	**-15**	-21	-4	-3	-69
Recent fire that burned all plants	**-73**	**-69**	**-72**	**-72**	**-71**	**-77**	**-77**	**-64**	**-63**	-107
Recent fire that burned some plants	**-24**	**-21**	-24	**-22**	**-23**	**-28**	-41	-19	**-17**	-62
Recent shrub fire	-12	-10	-13	-12	**-14**	-13	-11	-20	**-20**	1

Note: All values rounded to the nearest mile and **bold** cells indicate values significantly different than zero at the 5% level. Models 2, 3, and 4 use Krinsky and Robb (1986) 95% confidence intervals using the mean of the demographic variable. Confidence intervals for the other models were computed using the delta method.

2.7 Discussion and Conclusions

In this study, we use results from a choice experiment survey to model forest visitors' preferences for environmental attributes of national forest recreation sites and estimate willingness to pay for sites with different vegetation, water, and fire histories. The fire attributes span forest and chaparral vegetation types, include different burn intensities, and capture temporal effects of fire via old versus recent fires. We introduce and test for evidence of preference heterogeneity by employing conditional logit models with interactions, random parameters logit models, and latent class models.

The dominant vegetation type in much of southern California is chaparral, which is a shrubland. Many recreation sites in the southern portions of the Angeles National Forest and nearby forests mostly have chaparral nearby, with the exception of large picnic sites along rivers, where there is usually tree cover by the water. At higher altitudes, and also at greater driving distance from any respondents living in Los Angeles or its immediate suburbs, the Angeles National Forest is dominated by pine and conifer forests. Sites with some tree cover are favored by respondents, with sites with trees both near the parking lot as well as farther away being the most preferred. This indicates a preference for sites with long, shaded hiking trails as opposed to those that are more exposed.

Some of the busiest recreation sites in the national forest are those with streams or lakes. Many sites along a stream are popular picnic sites in addition to having hiking trails, as opposed to other sites without water near the parking lot, which may have long hiking trails, but are not picnic sites. It makes sense then, that across the board, sites with water nearby, farther away, or both, are highly preferred to sites that have no river, stream, or lake within hiking distance.[12]

[12] Our sampling design favored sites with many visitors. Future extensions of this work will incorporate sampling weights to better address potential differences in user groups at high and low use sites.

The study area is frequently affected by severe wildfires that sometimes close recreation sites and when sites re-open they can be left with visible burn scars that vary depending on the vegetation type and fire severity. We find evidence, as expected, that sites with visible effects from wildfires are less desirable than those with no visible effects of wildfires, but that as time and recovery increase, the effect is mitigated. Previous recreation literature has found that trips increase after a recent wildfire for a short time – however, we find that in the case of severe wildfires in California that burn all the vegetation, recent wildfires are larger dis-amenities than older forest fires or shrub fires. Recent forest fires that burned some plants, recent shrub fires, and old forest fires that are still visible also cause welfare losses, but less so than severe, recent forest fires.

These basic results are consistent across the three classes of models we use. As expected, the average preferences across models are roughly similar to the basic conditional logit, which only measure average preferences. While the other models reveal some heterogeneity, each model incorporates preference heterogeneity differently. In the conditional logit model, we interacted variables that may influence preferences with the site attributes which allows for a clear interpretation of how preferences vary with demographics. The interacted models suggest that experience with changing trips due to site closures or fire conditions do not contribute to preference heterogeneity, however, we do find evidence that different groups of people may have heterogeneous preferences across site attributes. Model 4 shows that Hispanic forest visitors are more likely than others to visit sites with trees nearby and shrubs far away, and less likely to visit sites with no water nearby but some far away. This is consistent with previous literature that shows that minority groups use public forest areas differently than other groups. In our random parameters model estimation, we find significant standard deviations for the vegetation and fire history attributes, suggesting that there is considerable heterogeneity in preferences for these characteristics. However, the standard deviation estimates for water are insignificant suggesting that the presence of lakes, rivers, or streams at a site is uniformly desirable.

Latent class models can be useful for identifying classes of people who have distinct preferences. To explore heterogeneity, we examined latent class models and found that fewer classes were preferred to more classes across a range of specifications. We present results from two latent class models. In the first model respondents with children under 18 are more likely to belong to a class of people for whom many of the site attributes – tree cover, the presence of water, and fire history – are significant drivers of their choices over recreation sites. Those with a higher annual income are less likely to be in that class and more likely to be in a class of respondents who are only sensitive to distance and recent fires. The second latent class model predicts that Hispanic forest visitors are more likely to belong to a class who have strong preferences for water at the site, and for trees both nearby and farther away, but are less sensitive to the fire history attributes.

The results identify two sources of heterogeneity in preferences for the vegetation, water, and fire history attributes of recreation sites that may be of interest to forest managers. The construction of the attribute levels allows us to draw some conclusions about how the welfare effects of forest fires change over time. We find significant evidence for differences in effects of fire over time. Sites that have been affected by wildfires are less preferred to sites with no visible fire history, but unlike some previous recreation literature, we find that recent wildfires cause greater welfare loss than older forest fires and that visible damage can have a significant effect on site choices. Second, we identify heterogeneity across groups of people. The urban national forests in our study area are an important recreational opportunity for the diverse residents of Los Angeles and Southern California. One of the most important demographic trends in this area is a large and growing Hispanic population, who, compared to other demographic groups, are under-represented among forest visitors. Managers have an interest in understanding how recreation preferences differ across user groups. Past literature has looked at preferences for levels of development and amenities and diversity in the types of activities that visitors engage in (Chavez et al. 2008). We find that there are also significant differences in preferences over environmental attributes of recreation sites that could provide insight into how management activities can differentially affect people. Improvements in water quality and protection of forest quality nearby parking or picnic areas appear more beneficial to some visitors such as those who are Hispanic, have young children, and those with lower household income, while trail maintenance and fire recovery in forested areas appear more valuable to visitors who are non-Hispanic, have higher household income, and do not have children.

APPENDICES

Appendix 2A: Coefficient Covariance Matrix

Table 2.10 Correlation Table for Random Parameters Logit Model 6

	Shrubs near, trees far	Trees near, shrubs far	Trees near, trees far	Old fire, all plants	Recent fire, all plants	Recent fire, some plants	Recent shrub fire
Shrubs near, trees far	0.072						
Trees near, shrubs far	-0.243	2.330**					
Trees near, trees far	-0.142	0.999*	1.752**				
Old fire, all plants	-0.079	0.365	0.641	0.330			
Recent fire, all plants	0.267	0.5	0.413	-0.087	2.499**		
Recent fire, some plants	0.146	-0.368	-0.454	-0.545	0.723	2.535**	
Recent shrub fire	0.043	0.379	0.180	-0.146	0.755	1.097*	2.233**

Appendix 2B: Robustness Checks for Essay 2

Table 2.11 Conditional Logit with Travel Cost

	Conditional Logit
Shrubs near, trees far	0.731***
	(0.000)
Trees near, shrubs far	0.682***
	(0.000)
Trees near, trees far	1.216***
	(0.000)
None near, some far	1.049***
	(0.000)
Some near, none far	1.049***
	(0.000)
Some near, some far	1.517***
	(0.000)
Old forest fire that burned all plants	-0.181
	(0.104)
Recent forest fire that burned all plants	-1.108***
	(0.000)
Recent forest fire that burned some plants	-0.349***
	(0.002)
Recent shrub fire	-0.169*
	(0.089)
Travel cost (one-way)	-0.069***
	(0.000)
Observations	4,290
AIC	2621.64
BIC	2691.64
Log Likelihood	-1299.82

Robust pval in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.12 Conditional Logit with Interactions using Travel Cost

	Experience x Fire	Hispanic x Attributes
Travel cost (one way)	-0.069***	-0.069***
	(0.000)	(0.000)
Shrubs near, trees far	0.728***	0.683***
	(0.000)	(0.000)
Trees near, shrubs far	0.688***	0.599***
	(0.000)	(0.000)
Trees near, trees far	1.216***	1.155***
	(0.000)	(0.000)
None near, some far	1.054***	1.155***
	(0.000)	(0.000)
Some near, none far	1.055***	1.052***
	(0.000)	(0.000)
Some near, some far	1.528***	1.554***
	(0.000)	(0.000)
Old forest fire that burned all plants	-0.147	-0.093
	(0.467)	(0.472)
Recent forest fire that burned all plants	-0.879***	-1.190***
	(0.000)	(0.000)
Recent forest fire that burned some plants	-0.379*	-0.365***
	(0.075)	(0.004)
Recent shrub fire	-0.342	-0.222*
	(0.135)	(0.055)
Hispanic x Shrubs near, trees far		0.184
		(0.557)
Hispanic x Trees near, shrubs far		0.347
		(0.143)
Hispanic x Trees near, trees far		0.208
		(0.512)
Hispanic x No water near, some far		-0.467**
		(0.022)
Hispanic x Some water near, none far		0.101
		(0.641)
Hispanic x Some water near, some far		-0.089
		(0.686)

Table 2.12 (cont'd)

Hispanic x Old fire, all		-0.323
		(0.173)
Hispanic x Recent fire, all		0.337
		(0.222)
Hispanic x Recent fire, some		0.155
		(0.586)
Hispanic x Recent fire, shrub		0.175
		(0.446)
Experience x Old fire, all	-0.042	
	(0.850)	
Experience x Recent fire, all	-0.280	
	(0.240)	
Experience x Recent fire, some	0.037	
	(0.871)	
Experience x Recent fire, shrub	0.211	
	(0.389)	
Observations	4,290	4,260
AIC	2626.68	2599.94
BIC	2722.14	2733.43
Log Likelihood	-1298.34	-1278.97

Table 2.13 Random Parameters Logit with No Correlation and Travel Cost

	Coef.	Std. Dev.
Travel cost (one-way)	-0.102***	
	(0.000)	
Shrubs near, trees far	1.036***	0.199
	(0.000)	(0.709)
Trees near, shrubs far	1.020***	1.210***
	(0.000)	(0.000)
Trees near, trees far	1.798***	1.020***
	(0.000)	(0.000)
None near, some far	1.509***	-0.587**
	(0.000)	(0.046)
Some near, none far	1.480***	0.681**
	(0.000)	(0.037)
Some near, some far	2.240***	-0.776**
	(0.000)	(0.021)
Old forest fire that burned all plants	-0.268*	0.474
	(0.087)	(0.309)
Recent forest fire that burned all plants	-1.613***	-0.991***
	(0.000)	(0.003)
Recent forest fire that burned some plants	-0.488***	1.304***
	(0.005)	(0.001)
Recent shrub fire	-0.293*	1.045**
	(0.061)	(0.010)
Observations	4,290	
AIC	2613.95	
BIC	2747.59	
Log Likelihood	-1285.97	

Table 2.14 Comparison of WTP using Models that used One-way Travel Cost

		Conditional Logit			**Random Parameters**
		No Interactions	Exp x Fire	Hisp x Attributes	No Corr
Vegetation	Shrubs near, trees far	**$ 11**	**$ 11**	**$ 11**	**$ 10**
	Trees near, shrubs far	**$ 10**	**$ 10**	**$ 10**	**$ 10**
	Trees near, trees far	**$ 18**	**$ 18**	**$ 17**	**$ 18**
Water	None near, some far	**$ 15**	**$ 15**	**$ 15**	**$ 15**
	Some near, none far	**$ 15**	**$ 15**	**$ 16**	**$ 14**
	Some near, some far	**$ 22**	**$ 22**	**$ 22**	**$ 22**
Fire History (farther away)	Old fire that burned all plants	-$ 3	-$ 3	-$ 2	-$ 3
	Recent fire that burned all plants	**-$ 16**	**-$ 16**	**-$ 16**	**-$ 16**
	Recent fire that burned some plants	**-$ 5**	-$ 5	**-$ 5**	**-$ 5**
	Recent shrub fire	-$ 2	-$ 3	-$ 3	-$ 3

Appendix 2C: Three and Four-Class Latent Class Models

Table 2.15 Three-class Latent Class Model with Hispanic, Income, and Children

		Class 1	Class 2	Class 3
Driving Distance (one-way)	Distance	-0.016***	0.017	-0.262***
		(0.003)	(0.015)	(0.025)
Vegetation	Shrubs near, trees far	1.371***	-2.587*	2.043**
		(0.257)	(1.338)	(0.889)
	Trees near, shrubs far	1.271***	-1.381	1.575**
		(0.218)	(1.083)	(0.788)
	Trees near, trees far	2.117***	-3.344**	4.996***
		(0.286)	(1.550)	(0.991)
Water	None near, some far	1.396***	0.980	3.664***
		(0.166)	(0.876)	(0.571)
	Some near, none far	1.755***	-0.230	3.670***
		(0.210)	(0.723)	(0.524)
	Some near, some far	2.228***	0.023	6.129
		(0.224)	(1.040)	NA
Fire History (farther away)	Old fire that burned all plants	-0.152	-0.515	-2.347***
		(0.201)	(0.687)	(0.660)
	Recent fire that burned all plants	-1.184***	-2.086**	-3.718
		(0.194)	(1.015)	NA
	Recent fire that burned some plants	-0.631***	0.530	-1.115*
		(0.205)	(0.699)	(0.644)
	Recent shrub fire	-0.003	-3.099***	-2.075**
		(0.183)	(1.193)	(0.810)

Table 2.15 (cont'd)

Class Membership	Has children under 18	1.214**	0.451
		(0.500)	(0.752)
	Income	-0.006**	-1.38E-4
		(0.003)	(0.004)
	Hispanic	-0.194	-1.088
		(0.478)	(1.022)
	Constant	1.806***	-0.226
		(0.469)	(0.842)
Observations	2,115		
CAIC	2786.46		
BIC	2745.46		
Log Likelihood	-1238.06		

Table 2.16 Four-class Latent Class Model with Hispanic, Income, and Children

		Class 1	Class 2	Class 3	Class 4
Driving Distance (one-way)	Distance	-0.016***	-1.302***	0.005	-0.531***
		(0.004)	(0.0296)	(0.016)	(0.045)
Vegetation	Shrubs near, trees far	0.163	170.6***	3.403***	6.927***
		(0.616)	(1.753)	(1.011)	(1.301)
	Trees near, shrubs far	1.258***	29.35	-0.626	4.634***
		(0.318)	NA	(0.858)	(1.006)
	Trees near, trees far	1.166***	235.4***	0.599	13.33***
		(0.294)	(1.095)	(1.291)	(1.570)
Water	None near, some far	1.522***	153.3	-0.0547	4.750***
		(0.402)	NA	(0.886)	(1.122)
	Some near, none far	1.844***	40.50***	0.690	6.380***
		(0.457)	(1.564)	(1.087)	(1.188)
	Some near, some far	2.450***	117.3***	-0.506	11.50***
		(0.636)	(1.434)	(1.361)	(2.070)
Fire History (farther away)	Old fire that burned all plants	0.0468	-62.68***	-2.747*	-4.622***
		(0.283)	(2.904)	(1.587)	(1.293)
	Recent fire that burned all plants	-0.375	-156.7***	-5.858**	-10.38***
		(0.491)	(1.387)	(2.738)	(1.382)
	Recent fire that burned some plants	-0.0920	-77.56***	-1.797*	-3.187**
		(0.276)	(1.318)	(0.991)	(1.534)
	Recent shrub fire	-0.412	52.17***	-0.444	-3.006***
		(0.258)	(1.053)	NA	(0.951)

Table 2.16 (cont'd)

Class Membership	Has children under 18	0.925	0.759	0.394
		(0.769)	(1.022)	(0.693)
	Income	-0.005	-0.021*	-0.004
		(0.003)	(0.011)	(0.004)
	Hispanic	0.456	-0.579	0.091
		(0.637)	(0.782)	(0.790)
	Constant	1.577***	1.854**	0.452
Observations	2,115			
CAIC	2840.09			
BIC	2784.09			
Log Likelihood	1208.10			

Appendix 2D: Onsite Survey Instrument (2016)

Interviewer: ______________ Site: ______________

Hi, I work with Michigan State University and I'm conducting interviews for the Forest Service for a research study that will help them serve visitors. Your participation is voluntary and all information is confidential. This survey should take 5 minutes.

1. Would you be willing to take a few minutes to participate in this interview?
   - ☐ Yes
   - ☐ No → *Thank you for your time. (END INTERVIEW)*

2. I need to select just one of you to complete this interview. Which of you had the most recent birthday and is 18 years of age or older?
   (Or say " I am hoping to speak with the person in your group who had the most recent birthday" and then prompt with the question if needed.)

3. What is your home ZIP code? ___________
   If visitor is from another country, zip code = 00000 → *proceed to Q3a, otherwise skip to Q4*
   If don't know / refuse to answer, zip code = 99999

3a. If visitor is from another country, select:
   - ☐ Canada
   - ☐ Mexico
   - ☐ South & Central America
   - ☐ Asia
   - ☐ Europe
   - ☐ Other _______________

4. What is the primary purpose of your visit to (site name)?
   - ☐ Working or commuting to work → *end interview*
   - ☐ Only stopping to use the bathroom → *end interview*
   - ☐ Only passing through, going somewhere else → *end interview*
   - ☐ Some other reason → *end interview*
   - ☐ Recreation → *proceed to Q5; if any other reason, end interview*

5. When do you plan to leave (site name) for the last time on this visit?
   - ☐ Not leaving this site today
   - ☐ Don't know
   - ☐ Leaving now
   - ☐ Leaving later today → Time: ______________

6. When did you first arrive at (site name) for this visit? Date and time: _________________

Section 2: National Forest Visit

7. On this visit to this NF, did you go or do you plan to go to any areas for recreation other than this one?

- ☐ Yes
- ☐ No

Questions 8-11 ask the visitor about the activities they participated in during their national forest visit. Since the activity choice list is very long, hand them the activity flash card then ask:

8. In which of the following activities have you participated or will you participate during **this NF visit**?

- ☐ Hiking or walking
- ☐ Bicycling, including mountain bikes
- ☐ Driving for pleasure on roads (paved, gravel, or dirt)
- ☐ Relaxing, hanging out, escaping heat
- ☐ Viewing/photographing wildlife or scenery
- ☐ Picnicking and family day gatherings
- ☐ Camping
- ☐ Fishing
- ☐ Canoeing or boating without a motor
- ☐ Boating with a motor
- ☐ OTHER (write in activity)___________________________

9. Which one of those is your primary activity for this recreation visit on **this NF**?

- ☐ Hiking or walking
- ☐ Bicycling, including mountain bikes
- ☐ Driving for pleasure on roads (paved, gravel, or dirt)
- ☐ Relaxing, hanging out, escaping heat
- ☐ Viewing/photographing wildlife or scenery
- ☐ Picnicking and family day gatherings
- ☐ Camping
- ☐ Fishing
- ☐ Canoeing or boating without a motor
- ☐ Boating with a motor
- ☐ OTHER (write in activity)___________________________

If Q7=No, skip to Q12.

10. In which of the following activities have you participated or will you participate at **this site**?

- ☐ Hiking or walking
- ☐ Bicycling, including mountain bikes
- ☐ Driving for pleasure on roads (paved, gravel, or dirt)

- ☐ Fishing
- ☐ Canoeing or boating without a motor
- ☐ Boating with a motor
- ☐ OTHER (write in activity)__________________________

11. Which one of those is your primary activity for this recreation visit at **this site**?
    - ☐ Hiking or walking
    - ☐ Bicycling, including mountain bikes
    - ☐ Driving for pleasure on roads (paved, gravel, or dirt)
    - ☐ Relaxing, hanging out, escaping heat
    - ☐ Viewing/photographing wildlife or scenery
    - ☐ Picnicking and family day gatherings
    - ☐ Camping
    - ☐ Fishing
    - ☐ Canoeing or boating without a motor
    - ☐ Boating with a motor
    - ☐ OTHER (write in activity)__________________________

12. Including this visit, about how many times have you come to **this NF** for recreation in the past 12 months? _________

Section 3: Demographics

> *The next questions provide statistics about the basic demographics of forest visitors. This allows the forest managers to better understand who their clientele are.*

13. How many people, including you, traveled here in the same vehicle as you? _______

14. How many of those people are less than 18 years old? _________

15. What is your age? __________

16. Record:
    - ☐ Male
    - ☐ Female

17. Are you Hispanic or Latino?
    - ☐ Yes
    - ☐ No
    - ☐ Refused

18. With which racial group(s) do you most closely identify?
    - ☐ American Indian / Alaska Native

- ☐ Native Hawaiian or other Pacific Islander
- ☐ White
- ☐ Refused

<u>Section 4: Contact Info</u>

Do you have an e-mail address where we can send you a short follow-up survey? The invitation would come in a couple weeks from Michigan State University. It is strictly confidential and your e-mail would never be used in any other way. *Read their email back to them to make sure you have it written correctly.*

Email: ____

(*Thank you. We will send you a link to the follow-up survey in August.)*

If the respondent was unwilling to share their email address, ask for a mailing address:
Would you be wiling to share your mailing address instead?

Full name: ____
Address Line 1: ____
Address Line 2: ____
City, State, Zip Code: ____

Thank you for your time!

Date: ____________________________
Interview end time: ________________

Appendix 2E: Online Survey Instrument (2017)

The following pages show images of a paper version of the survey that was mailed in 2017 (Figures 2.4a - 2.4m). The survey was originally 8.5 by 11 inches but is downscaled here to fit the pages.

Southern California National Forest Visitation Survey

Consent to Participate in a Survey

The purpose of this study is to understand how people recreate in National Forests and help serve visitors.

Your survey responses are confidential. Participation is voluntary and you may choose not to participate at all, refuse to answer certain questions, or stop the survey at any time.

If you have concerns or questions about this study, please contact Dr. Cloe Garnache at cloegarnachesurvey@anr.msu.edu.

1 To proceed with the survey and indicate your voluntary participation, please mark "Continue" and turn to the next page.

☐ Continue

1

Figure 2.4 Image of Paper Version of Survey (originally 8.5" by 11")

Southern California National Forest Visitation Survey

National Forest Sites in Southern California

This survey asks questions about visits to **National Forest sites in Southern California**.

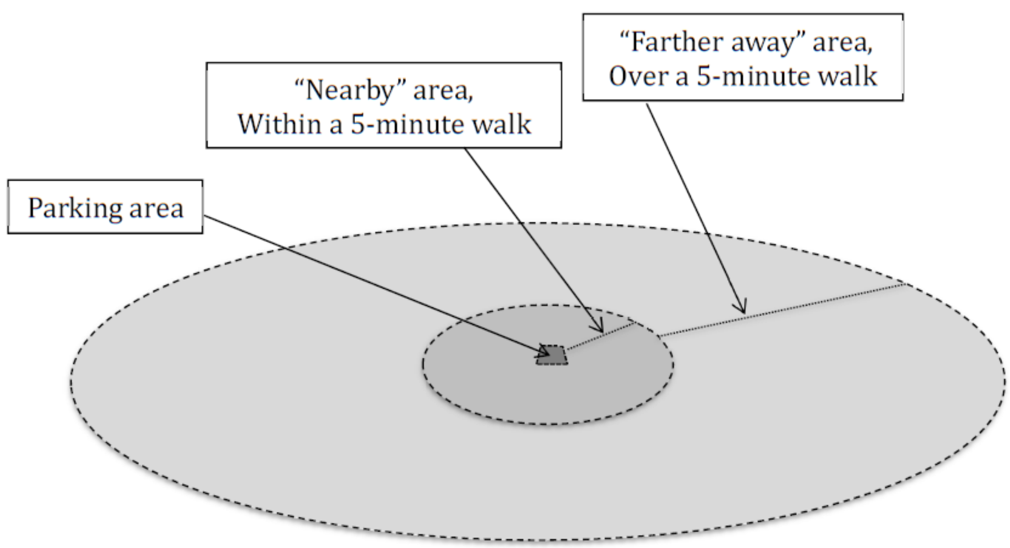
When the survey refers to "National Forests" it means National Forest sites in Southern California in the *Los Padres*, *Angeles*, *San Bernardino* and *Cleveland* National Forests.

Areas near and farther away from parking area

The questions will refer to

- Areas **near** the parking area that are within a 5-minute walk
- Areas **farther away** from the parking area that are over a 5-minute walk

The figure below illustrates the **nearby** and **farther away** areas.



2

Figure 2.4 (cont'd)

Southern California National Forest Visitation Survey

Plants

- National Forest sites can have different types of trees and shrubs, which affect shade, views, and the uses of the site.
- The plants near the parking area (within a 5-minute walk) can differ from the plants farther away.

An example of **shrubs**

2 Have you ever visited a National Forest site that had any of the following:

	Yes	No
Trees near the parking area (within a 5-minute walk)	☐	☐
Trees farther away (over 5-minute walk)	☐	☐
Shrubs near the parking area (within a 5-minute walk)	☐	☐
Shrubs farther away (over 5-minute walk)	☐	☐

3

Figure 2.4 (cont'd)

Southern California National Forest Visitation Survey

Lakes and Streams

National Forest sites may have lakes and streams near the parking area (within a 5-minute walk), farther away (over a 5-minute walk but less than an hour), or farther.

3 Have you ever visited a National forest site that had any of the following:

	Yes	No
Streams near the parking area (within a 5-minute walk)	☐	☐
Streams farther away (over a 5-minute walk)	☐	☐
Lakes near the parking area (within a 5-minute walk)	☐	☐
Lakes farther away (over a 5-minute walk)	☐	☐

4 How important is the distance to lakes and streams when you decide which National Forest site to visit?

- ☐ Very important
- ☐ Somewhat important
- ☐ Not important

Fire

- Fires sometimes happen in National Forests.
- After a fire, sites are closed until it is safe for visitors to return.
- After a fire, effects of the fire such as burned trees and shrubs may be visible for some time.

5 Were you aware that a National Forest site cannot be re-opened after a fire until the site is determined to be safe for visitors?

- ☐ Yes
- ☐ No

6 Have you ever seen a National Forest site that had any of the following:

	Yes	No
Presence of past fire near the parking lot (within a 5-minute walk)	☐	☐
Presence of past fire farther away (over a 5-minute walk)	☐	☐

4

Figure 2.4 (cont'd)

Southern California National Forest Visitation Survey

Effects of Forest Fires

- Some forest fires only burn **some** small plants and the bottom of trees.
- Other forest fires burn **all** plants and trees.
- After some years, new grass and shrubs grow. The older the fire, the more plants grow back. After 5 to 10 years small trees grow.

Example of past fires where **all plants and trees burned**; after some years plants grow back. **Left**: Recent fire (less than 5 years old); **Right**: Old fire (older than 5 years).

Example of past fires where **some plants burned** but the tops of trees did not burn; after some years grass and shrubs grow back and the fire is less visible.

7	Have you ever seen a National Forest site that had any of the following:	Yes	No
	Forest fire where **all** plants had burned	☐	☐
	Forest fire where **some** plants had burned	☐	☐
	Shrubs that burned	☐	☐
	Other burned plants	☐	☐

5

Figure 2.4 (cont'd)

Southern California National Forest Visitation Survey

Shrub fires

- If an area is **mostly shrubs**, a fire usually burns all the plants and shrubs.
- New grass and plants usually start growing back after one year.

Example of **new** shrub fires (less than 1 year old)

Example of **recent** shrub fires (1 to 4 years old) with new grass and plants

8 Have you ever seen a National Forest site that had any of the following:	Yes	No
Past shrub fire within 1 year (no new grass or plant growth)	☐	☐
Past shrub fire 1-4 years old (some new grass and plant growth)	☐	☐
Other burned plants	☐	☐

6

Figure 2.4 (cont'd)

Southern California National Forest Visitation Survey

Site Choice (1 of 3)

Next, you will be presented with some Southern California National Forest sites to choose from.

Assume all sites:

- Have picnic tables and restrooms,
- Are safe
- Have adequate parking
- Have **no history of fire near** the parking area (within 5-minute walk).

Assume anything not listed is the same across sites.

Please review the site descriptions in the table and answer carefully. The results will help the U.S. Forest Service manage National Forests.

What the site is like:	**Site A**	**Site B**
Plants	Shrubs nearby Trees farther away	Shrubs nearby Trees farther away
Lakes or streams	Some nearby Some farther away	Some nearby None farther away
Fire history farther away (Over a 5-minute walk)	None visible	Recent forest fire that burned some plants
One-way driving distance from home (miles)	110	10

9 Which of these National Forest sites would you prefer to visit?

I prefer: ☐ Site A ☐ Site B

10 If Site B were not available, would you prefer to visit **Site A** or do something else?

I prefer: ☐ Site A ☐ Do something else

11 If Site A were not available, would you prefer to visit **Site B** or do something else?

I prefer: ☐ Site B ☐ Do something else

7

Figure 2.4 (cont'd)

Southern California National Forest Visitation Survey

Site Choice (2 of 3)

What the site is like:	Site C	Site D
Plants	Shrubs nearby Shrubs farther away	Shrubs nearby Trees farther away
Lakes or streams	None nearby Some farther away	None nearby None farther away
Fire history farther away (Over a 5-minute walk)	None visible	Old forest fire that burned all plants (some new grass and plants)
One-way driving distance from home (miles)	10	80

12 Which of these National Forest sites would you prefer to visit?

I prefer: ☐ Site C ☐ Site D

13 If Site D were not available, would you prefer to visit **Site C** or do something else?

I prefer: ☐ Site C ☐ Do something else

14 If Site C were not available, would you prefer to visit **Site D** or do something else?

I prefer: ☐ Site D ☐ Do something else

8

Figure 2.4 (cont'd)

Southern California National Forest Visitation Survey

Site Choice (3 of 3)

What the site is like:	Site E	Site F
Plants	Trees nearby Shrubs farther away	Trees nearby Shrubs farther away
Lakes or streams	None nearby None farther away	Some nearby None farther away
Fire history farther away (Over a 5-minute walk)	Recent shrub fire (some new grass and plants)	None visible
One-way driving distance from home (miles)	10	110

15 Which of these National Forest sites would you prefer to visit?

I prefer: ☐ Site E ☐ Site F

16 If Site F were not available, would you prefer to visit **Site E** or do something else?

I prefer: ☐ Site E ☐ Do something else

17 If Site E were not available, would you prefer to visit **Site F** or do something else?

I prefer: ☐ Site F ☐ Do something else

9

Figure 2.4 (cont'd)

Southern California National Forest Visitation Survey

<u>Changes at the Site You Visited</u>

The questions on this page ask about the site where you were interviewed. After this page, all questions refer to National Forests in Southern California

The site <u>at which you were interviewed</u> had **trees nearby and trees farther away**. Now suppose that, *before* you chose to visit <u>this site</u>, you learned that there had previously been a fire there.

Assume the fire was put out; this site was deemed safe and was re-opened.

Nothing else has changed at this site except the amount of plants that burned.

18 The table below presents some scenarios for the site **where you were interviewed.** For each scenario, please indicate whether you would you have visited this site, visited a different site (either in the same or a different National Forest), or done something else instead.

	Yes, I would have visited this site	No, I would have visited another National Forest site	No, I would have done something else
Suppose a **recent** fire had burned **some** plants **near** the parking area	☐	☐	☐
Suppose a **recent** fire had burned **all** plants **near** the parking area	☐	☐	☐
Suppose an **old** fire had burned **all** plants **near** the parking area and you can see some new grass and plants growing back.	☐	☐	☐
Suppose a **recent** fire had burned **some** plants **farther away.**	☐	☐	☐
Suppose a **recent** fire had burned **all** plants **farther away.**	☐	☐	☐
Suppose an **old** fire had burned **all** plants **farther away** and you can see some new grass and plants growing back.	☐	☐	☐

Figure 2.4 (cont'd)

Southern California National Forest Visitation Survey

19 In the table below, please indicate how much you agree or disagree with the following statements.

	Strongly Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Strongly Agree
The presence of lakes and streams nearby affects my decision to visit a site	☐	☐	☐	☐	☐
The types of plants affect my decision to visit a site	☐	☐	☐	☐	☐
The presence of burned plants affects my decision to visit a site	☐	☐	☐	☐	☐
Wildfires are a natural part of National Forests	☐	☐	☐	☐	☐
I am concerned about safety when visiting a site where past fires are visible	☐	☐	☐	☐	☐
I am concerned that air quality may be poor at sites where past fires are visible	☐	☐	☐	☐	☐

20 In the past two years, how many times have you visited a National Forest site?

- ☐ 1 or 2 times
- ☐ 3-5 times
- ☐ 6-10 times
- ☐ 11-25 times
- ☐ More than 25 times

11

Figure 2.4 (cont'd)

Southern California National Forest Visitation Survey

21 In the past two years, how many times have you...

	Never	1 or 2 times	3 to 5 times	More than 5 times
...decided not to visit a National Forest site because you were concerned it might be closed due to a current or recent fire?	☐	☐	☐	☐
...decided not to visit a National Forest site because you knew your preferred site was closed?	☐	☐	☐	☐
...tried to visit a National Forest site but could not get to it because of a fire or site closure?	☐	☐	☐	☐
...changed the National Forest site you had planned to visit because of a road closure?	☐	☐	☐	☐
...changed the National Forest site you had planned to visit because you were concerned about air quality due to a fire?	☐	☐	☐	☐
...decided not to visit a National Forest site (or delay a visit) because you were concerned about air quality due to a fire?	☐	☐	☐	☐
...used a website to learn about air quality near a National Forest site because you were concerned about smoke from a fire?	☐	☐	☐	☐

12

Figure 2.4 (cont'd)

Southern California National Forest Visitation Survey

Demographics

The following information will help the Forest Service plan for the future. All responses are confidential, and individual answers will never be reported.

22 What is the highest level of education you have completed?

- ☐ Less than high school degree
- ☐ High school degree
- ☐ Some college, including Associate's degree
- ☐ Bachelor's degree
- ☐ Graduate degree

23 What is your annual household income?

- ☐ Under $25,000
- ☐ 25,000-49,999
- ☐ 50,000-74,999
- ☐ 75,000-99,999
- ☐ 100,000-149,999
- ☐ 150,000-199,999
- ☐ Over 200,000
- ☐ Don't know

24 Which of the following best describes your current employment status?

- ☐ Employed full time
- ☐ Employed part time
- ☐ Unemployed
- ☐ Retired
- ☐ Student
- ☐ Other (please specify): ________________

25 Do you have any children under 5 years old living with you?

- ☐ Yes
- ☐ No

26 Do you have any children ages 5 to 18 years old living with you?

- ☐ Yes
- ☐ No

Thank you for completing this survey!

Please place this survey in the prepaid envelope, and mail it to Professor Cloé Garnache, Box 219, 211 Agriculture Hall, 446 W. Circle Drive, Michigan State University, East Lansing, MI 48824.

13

Figure 2.4 (cont'd)

Appendix 2F: Disposition Tables

Table 2.17 Disposition Codes for Onsite Survey (2016)

Disposition	Description	Freq.	Percent
0	Declined to participate	1,300	35.61
1	Not recreating	60	1.64
2	Incomplete survey	9	0.25
3	No contact information	505	13.83
4	Contact information	1,755	48.07
5	Less than 18 years old	16	0.44
6	Not contacted (duplicate email or no zip code)	6	0.16
	Total	3,651	100.00

Table 2.18 Disposition Codes for Onsite Survey (2017)

Disposition	Description	Freq.	Percent
0	Declined to participate	1,404	44.05
1	Not recreating	49	1.54
2	Incomplete survey	4	0.13
3	No contact information	481	15.09
4	Contact information	1,245	39.06
6	Not contacted (duplicate email or no zip code)	4	0.13
	Total	3,187	100.00

Table 2.19 Disposition Codes for Online Survey (2016)

Disposition	Description	Freq.	Percent
0	Did not respond	904	51.39
1	Did not continue past the consent page	38	2.16
2	Incomplete survey	110	6.25
3	Complete survey	552	31.38
4	Incorrect contact information	135	7.67
5	Refusal	16	0.91
6	Did not record ID number	4	0.23
	Total	1,759	100.00

Table 2.20 Disposition Codes for Online Survey (2017)

Disposition	Description	Freq.	Percent
0	Did not respond	683	55.04
1	Did not continue past the consent page	26	2.10
2	Incomplete survey	69	5.56
3	Complete survey	323	26.03
4	Incorrect contact information	130	10.48
5	Refusal	10	0.81
	Total	1,241	100.00

Appendix 2G: Attribute Trade-offs in WTP

In addition to expressing the attribute trade-offs in willingness to drive (WTD), as in the main text, the WTD can be converted into willingness to pay units using travel costs per mile. We estimate average travel cost per mile using the following formula:

$$Travelcost = distance * (driving\ cost) + travel\ time * \frac{1}{3}\left(\frac{annual\ income}{2000}\right) \quad (9)$$

Driving costs are calculated using the 2016 and 2017 AAA Your Driving Cost handbook; driving costs are equal to the cost of fuel, tires, and oil plus marginal depreciation costs for a medium sized sedan that drives 15,000 miles per year. For travel time, we assume that individuals drive 45 miles per hour on average, and annual income is self-reported in the survey. Using this formula, our travel cost estimate is $.236 per mile in 2017 CPI-adjusted dollars.

Translating the willingness-to-drive to a dollar value,[13] the average willingness to pay for shrubs nearby and trees farther away or for trees nearby and shrubs farther away across all models is about $10 one way. The average across all models of willingness to pay for trees nearby and farther away is about $20, and for water nearby and farther away is $25. The average willingness to pay for a recent fire that burned all plants is -$17 one way or $34 round-trip, while for other fires, the willingness to pay is about -$10 per round trip. Willingness to pay values are found in Table 2.21.

[13] The conditional logit and random parameter logits presented in this essay were also run using travel cost instead of distance, and the resulting WTP values are nearly the same as when willingness to drive is converted to WTP using average travel cost.

Table 2.21 Willingness to Pay One-Way Using Average Travel Cost

	Conditional Logit				Random Parameters		Latent Class			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)		(8)	
							Class 1	Class 2	Class 1	Class 2
Vegetation										
Shrubs near, trees far	**$ 11**	**$ 11**	**$ 11**	**$ 11**	**$ 10**	**$ 11**	**$ 24**	$ 1	$ 4	$ 48
Trees near, shrubs far	**$ 11**	**$ 10**	**$ 11**	**$ 10**	**$ 10**	**$ 11**	**$ 23**	-$ 1	$ 2	$ 50
Trees near, trees far	**$ 19**	**$ 18**	**$ 19**	**$ 18**	**$ 18**	**$ 19**	**$ 38**	$ 1	$ 7	$ 74
Water										
None near, some far	**$ 17**	**$ 16**	**$ 17**	**$ 17**	**$ 17**	**$ 17**	**$ 32**	$ 3	**$ 9**	$ 50
Some near, none far	**$ 17**	**$ 15**	**$ 17**	**$ 17**	**$ 16**	**$ 17**	**$ 38**	-$ 1	$ 6	$ 75
Some near, some far	**$ 23**	**$ 22**	**$ 23**	**$ 23**	**$ 23**	**$ 24**	**$ 46**	$ 5	**$ 11**	$ 82
Fire History (farther away)										
Old fire that burned all plants	-$ 3	-$ 3	-$ 3	-$ 3	-$ 3	**-$ 4**	-$ 5	-$ 1	-$ 1	-$ 16
Recent fire that burned all plants	**-$ 17**	**-$ 16**	**-$ 17**	**-$ 17**	**-$ 17**	**-$ 18**	**-$ 18**	**-$ 15**	**-$ 15**	-$ 25
Recent fire that burned some plants	**-$ 6**	**-$ 5**	-$ 6	**-$ 5**	**-$ 5**	**-$ 7**	-$ 10	-$ 4	**-$ 4**	-$ 15
Recent shrub fire	-$ 3	-$ 2	-$ 3	-$ 3	**-$ 3**	-$ 3	-$ 3	-$ 5	**-$ 5**	$0.25

Note: Values in bold indicate the WTP is significant at the 5% level using the delta method

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CHAPTER 3. Estimating the Impact of Fires on Recreation in the Angeles National Forest Using Combined Revealed and Stated Preference Methods

3.1 Introduction

A multitude of factors including fire suppression and exclusion, drought, warming temperatures, and increased human activity have made wildfire season in the Western United States more intense and severe than ever in recent years. California, as the most populous state and home to many unique national parks and forests, is especially vulnerable to the financial, health, and recreational impacts of these wildfires. The 2017 fire season was particularly destructive. In December 2017 southern California experienced an outbreak of ten separate wildfires in and around the Los Angeles metropolitan area, many starting in one of the four national forests that surround the area. These national forests are an important outdoor recreation opportunity for a population of millions of people in Los Angeles, San Diego, and surrounding cities. A review of 49 studies estimated that access to recreational sites in the Pacific western states has an average estimated value of $35 per trip in 2018 dollars (Loomis 2005). Road closures, site closures, and lasting site damage due to wildfires every season impact patterns of recreation in these high-use national forests. With wildfire intensity and severity expected to increase throughout the west, there is a need to understand how wildfire activity affects forest recreation in southern California. This essay examines the impacts of fire activity in national forests by using revealed and stated preference data on site choice in one of the most heavily-used national forests in the country.

The study area focuses on the Angeles National Forest. This forest is the largest area of open space in Angeles County and an important source of outdoor recreation for the dense urban population of Los Angeles and its suburbs, receiving over 3 million visits annually from local trips as well as nationwide and international visitors (Garnache et al. 2018). Vegetation in the forest is primarily chaparral, with mixed conifer and hardwood forests at higher altitudes. Both these predominant species are prone to fire; the forests experience both mild surface fires and intense crown fires, while chaparral primarily experiences intense, stand-burning fires but recovers more quickly. Sites in the Angeles National Forest span a wide variety of activities from hiking to fishing, picnicking, historical sites, and camping. Variation in land cover, site attributes, and burn and recovery patterns, make this a unique area to study the effects of visible fire damage to forest visitors.

There is a growing literature on the effects of wildfire on outdoor recreation. An early contingent valuation study by Vaux, Gardner, and Mills (1984) gave university students at UC Davis a series of photographs to elicit preferences over fire damage. The photographic series they used showed typical forest vegetation before and after fire in a series of western conifer forest including Southern California. The respondents were asked which series they preferred given that both represented typical recreation areas nearby. They found that in general intense fires are detrimental, while more moderate fires may increase welfare.

Instead of asking people how they react to fire, some studies use revealed preference data and recreation demand models. Englin et al. (1996) use data from canoe registrations in Manitoba to estimate the impacts of fire damage along popular canoe routes in a state park ten years after a series of large fires, finding a per-trip welfare loss of $15 per lost trip in 1993, ten years after the fires. Baerenklau et al. (2010) use a combination of geographic data and zonal travel cost models to map recreational value in the San Bernardino National Forest, which is adjacent to Angeles National Forest on the eastern side. They find that on average the value of a lost trip to a trailhead in the San Jacinto Wilderness is $19, but that recreational value is highly spatially concentrated in higher elevations, suggesting that a major wildfire – such as the 2006 Esperanza Fire which affected the forest – would have varying costs across landscapes.

Much of the literature into the cost of fires on recreational sites combines revealed preference (RP) and stated preference methods (SP) (Hesseln et al. 2003; Hesseln, Loomis, and González-Cabán

2004; Boxall and Englin 2008; Hilger and Englin 2009; Rausch, Boxall, and Verbyla 2010; Duffield et al. 2013). Revealed preference data can be used jointly with stated preference data from contingent valuation (e.g. Loomis 1997), discrete choice experiments (e.g. Christie, Hanley, and Hynes 2007), or contingent behavior methods (e.g. Englin and Cameron 1996) to draw on the strengths of both approaches. A consistent finding of this literature is that forest fires decrease recreational value, but that there is heterogeneity across groups of recreationists and types of fires. Englin, Loomis, and González-Cabán in a pair of papers (Loomis, González-Cabán, and Englin 2001; Englin, Loomis, and Gonzalez-Caban 2001), and work by Hesseln et al. (2003; 2004) pool data on actual trips per season with people's intended trips following a fire. They each find different effects depending on the intensity of the fire and the time since it occurred. Englin, Loomis, and González-Cabán (2001) find evidence of an "s-shaped" path of damages, suggesting that as an area recovers from a fire there may be some benefits as well as costs to recreationists. Similarly, Boxall and Englin (2008) find both positive and negative parameters on burn variables depending on the time since fire. This suggests that as a forest recovers, there may be some benefits to a recent fire – perhaps some people are interested in the regrowth or prefer a less obstructed view of other scenery. The non-linear recovery pattern of damages lasts for several decades (Englin, McDonald, and Moeltner 2006; Boxall and Englin 2008). Most of these studies take place in mountainous forested regions – the Rocky Mountains and western Canada and none of these studies take place in chaparral.

Contingent behavior in the recreation literature has mostly been used to estimate hypothetical trips per year or season following a change. We take an alternate approach similar to that used by Adamowicz, Louviere, and Williams (1994), Boxall et al. (2003), and most-closely related to Parsons and Stefanova (2011) in which the respondents' task is to decide whether an observed trip would have changed given various fire scenarios. This way, discrete decisions over scenarios are easily comparable to discrete site choice decisions in the RP data. In addition, the approach helps to ground respondents in a real decision for which we have trip data.

Given that wildfires are expected to become more frequent, there is a greater need to understand the effects of site closures and the continuing welfare effects of wildfire burn scars on the landscape. In this study we use visitation data to estimate a multi-site zonal travel cost model of demand for trips to sites in the Angeles National Forest. Contingent behavior responses are embedded within the demand system and the implied fire preference parameters are estimated using contraction maps, allowing us to value both site closures and the impacts of fire history on sites after they reopen. Results contribute to forest management when facing increasing threats of site closures by providing insight into potential impacts during and after closures in a popular urban national forest. Of the fire scenarios presented, recent forest fires are the costliest, causing estimated welfare losses of up to $2.2 million per summer season for one affected site. The remainder of this essay is organized as follows: Section 3.2 describes empirical strategy used to estimate the effects of fire. Section 3.3 describes the sampling strategy for the onsite survey and the data, and Section 3.4 presents model results and welfare estimates. Section 3.5 concludes.

3.2 Empirical Strategy

This essay combines data on revealed site choice with information on stated choices under several wildfire scenarios. First, we collected onsite visitation data at day use sites in the Angeles National Forest. Random sampling of recreation sites was stratified by expected use level (high or low), weekend or weekday, and morning or afternoon. We followed up with an online survey to collect contingent behavior data. The empirical strategy exploits both the onsite and contingent behavior data to estimate welfare effects of fires. Using respondents' observed site choice, we employ a multi-site zonal travel cost model following the approach developed by von Haefen et al. (2015) for the Deepwater Horizon oil spill. The zonal model uses on-site sampling and intercept probabilities to estimate rates of visitation from each origin zip code, allowing us to estimate a multi-site recreation demand system with a full set of alternative specific constants (ASCs). This model provides estimates of visitation to each site under unchanged conditions which are then calibrated via contraction maps to estimates of the percentage of visitors who would have still visited the site at which they were intercepted under alternate fire history scenarios.

3.2.1 Zonal Data Set

Onsite trip data for this essay was collected June – August 2016 in the Angeles National Forest. Visitors were intercepted at hiking and picnicking sites; our random sampling strategy stratified sites according to the number of visits they generally receive over the weekend, and sampling times were stratified according to time of the day and day of the week (morning or afternoon, and weekend or weekday). Interviewers intercepted visitors as they exited the main hiking trail at the site or approached their vehicles to exit and kept a count of the number of exiting vehicles in each work shift. Sampling weights were constructed using the intercept probabilities which take into account the count of visitors to each sampled site as well as the probability of sampling that site. Using the trip intercept data and sampling weights, we estimate visitation to each site from each origin zip code. The zip code-level visitation is then used to estimate a multi-site zonal travel cost model that included non-participation using a method developed for the Deepwater Horizon oil spill (von Haefen et al. 2018)[14] and recently implemented to estimate the impact of the Thomas fire in California (Garnache and Lupi 2018). The model is specified as a repeated random utility model (RRUM; Morey et al. 1993) using the zonal data and treating each origin as if it is composed of a representative agent from that zone. This section

[14] von Haefen et al. (2018) show a multi-site zonal model that included non-participation that was estimated using site intercept data yielded welfare measures that are strikingly similar to those of a multi-site model with non-participation that was estimated from a large general population sample of individuals (English et al. 2018).

describes the creation of the zonal data set, and a later section lays out the RRUM theory, choice probabilities and welfare measures.

To create the zonal dataset, estimated trips are needed for each origin zone and destination sites. Let $j = 0, \ldots, J$ be the set of sites in our dataset; j=0 corresponds to the outside option, or no-trip option in a RRUM. After removing sites for which we have no intercept data, e.g. no observations of individuals' origin zones, the total number of sites in the choice set is J=31, and the total number of alternatives, including no-trip, is J+1=32. For each origin zip code i we identify the one or more sites visited by individuals from that zip code. Let T_{ij} be the estimated total number of trips from zip code i to site j, derived from the survey sampling probabilities, where N_i is the set of intercepted individuals who live in zip code i, and w_{nj} is the probability that individual n was intercepted at site j, which is derived from the sampling design. Trips from each origin to each site are estimated by

$$T_{ij} = \sum_{n=1}^{N_i} \frac{1}{w_{nj}} \qquad j \neq 0 \tag{1}$$

We can also define T_i, the total number of trips from zip code i across all sites by summing T_{ij} over the J sites in the choice set:

$$T_i = \sum_{j=1}^{J} T_{ij} \tag{2}$$

The total number of trips from all zip codes to a site j, T_j, is given by the sum of T_{ij} over the I origin zip codes in the dataset.

$$T_j = \sum_{i=1}^{I} T_{ij} \qquad j \neq 0 \tag{3}$$

For each zip code the T_{ij} will serve as the weights in our estimation of the zonal RRUM. Following von Haefen et al (2018), we use the zip code population to construct the number of times in each origin that j=0 is chosen:

$$T_{i0} = A * pop_i - T_i \tag{4}$$

where A is a scaling factor that allows the total choice occasions in zip code i to be greater than the population pop_i. A is defined as follows:

$$A = \max_i \left\{ 1.1 * \frac{T_i}{pop_i} \right\} \tag{5}$$

The aggregated zonal dataset contains trips for each origin-destination pair and the total number of choice occasions for each origin zip code, CO_i, which equals $A * pop_i$.

3.2.2 Site Choice Model

Site choice is modeled using the RP data following random utility maximization (RUM) theory. We have a sample of individuals from i zip codes, each with a set of J potential sites to visit; in our data j = 0, 1, …, 31, where j=0 is the no-trip option. In our zonal model assume an individual from zip code i makes a choice of site j from a set of sites J. The utility for a person from zip code i at some site j≠0 has an observed component and a random error term.

$$U_{ij} = V_{ij} + \varepsilon_{ij} = travelcost_{ij}\beta_{travelcost} + \alpha_j + \varepsilon_{ij} \qquad j \neq 0 \tag{6}$$

The deterministic portion of utility depends on the travel cost from zip code i to site j and an alternative specific constant α_j that captures utility from attributes of site j that do not vary across individuals.[15] The utility for a person from zip code i from the no-trip option (j = 0) depends on the demographic characteristics of the zip code.

[15] Each of the J sites has a fixed effect, α_j, commonly referred to as alternative specific constants (ASCs). Since random utility models are only defined up to utility differences, we can only identify ASCs for J of the J+1 alternatives.

$$U_{i0} = V_{i0} + \varepsilon_{i0} = med\ \ income_i \gamma_{income} + med\ age_i \gamma_{age} + pct\ college_i \gamma_{college} + pct\ hispanic_i \gamma_{hispanic} + \varepsilon_{i0} \tag{7}$$

The individual chooses site *j* only if the utility of site *j* is greater than all other sites in the choice set, including the no-trip option. The probability of observing that individual *i* goes to site *j* is expressed

$$P_{ij} = P_{i\ trip} P_{ij|trip} \qquad j \neq 0 \tag{8}$$

where $P_{i\ trip}$ is the probability of taking a trip, and $P_{ij|trip}$ is the conditional probability of site *j* given that the respondent takes a trip is taken. Assuming the error term has a GEV distribution, the probabilities of site *j*≠0 take the nested-logit form and are equal to

$$P_{i,trip} = \frac{\left[\sum_{k=1}^{J} exp\left(\frac{1}{\tau} V_{ik}\right)\right]^{\tau}}{exp(V_{i0}) + \left[\sum_{k=1}^{J} exp\left(\frac{1}{\tau} V_{ik}\right)\right]^{\tau}} \tag{9}$$

$$P_{ij|trip} = \frac{exp\left(\frac{1}{\tau} V_{ij}\right)}{\sum_{k=1}^{J} exp\left(\frac{1}{\tau} V_{ik}\right)} \tag{10}$$

where τ is the nesting parameter, which captures the correlation between alternatives in the nest with recreation sites. Then the weighted log-likelihood function is

$$LL = \sum_{i=1}^{I} \left[T_{i0} y_{i0} ln(P_{i0}) + \sum_{j=1}^{J} T_{ij} y_{ij} ln\left(P_{ij}\right) \right] \tag{11}$$

where y_{ij}=1 if an individual from zip code *i* visits site *j*, and 0 otherwise, and T_{ij} is the number of choice occasions for which a person from zip code *i* visits site *j*.

The number of predicted trips to site *j* is equal to the sum over zip codes of the number of choice occasions in zip code *i*, T_i, times the probability P_{ij} given by the formula:

$$Trips_j = \sum_{i=1}^{I} T_i P_{ij} \tag{12}$$

Our welfare predictions rely on calibration of the RRUM site choice model to the contingent behavior data. For each site *j* under some fire history scenario *s* we add by adding an additional term δ_j^s to the estimated ASC. Then for each fire type we take the weighted average $\bar{\delta}^s$ to use in welfare analysis. For each fire type, the average welfare loss for a fire *s* at site *j* is given by the log-sum equation:

$$V_j^s = \sum_i T_i \frac{1}{\beta}\left[ln\left(exp(V_{i0}) + \left[\sum_k exp\left(\frac{V_{ik}+I_j[\bar{\delta}^s]}{\tau}\right)\right]^{\tau}\right) - ln\left(exp(V_{i0}) + \left[\sum_k exp\left(\frac{V_{ik}}{\tau}\right)\right]^{\tau}\right)\right] \quad (13)$$

In this equation $I_j[\bar{\delta}^s] = \begin{cases} \bar{\delta}^s \ if \ site = j \\ 0 \ if \ site \neq j \end{cases}$ is an indicator function; if site=*j* we add the weighted average $\bar{\delta}^s$ to the utility for site *j* and T_i is the number of choice occasions in zip code *i*. To get an estimate of value per lost trip, we divide the total welfare loss by the change in predicted trips with and without fire.

$$\widetilde{V_j^s} = \frac{\sum_i T_i \frac{1}{\beta}\left[ln\left(exp(V_{i0}) + \left[\sum_k exp\left(\frac{V_{ik}+I_j[\bar{\delta}^s]}{\tau}\right)\right]^{\tau}\right) - ln\left(exp(V_{i0}) + \left[\sum_k exp\left(\frac{V_{ik}}{\tau}\right)\right]^{\tau}\right)\right]}{\sum_{i=1}^{I} T_i P_{ij} - \sum_{i=1}^{I} T_i P_{ij}^s} \quad (14)$$

To estimate the value of site closures, we add term δ_j^0 to the relevant estimated ASCs, which is a constant that drives predicted trips to closed sites to zero. Total welfare loss from site closure is given by Equation (15) where $I_j[\delta_j^0] = \begin{cases} \delta_j^0 \ if \ site \ j \ \in C \\ 0 \ if \ site \ j \notin C \end{cases}$ and *C* is the set of closed sites.

$$V_C = \sum_i T_i \frac{1}{\beta}\left[ln\left(exp(V_{i0}) + \left[\sum_k exp\left(\frac{V_{ik}+I_j[\delta_j^0]}{\tau}\right)\right]^{\tau}\right) - ln\left(exp(V_{i0}) + \left[\sum_k exp\left(\frac{V_{ik}}{\tau}\right)\right]^{\tau}\right)\right] \quad (15)$$

3.2.3 Calibration to SP Data and Welfare Measures

The two-level nested logit model is estimated using the zonal dataset created from onsite trip data. While it can be used to estimate the effect of fire-induced site closures, we would like to estimate the welfare impacts of wildfire histories on recreation sites after they reopen following fires. To do this, we use the data on respondents' changes to site choice from the contingent behavior questions in the online survey. This approach of calibrating the model to outside data on site visitation has been employed by English et al. (2018). In our case we choose adjustments to site alternative-specific constants such that the estimated pattern of demand matches the changes to visitation from the survey contingent behavior questions. For each fire scenario *s* in the dataset we have a percentage reduction in trips to some affected site *j*, or target trips to site *j*. We adjust the alternative specific constants to site *j* so that

$$\alpha_j^s = \alpha_j + \delta_j^s, \qquad j \neq 0 \tag{16}$$

These δ_j^s solve the problems that equates predicted trips under fire and no fire conditions:

$$Trips_j^s = \sigma Trips_j, \qquad j \neq 0 \tag{17}$$

Here, σ is the proportion of respondents who chose "I would go to the same site" when presented with scenario *s* found in Table 3.4 (noting that not all fires occur at each site; a site in an area with predominantly trees cannot have a shrub fire nearby). For each site in the choice set and each relevant fire scenario we solve for some δ_j^s using a contraction mapping (Berry et al, 1995; Murdock 2006). The contraction mapping algorithm is specified in terms of predicted trips to site j and iteratively guesses values of $\widehat{\delta_j^s}$ so that $\widehat{Trips_j^s}$ and $Trips_j^s$ are arbitrarily close. It is given by the equation

$$\widehat{\delta_{j,k+1}^s} = \widehat{\delta_{j,k}^s} + \ln\left(\widehat{Trips_j}\right) - \ln\left[f\left(X, \widehat{\delta_{j,k}^s}\right)\right] \tag{18}$$

where *k* indexes iterations. For each iteration, the guess is updated by adding the difference in logs between estimated trips to site *j* and target trips to site *j*.

3.3 Data

3.3.1 Onsite Survey Sampling Strategy and Design

This chapter uses data from a two-stage survey. The first stage was conducted in-person during the summer of 2016, with a follow-up online survey in the winter. The onsite recreation survey conducted June 17 – August 14, 2016 intercepted visitors at a total of forty trailheads and day use sites in the Angeles National Forest. During the summer, eight enumerators were assigned to six-hour shifts that occurred either in the morning (8 AM – 2 PM) or in the afternoon (2 PM – 8 PM). For each week of the survey, five "weekday" slots were drawn from nine potential weekday shifts; all five possible "weekend" – weekends included Friday afternoons – shifts were drawn on each week for which all workers were available. On each assigned shift, two sites were selected. Each shift followed a clustered sampling strategy in which sites were separated by location into one of three clusters; first, a cluster was drawn, and then two sites within that cluster. Within each cluster, sites were stratified by the number of visits they generally receive on a weekend – high or low use.

At low-traffic sites, or where the parking lot was easily monitored, enumerators intercepted people as they approached their vehicle to leave, while one person per shift was recorded exiting vehicle traffic. At some heavily used trailheads, enumerators intercepted people as they returned from a hike, as one person recorded the number of individuals exiting the trail. Visitation counts based on vehicles were converted to people using the data from the intercepts on the number of people per vehicle. With these exit counts and the total number of interviews at a site during a given shift, we estimate the probability that an individual was interviewed conditional on being at that recreation site on that day. The sampling weights for the site strata were used to calculate the probability that a site was drawn in any particular work shift. Finally, we estimated the probability that interviews were conducted during a work shift given the time of day and day of the week. These three were combined to form an intercept probability equal to the probability of intercepting an individual at a given site during a given shift.

The onsite survey received a response rate of 62%. This percentage includes only complete responses by people who were recreating at the national forest site.[16] Respondents provided information about their trip, main activity in the forest, demographic information, and were asked to provide an email or mailing address for a follow-up online survey.[17] Of 2266 complete in-person interviews, 1755 (77.7%) respondents provided either an email address (1685) or mailing address (70) for the web survey.

3.3.2 Online Survey Design

In the online follow-up survey, respondents are first primed on major attributes of interest – vegetation, the presence of water at the site, and fire history. Vegetation and water were chosen as they are likely to be some of the most salient environmental attributes for visitors: the Angeles National Forest has diverse vegetation but can be broadly classified into forest or chaparral, and recreation sites with a stream or lake attract different visitors and different activities than those without. Respondents are also asked to think about attributes "nearby" and "farther away" from the parking area because pretesting suggested that some people differentiated between whether a fire had been off in the distance or was visible in the area around the parking lot and picnic areas, which tend to be right by the parking lots.[18] Thus, nearby was defined as the area within a 5-minute walk from the parking area, and farther away was defined as the area beyond a 5-minute walk. Next, respondents were introduced to the vegetation types and to fire impacts for chaparral and forests prior to receiving two to six contingent behavior questions depending on the vegetation type at the site they visited. We

[16] Disposition codes for the onsite and online surveys are provided in the Appendix 2F of Essay 2.

[17] See the appendix for replicas of the paper versions of on-site and online survey instruments.

[18] Survey development included 49 in-person interviews conducted at Angeles National Forest (ANF) recreation sites in July 2015, with some testing our site intercept instrument and some probing what people would do in response to fires. Paper questionnaires were tested in 15 in-person interviews at ANF in May 2016. In Fall 2016, the online instrument was tested in a webinar setting in four individual cognitive interviews with people previously intercepted at ANF.

also collected information on respondents' national forest visits, attitudes towards sites with visible fire history, and how they receive information about national forest site closures and fire conditions.

Contingent behavior questions were tailored to the type of site at which the respondent was intercepted. There were three possible sets of questions corresponding to vegetation at their site: 1) trees nearby and trees farther away, *tree/tree*; 2) trees nearby and shrubs farther away, *tree/shrub*; 3) shrubs nearby and shrubs farther away, *shrub/shrub*. The number of contingent behavior scenarios depends on the site type because not all types of fire are feasible at every vegetation combination.

Forest fires can be broadly categorized as either high-intensity crown fires, which burn all plants to the crown of the trees, or surface fires which burn the grasses and scorch tree trunks, but do not reach to the tops of trees. High-intensity forest fires leave large areas of burned vegetation visible from long distances that may take years to recover. Low-intensity surface fires are more difficult to see from a distance, however, close up they leave lasting marks at recreation sites. Chaparral fires tend to burn with high intensity, and also recover more quickly than trees; sometimes, after a year it is difficult to see where chaparral burned. Therefore, for the contingent behavior scenarios we assume that past fires that burned in areas of mostly trees could have burned *some plants* or *all plants* and could have been *recent* or *old* fires. Both types of fires (tree or shrub) could have been *near* the parking lot or *farther* away. However, we assume old forest fires that burned only some plants are not visible farther away and were not included. Fires that burn in areas of mostly shrubs we assume can only burn *all* plants, and could only be *recent*, as fires more than a couple years old are not visible. Therefore, respondents with an intercept site that was tree/tree saw contingent behavior questions with six possible past fire combinations, respondents to tree/shrub sites saw four scenarios, and respondents to shrub/shrub sites saw two contingent behavior scenarios.

Contingent behavior scenarios correspond with the predominant vegetation at sites at which respondents were intercepted: see Table 3.1 for a list of the three site vegetation categories and their fire history scenarios. Sites were categorized according to their vegetation nearby (within a 5-minute walk of the parking area) and farther away (more than 5-minutes but less than an hour's hike). Vegetation types were defined according to what visitors would see and how sites are used. For example, nearby was "mostly trees" if there was some shade present, for example a group of trees near a picnic table, and "mostly shrubs" otherwise. Sites were "mostly trees" farther away if the major trail from the parking lot followed a shaded path, and "mostly shrubs" if the path was exposed. We used a combination of visual evidence from visiting each site, aerial images from Google Earth, and information about major hikes in the area to determine vegetation type.

Table 3.1 Contingent Behavior Scenarios for Each Vegetation Type

Vegetation type	Contingent Behavior Scenarios
Trees near, trees far	Old fire that burned all plants farther away Old fire that burned all plants nearby Recent fire that burned all plants farther away Recent fire that burned all plants nearby Recent fire that burned some plants farther away Recent fire that burned some plants nearby
Trees near, shrubs far	Old fire that burned all plants nearby Recent fire that burned all plants nearby Recent shrub fire farther away Recent fire that burned some plants nearby
Shrubs near, shrubs far	Recent shrub fire farther away Recent shrub fire nearby

The online survey ran from November 2016 to January 2017. Email addresses were contacted a total of 8 times and mailing addresses 6 times. Overall 662 out of 1755 people contacted (38%) responded to the survey. The majority (576) were at sites where there were trees both nearby and farther away and saw six contingent behavior scenarios. Descriptive statistics for the full dataset of onsite survey respondents are in Table 3.2; we have information on education and income for online survey respondents only.

Table 3.2 Descriptive Statistics for Onsite Survey Respondents

Variable	Mean	Min	Max	N
Age (years)	37	18	87	3,124
Male (0/1)	0.63	0	1	3,141
Hispanic (0/1)	0.39	0	1	3,130
White (0/1)	0.54	0	1	2,907
College degree (0/1)	0.67	0	1	774
Income ($1000)	101.23	12.50	250.00	716
One-way distance to site visited (miles)	47.12	1.30	558.80	3,150
Hiker	0.71	0.00	1.00	3,150

3.3.3 Contingent Behavior Data

We derive welfare estimates of the eight different fire scenarios presented in the contingent behavior section of the online survey. For each fire scenario, we have an estimate of the percent of trips to a site that would switch to either another site or no trip. Table 3.3 shows responses from the online survey data: the worst fire scenario, which causes the most switching, is a recent fire that burned all plants farther away from the parking lot. Fifty-eight percent of respondents would continue to go to the same site, while 36% would go to a different site, and 6% would do something else. Roughly 10-15% of trips are altered in scenarios with fires that burn only some plants, or an old fire near the parking area.

Table 3.3 Contingent Behavior Responses to Fire Scenarios

Fire Scenario	Do Something Else	Go to Another Site	Go to the Same Site	Vegetation Types
Old all, far	2.92%	12.69%	84.39%	Tree/tree
Old all near	1.89%	7.35%	90.76%	Tree/tree Tree/shrub
Recent all far	6.42%	35.90%	57.69%	Tree/tree
Recent all near	4.38%	30.89%	64.74%	Tree/tree Tree/shrub
Recent far shrub	2.23%	12.26%	85.51%	Tree/shrub Shrub/shrub
Recent near shrub	3.86%	4.41%	91.73%	Shrub/shrub
Recent some far	0.80%	12.81%	86.39%	Tree/tree Tree/shrub
Recent some near	1.86%	10.62%	87.52%	Tree/tree

3.3.4 Summary Statistics

Summary statistics for the zonal dataset and the individual data prior to aggregation are found in Table 3.4. The zonal dataset was created with data from onsite interviews conducted in 2016. In 2016 intercepted individuals were on average 38 years old. Sixty-four percent were men, and 68% college educated. Household income was relatively high, \$103,000 annually, and the majority (58%) of respondents were white, and the largest minority was people of Hispanic or Latino origin (36%). Our dataset consists of 2,045 individuals from 467 origin zip codes.[19] The average value of T_{ij}, or the number of trips from zip code i to site j, is 593, while the average number trips from any given zip code 1,568. The number of trips to a site j ranges from 146 to 320,044 with an average of 23,617, and the total number of trips to any site is 732,127.

[19] For the current version of this chapter we limit the data to individuals from zip codes in California only and individuals for which we had previously estimated distances and travel costs from PC Miler

The travel cost from zip code to site latitude and longitude is calculated:

$$Travelcost_{ij} = distance * (\$.23\ per\ mile) + travel\ time * \frac{1}{3}\left(\frac{annual\ income}{2000}\right) \quad (6)$$

Where *distance* is round-trip distance and *travel time* is round-trip travel time in hours calculated by PC Miler. The cost of driving per mile is calculated using the 2016 AAA Your Driving Costs report and includes both operating costs and the marginal cost of depreciation using values for a medium-sized sedan driving 15,000 miles per year[20]. The opportunity cost of time is the one-third median household income of the zip code divided by 2000[21], or roughly one-third the hourly wage.

[20] Operating costs (fuel, tires, and oil) are $.1753 per mile, and the average marginal depreciation per mile is (290+225)/10,000 = $.0515 per mile, for a total per mile driving cost of $.2268

[21] Assumes a 40-hour work week, and 50 weeks worked per year

Table 3.4 Descriptive Statistics for the Zonal Dataset

	Variable	Mean	Min	Max	N
Individual-Level Demographics	Age (years)	38	18	84	2,032
	Male (0/1)	0.64	0	1	2,045
	Hispanic (0/1)	0.36	0	1	2,038
	White (0/1)	0.58	0	1	1,881
	College degree (0/1)	0.68	0	1	500
	Income ($1000)	103.10	12.50	250.00	463
Aggregating Variables	Trips from zip code *i* to site *j* (T_{ij})	593	29	12,024	1,234
	Trips from zip code *i* (T_i)	1,568	45	13,008	467
	Trips to site *j* (T_j)	23,617	146	320,044	31
Zip Code-Level Demographics	Median household income ($)	67,732.70	12,370.00	195,051.00	1,699
	College degree (%)	20.11	2.21	47.57	1,701
	Median age (years)	37	21	66	1,701
	Hispanic (%)	59.76	2.10	98.34	1,701
	White (%)	59.27	11.85	96.88	1,701
	Unemployment rate (%)	8.51	0.00	26.20	1,701
Trip Statistics	Round-trip distance to any site (miles)	147.14	2.00	1,199.00	52,731
	Round-trip travel cost to any site ($)	68.54	1.17	578.08	52,669
	Round-trip distance to site visited (miles)	116.75	2.60	1,117.60	1,234
	Round-trip travel cost to site visited ($)	55.66	1.76	574.49	1,233

Table 3.4 includes descriptive statistics for the zonal data set. The section on individual-level demographics are descriptive statistics for the individuals whose weights were then aggregated at the zip code level. Aggregating variables including T_{ij}, T_i, and T_j are used to develop the zip code level data set and weights used for estimation. Zip code-level demographics are taken from the US Census Bureau 2016 American Community Survey 5-year estimates. Trip statistics are summary statistics for distance and travel cost between zip codes and sites.

3.4 Results

3.4.1 Site Choice Model

Estimated parameters for the site choice model are presented in Table 3.5. The travel cost parameter is negative and significant, indicating that sites with a higher travel cost are less likely to be chosen. A full set of *J* ASCs were estimated, with the no-trip ASC $\alpha_0 = 0$; for brevity the coefficients are omitted from Table 3.5. The nesting parameter τ is between 0 and 1, and significantly different from 1. It is a measure of the correlation between the sites in the Trip nest, and implies that the nested logit model, which allows for correlation within alternatives in a nest, is a better fit for our data than the conditional logit model. The participation level parameters, which are interacted with the *J*=0 no trip alternative, show that origins with higher median household income, age, education and percentage non-Hispanics have higher participation levels (are less likely to choose the not rip option). The standard errors and confidence interval in Table 3.5 were estimated by constructing bootstrapped samples of the individual-level trip data[22].

The site choice model allows us to estimate the welfare effects of site closures. Major wildfires often cause recreation sites to close either while the fire is suppressed or in the case of areas that sustain major infrastructure damage, sites sometimes remain closed for months or years. We find that the average per-trip welfare loss from the closure of a day-use site range from $24 to $29 per trip. The closure of high-use sites for an entire season results in welfare loss up to $9 million (a table describing welfare loss from site closure can be found in the appendix).

[22] The dataset of individuals was expanded so that the person's frequency in the data was proportional to their resampling probability. Replicate datasets were then drawn for each site so that the number of trips in each site remained the same.

Table 3.5 Site Choice Model Results

Level	Variable	Coef.	Std. Err.	95% Confidence Interval	
Trip	Travel cost	-0.017***	1.82E-04	-0.018	-0.017
	Nesting parameter	0.419***	0.005	0.410	0.427
No trip	Median household income	-1.96e-06***	1.15E-07	-2.16E-06	-1.74E-06
	Median age	-0.057***	3.62E-04	-0.057	-0.056
	Pct college graduate	-1.591***	0.025	-1.640	-1.551
	Pct Hispanic	0.866***	0.011	0.843	0.889
	Log likelihood	-5910159.1			
	N	4.797e+09			

Note: For brevity the site-specific constants (the ASCs) are not presented here.

3.4.2 Welfare Effects of Fire

In this section we present results from the contraction map and estimate the welfare impacts of our eight fire scenarios, which are specific to the type of vegetation found at the recreation site. The eight scenarios are:

1. Old forest fire that burned all plants farther away
2. Old forest fire that burned all plants nearby
3. Recent forest fire that burned all plants farther away
4. Recent forest fire that burned all plants nearby
5. Recent shrub fire farther away
6. Recent shrub fire nearby
7. Recent forest fire that burned some plants farther away
8. Recent forest fire that burned some plants nearby

For each site *j* and fire scenario *s* we estimate a set of parameters δ_j^s that equate the expected trips to site j with predicted trips using the site choice model. Table 3.6 shows the average $\bar{\delta}^s$ and the

95% confidence intervals for $\bar{\delta}^s$ computed using the bootstrapped datasets, weighted by predicted trips to sites.[23] In Table 3.6 σ is the proportion of people who would choose to go to the same site under the given scenario. The parameters $\bar{\delta}^s$ are used as inputs into the welfare estimation[24].

Table 3.6 Weighted Average of Delta from Contraction Map

Fire Scenario	$\bar{\delta}^s$	Confidence Interval ($\bar{\delta}^s$)	σ	Vegetation types
Old all far	-0.0873	(-0.0888, -0.0858)	84.39%	Tree/tree
Old all near	-0.0490	(-0.0499, -0.0482)	90.76%	Tree/tree Tree/shrub
Recent all far	-0.2747	(-0.2795, -0.2698)	57.69%	Tree/tree
Recent all near	-0.2144	(-0.2182, -0.2105)	64.74%	Tree/tree Tree/shrub
Recent far shrub	-0.0682	(-0.0696, -0.6685)	85.51%	Tree/shrub Shrub/shrub
Recent near shrub	-0.0377	(-0.0385, -0.3694)	91.73%	Shrub/shrub
Recent some far	-0.0754	(-0.0767, -0.0741)	86.39%	Tree/tree Tree/shrub
Recent some near	-0.0672	(-0.0684, -0.0660)	87.52%	Tree/tree

For each fire *s* we calculate the total welfare loss for one summer season[25] with the fire at site *j*, the change in predicted trips to site *j* under the change, and the value per lost trip $\widetilde{V_j^s}$. Naturally when we compare across the sites, sites with larger numbers of trips experience larger losses, making it sensible to report the value per lost trip. Table 3.7 shows weighted average value per lost trip for each scenario – welfare losses range from $24.94 per lost trip to $29.52 per lost trip. Results are as expected, with forest fires mattering more than shrub fires, and fires farther away from the parking area

[23] The bootstrapping for these calculations has not yet accounted for the underlying variation in each σ.
[24] The site-specific estimates δ_j^s are presented in the appendix

[25] Welfare estimates correspond to the sampling period for the intercept survey, early June to mid-August

mattering more than fires nearby the parking area. Given that a large majority of respondents were hikers – roughly 70% of intercepts – it is reasonable to expect that fire conditions at some distance from the parking area will have a greater welfare impact than conditions nearby, where the average respondent spends less time. However, the overall difference in the estimates per lost trip between nearby and farther away is small in magnitude (around $1 per lost trip). The large differences in value lost are between shrub fires and forest fires; per-lost-trip from shrub fires either nearby or farther away is around $25, while for forest fires it is $29 per lost trip. This is potentially because shrubs or chaparral grow back relatively quickly after a fire, and because visitation is lower at these sites. Our presented scenarios were on a time scale at which there would be significant regrowth in chaparral areas; we only ask respondents to consider shrub fires 1-3 years old, whereas chaparral areas generally see significant regrowth within one year.

Table 3.7 Trip Predictions and Welfare Estimates for a Past Fire Affecting a Single Site

Fire Scenario	Welfare loss	Confidence Interval (Welfare loss)	Δ Trips to site j	Confidence Interval (Δ Trips)	Value per lost trip
Old all far	$ 951,186	($ 914,513, $ 982,420)	30,263	(29,072, 31,240)	$ 29.47
Old all near	$ 488,600	($ 469,699, $ 504,619)	15,589	(14,973, 16,094)	$ 28.94
Recent all far	$ 2,535,967	($ 2,437,628, $ 2,618,989)	83,196	(79,932, 85,878)	$ 28.73
Recent all near	$ 1,843,208	($ 1,771,761, $ 1,903,490)	60,436	(58,056, 62,387)	$ 28.32
Recent far shrub	$ 175,601	($ 168,783, $ 181,304)	6,990	(6,717, 7,215)	$ 24.94
Recent near shrub	$ 103,572	($ 99,554, $ 106,940)	4,139	(3,978, 4,273)	$ 24.99
Recent some far	$ 830,337	($ 798,341, $ 857,609)	26,361	(25,323, 27,212)	$ 29.52
Recent some near	$ 658,974	($ 633,464, $ 680,573)	21,093	(20,260, 21,775)	$ 28.86

Note: Welfare loss, change in trips, and value per lost trip are a weighted average across sites for the summer season. 95% confidence intervals were computed using the bootstrapped datasets.

For each recreation site in the choice set, the contraction mapping used to estimate welfare losses calibrates that site's ASC until the new predicted trips to the site are equal to the predicted trips under some fire scenario according to responses from the survey data. However, for each fire scenario we also have a contingent behavior estimate of the percentage of respondents who would have stayed at home rather than take a trip to another site in the forest. The contraction mapping results do not take into account the percentage of people who stated they would go to another site in the forest or stay at home. Rather, the pattern of substitution away from the site in question is determined by the estimated parameters from the zonal travel cost model. Table 3.8 compares how the estimated distribution of diverted trips from site *j* after a fire using our calibrated ASCs differs from respondents' stated behavior in the contingent behavior data. Overall, we find that our model predictions for continuing to go to the same site are very close. However, the estimated nested logit model structure is less likely to predict that people will choose the no-trip option than our survey respondents stated preferences. For each of the fire scenarios, with the exception of recent forest fires that burned all plants, roughly 2% of respondents would choose the no-trip option. For recent forest fires that burned all plants, that number is closer to 8% who would choose to do something else rather than recreate in the forest. The model predicts well below 1% choosing to do something else for all possible scenarios, and nearly all diverted trips going to other recreation sites in the forest.

Table 3.8 Comparison of Stated Preference Data and Nested Logit Predictions

	Survey Responses			Model Predictions Using $\bar{\delta}^s$		
Fire Scenario	**Do something else**	**Go to another site**	**Go to the same site**	**Do something else**	**Go to another site**	**Go to the same site**
Old all far	2.92%	12.69%	84.39%	0.0111%	15.77%	84.22%
Old all near	1.89%	7.35%	90.76%	0.0057%	9.36%	90.63%
Recent all far	6.42%	35.90%	57.69%	0.0295%	42.45%	57.52%
Recent all near	4.38%	30.89%	64.74%	0.0215%	35.46%	64.52%
Recent far shrub	2.23%	12.26%	85.51%	0.0020%	14.49%	85.51%
Recent near shrub	3.86%	4.41%	91.73%	0.0012%	8.27%	91.73%
Recent some, far	0.80%	12.81%	86.39%	0.0097%	13.76%	86.23%
Recent some near	1.86%	10.62%	87.52%	0.0077%	12.63%	87.36%

Note: Model predictions are averaged across the results for each of the 31 sites.

3.4.3 Station Fire

To illustrate the temporal effect of wildfires in the Angeles National Forest we estimate the welfare effects of three different fire scenarios, using a group of sites affected by the Station Fire (2009) as an example.[26] The Station Fire is one of the largest wildfires in Angeles County – it burned for nearly two months (August- October 2009) and affected 160,577 acres, mostly in the southwestern portion of the Angeles National Forest. Figure 3.1 shows the extent of the burn scar as captured by the MODIS satellite in September 2009 (NASA 2009). In addition to causing fire damage at recreation sites, over 40 miles of the Angeles Crest Highway, which runs through the forest and provides access to campgrounds, trailheads, and visitors' centers in the forest, remained closed after the fire due to continued risk from debris and mudslides until June 2011 (*Pasadena Star-News* 2011). In addition to site closures within the fire perimeter, the Angeles Crest Highway closure prevented visits to unaffected sites north of the fire perimeter for the better part of two years. Twelve of the sampled sites from the intercept survey are located within the burn scar, ten of them along the Angeles Crest Highway. An additional five sites are accessible only by the highway but were not in the fire perimeter. Even after the opening of sites, our model results suggest there will be impacts if effects of fire are visible at sites. Lasting damage from the Station Fire was still visible at many of the affected forested sites during our site visits in 2016, seven years after the fire. To illustrate the dynamic effect of the Station Fire we model three scenarios, each lasting one season: (1) a highway closure that prevents access to all sites on the Angeles Crest Highway; (2) a recent fire that burned all vegetation (both forests and shrubs) far from the parking area within the Station Fire burn scar; and (3) an old fire that

[26] The purpose here is to apply the model to this scenario to illustrate how the model addresses the immediate, mid, and longer-term effects of a large fire on recreation sites. This is not meant to be an exact recreational damage assessment of the station fire.

burned all vegetation far from the parking area within the Station Fire burn scar (at a time when far shrub fires would no longer be noticeable).

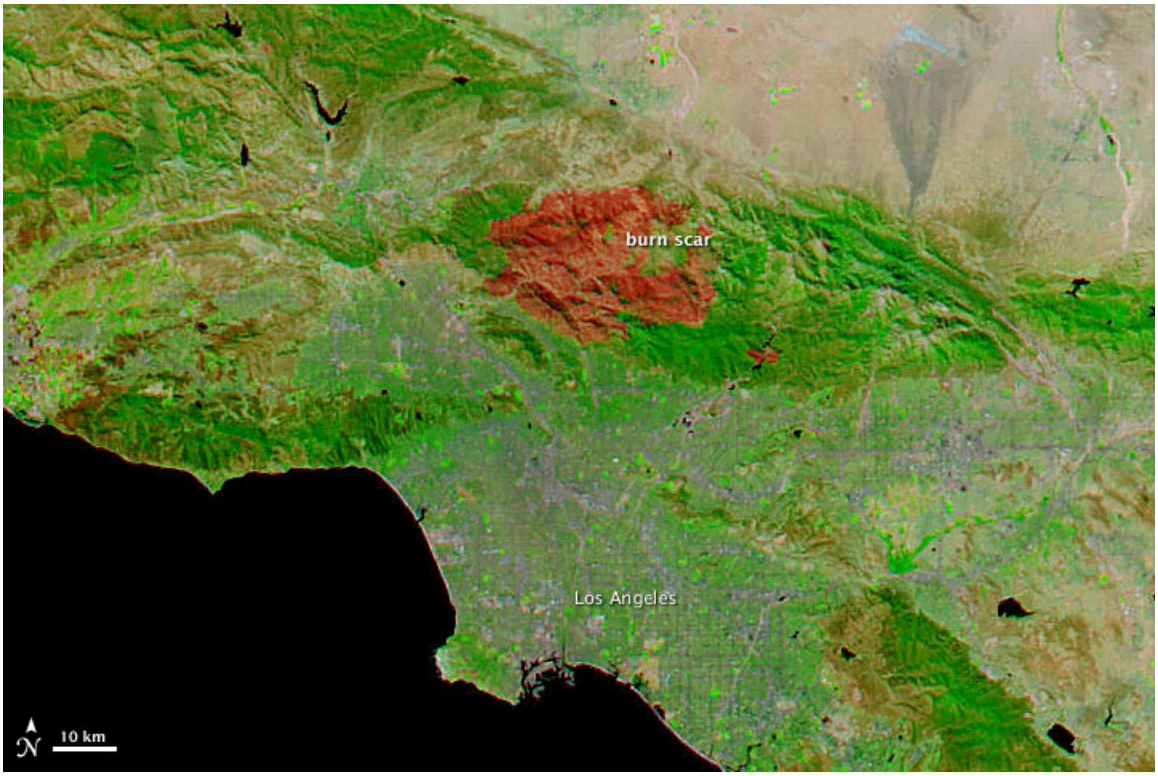

Figure 3.1 Station Fire Burn Scar on Sept. 16, 2009

The sites used in the analysis with their predicted trips under the status quo are shown in Table 3.9. They are predominantly sites that provide access to major trails located in forested areas although four sites are located in less shaded shrubland. In the road closure scenario all sites on the Angeles Crest Highway are inaccessible and receive no trips. We estimate that, in the first scenario, the fire and highway closure would have caused $2.8 million in forest recreation-related welfare losses. The second scenario is a recent fire that burned all vegetation (trees or shrubs) far from the parking area. We find that in the year after re-opening, when fire effects would be clearly visible at recreation sites, the Station Fire would have caused 22,196 diverted trips to the affected sites, resulting in a total welfare loss of about $563,000. Later, as vegetation began to recover in our third scenario, fire damage would still affect roughly 6,870 trips to the forest and cause welfare losses of about $171,000.

Table 3.9 Sites Affected by Station Fire

Site	Burn perimeter	Angeles Crest Hwy	Predicted summer trips
Buckhorn Picnic Area	Yes	Yes	850
Charlton Flat Picnic Area	Yes	Yes	3,686
Chilao Visitor Center	Yes	Yes	1,112
Devil's Canyon Trailhead	Yes	Yes	202
Josephine/Colby Road Trailhead	Yes	Yes	678
Mt. Wilson Observatory	Yes	Yes	5,212
Red Box Picnic Area	Yes	Yes	11,299
Hidden Springs Picnic Area	Yes	No	357
Stonyvale Picnic Area	Yes	No	3,969
Wildwood Picnic Area	Yes	No	19,675
Islip Saddle Trailhead	No	Yes	5,841
Eagle Roost Picnic Area	No	Yes	631
Grassy Hollow Visitor Center	No	Yes	12,609
Inspiration Point	No	Yes	8,432
Vincent Gap	No	Yes	763

3.5 Conclusions

The Angeles National Forest is one of the most important areas of outdoor recreation for people in Los Angeles County as well as visitors from farther away. In recent years the forest has frequently experienced wildfires in the forest boundary, often causing road closures and site closures, sometimes causing lasting damage. In 2016 the Sand Fire consumed a large section of the forest near Santa Clarita, causing site closures that are still in place two years later. Even when recreation sites reopen, popular hikes and picnic sites may have visible fire damage.

This essay uses combined revealed preference and stated preference data to estimate the welfare impacts of fire at recreation sites in the forest. In particular, we use stated response data for several types of fires that could previously have occurred at the site they were intercepted at, for which respondents stated whether they would go to the same site, go to some other national forest site, or choose to do something else. A multi-site zonal recreation demand model was estimated with the intercept revealed preference data, and it was calibrated to the contingent behavior results in order to estimate the demand and welfare impacts of fires after sites reopen.

From our nested logit zonal model specification, we find that there is significant correlation between site alternatives. Individuals from zip codes that are on average wealthier and more educated are more likely to take trips to the Angeles National Forest; individuals in areas that are less wealthy or have a higher share of Hispanics are less likely to recreate in the forest. Our multi-site zonal model is specified using alternative-specific constants; we use contraction maps to calibrate these site constants to estimate the change in site characteristics that results in the same number of reduced trips as in the contingent behavior data. We find welfare loss of forest fires of roughly $29 per lost trip. When considering the average effect of a past fire on a single site, a recent forest fire that burned all plants farther away has the greatest total welfare loss, $2.5 million, followed by a recent forest fire that burned all plants nearby, at $1.8 million. This suggests that increasing fire activity in the national forest as well as other wilderness areas in California not only have immediate economic impacts from potential destruction of property and loss of life, but that indirect welfare losses to recreation continue for years afterwards.

The largest wildfires in the forest do not affect one site at a time. Usually several in the same area are impacted, and in some cases, such as the Station Fire in 2009, over ten major day use, hiking, and camping areas experience fire damage. For large wildfires that impact multiple sites, our single site welfare estimates are an understatement of the actual impact. To demonstrate how large fires such as the Station Fire can have a lasting impact over time, we model the welfare effects of a fire and road closure that affected many major hiking and picnic sites both within and outside of the Station Fire burn perimeter. We also illustrate how major wildfires have lasting impacts over time by modeling recent and older fires that burn all plants farther away from the parking area on hiking trails. The model predicts that in the summer after the fire when sites were inaccessible, the Station fire caused welfare losses of over $2 million. After re-opening but while significant damage was still visible, it caused over 20,000 altered trips to the forest, and years later even as the forest began to recover and shrubs had recovered, the impacted sites still see 5,000 fewer visits per year.

Finally, the substitution pattern in our calibrated zonal model predicts many fewer no-trips than suggested by our stated preference data. In the contingent behavior data, 1-6% of trips to sites are diverted to the stay-home option under our fire scenarios. In our calibrated demand model we predict 0.002% of those trips become stay-home when there is a shrub fire. Under the worst-case scenario, a recent forest fire that burned all plants farther away, we predict 0.0295% of the trips become stay-home option. Future extensions to this work should consider the stated preference substitution between other sites and no-trip in order to more accurately predict the pattern of stated responses to fire.

APPENDICES

Appendix 3A: Recreation sites in zonal data set and predicted trips

Table 3.10 Recreation Sites and Predicted Trips

Site	Vegetation	Predicted summer trips
East Fork Trailhead	shrub/shrub	51,904
Elizabeth Lake Canyon Road	shrub/shrub	1,040
Josephine/Colby Road Trailhead	shrub/shrub	678
Upper Bear Creek Trailhead	shrub/shrub	168
Barrett Stoddard Road	tree/shrub	1,517
Bear Divide Vista Picnic Area	tree/shrub	4,781
Elizabeth Lake Picnic Area	tree/shrub	1,353
Frenchman's Flat	tree/shrub	3,652
Hidden Springs Picnic Area	tree/shrub	357
Stonyvale Picnic Area	tree/shrub	3,969
West Fork	tree/shrub	66,450
Wildwood Picnic Area	tree/shrub	19,675
Buckhorn Picnic Area	tree/tree	850
Chantry Flat Picnic Area	tree/tree	318,695
Charlton Flat Picnic Area	tree/tree	3,686
Chilao Visitor Center	tree/tree	1,112
Devil's Canyon Trailhead	tree/tree	202
Eagle Roost Picnic Area	tree/tree	631
Grassy Hollow Visitor Center	tree/tree	12,609
Icehouse Canyon Trailhead	tree/tree	85,395
Inspiration Point	tree/tree	8,432
Islip Saddle Trailhead	tree/tree	5,841
Jackson Lake Picnic Area	tree/tree	4,911
Mt. Wilson Observatory	tree/tree	5212
Red Box Picnic Area Area	tree/tree	11299
San Antonio Falls Trailhead	tree/tree	94524
Switzer Picnic Area	tree/tree	20887
Three Points Trailhead	tree/tree	762
Vincent Gap	tree/tree	763
Vista Picnic Area	tree/tree	537
Windy Gap Trail	tree/tree	149

Appendix 3B: Site Closure

Table 3.11 Welfare Impacts of Site Closure by Site

Site	Welfare loss from site closure for summer season
Islip Saddle Trailhead	$ 140,378
Elizabeth Lake Canyon Road	$ 24,927
Barrett Stoddard Road	$ 36,346
Bear Divide Vista Picnic Area	$ 114,848
Buckhorn Picnic Area	$ 20,357
Chantry Flat Picnic Area	$ 9,112,321
Charlton Flat Picnic Area	$ 88,427
Chilao Visitor Center	$ 26,631
Devil's Canyon Trailhead	$ 4,827
Eagle Roost Picnic Area	$ 15,114
East Fork Trailhead	$ 1,272,097
Elizabeth Lake Picnic Area	$ 32,473
Frenchman's Flat	$ 87,896
Grassy Hollow Visitor Center	$ 304,189
Hidden Springs Picnic Area	$ 8,548
Icehouse Canyon Trailhead	$ 2,158,100
Inspiration Point Area	$ 202,918
Jackson Lake Picnic Area	$ 117,950
Josephine/Colby Road Trailhead	$ 16,236
Mt. Wilson Observatory	$ 125,086
Vincent Gap	$ 18,288
Red Box Picnic Area	$ 272,061
San Antonio Falls Trailhead	$ 2,397,999
Stonyvale Picnic Area	$ 95,216
Switzer Picnic Area	$ 505,392
Three Points Trailhead	$ 18,245
Upper Bear Creek Trailhead	$ 4,014
Vista Picnic Area	$ 12,854
West Fork	$ 1,639,062
Wildwood Picnic Area	$ 475,993
Windy Gap Trail	$ 3,574

Appendix 3C: Site-specific delta and welfare estimates

Table 3.12 Estimates of δ_j for All Sites and Fire Scenarios

Site	Vegetation	Old, all, far	Old, all, near	Recent, all, far	Recent, all, near	Recent, far, shrub	Recent, near, shrub	Recent, some, far	Recent, some, near
East Fork Trailhead	shrub/shrub					-0.0684	-0.0378		
Elizabeth Lake Canyon Road	shrub/shrub					-0.0657	-0.0362		
Josephine/ Colby Road	shrub/shrub					-0.0656	-0.0362		
Upper Bear Creek Trailhead	shrub/shrub					-0.0655	-0.0361		
Barrett Stoddard Road	tree/shrub		-0.0406		-0.1822	-0.0656			-0.0559
Bear Divide Vista Picnic Area	tree/shrub		-0.0408		-0.1830	-0.0659			-0.0561
Elizabeth Lake Picnic	tree/shrub		-0.0407		-0.1826	-0.0658			-0.0560
Frenchman's Flat	tree/shrub		-0.0410		-0.1835	-0.0661			-0.0563
Hidden Springs Picnic	tree/shrub		-0.0406		-0.1821	-0.0655			-0.0558
Stonyvale Picnic	tree/shrub		-0.0407		-0.1826	-0.0658			-0.0560
West Fork	tree/shrub		-0.0429		-0.1909	-0.0692			-0.0589
Wildwood Picnic Area	tree/shrub		-0.0414		-0.1850	-0.0668			-0.0569

Table 3.12 (cont'd)

Buckhorn Picnic	tree/tree	-0.0711	-0.0406	-0.2304	-0.1821			-0.0613	-0.0558
Chantry Flat Picnic Area	tree/tree	-0.0961	-0.0554	-0.2987	-0.2390			-0.0831	-0.0758
Charlton Flat Picnic Area	tree/tree	-0.0713	-0.0407	-0.2309	-0.1825			-0.0614	-0.0560
Chilao Visitor Center	tree/tree	-0.0711	-0.0406	-0.2304	-0.1822			-0.0613	-0.0559
Devil's Canyon Trailhead	tree/tree	-0.0711	-0.0406	-0.2303	-0.1820			-0.0613	-0.0558
Eagle Roost Picnic	tree/tree	-0.0711	-0.0406	-0.2304	-0.1821			-0.0613	-0.0558
Grassy Hollow Visitor Center	tree/tree	-0.0720	-0.0412	-0.2329	-0.1842			-0.0621	-0.0566
Icehouse Canyon Trailhead	tree/tree	-0.0781	-0.0447	-0.2496	-0.1981			-0.0674	-0.0614
Inspiration Point	tree/tree	-0.0717	-0.0410	-0.2320	-0.1835			-0.0618	-0.0563
Islip Saddle Trail Head	tree/tree	-0.0715	-0.0409	-0.2315	-0.1831			-0.0616	-0.0562
Jackson Lake Picnic	tree/tree	-0.0714	-0.0408	-0.2313	-0.1829			-0.0616	-0.0561
Mt. Wilson Observatory	tree/tree	-0.0713	-0.0408	-0.2311	-0.1827			-0.0615	-0.0560
Vincent Gap	tree/tree	-0.0711	-0.0406	-0.2304	-0.1821			-0.0613	-0.0558
Red Box Picnic Area	tree/tree	-0.0718	-0.0410	-0.2322	-0.1836			-0.0619	-0.0564
San Antonio Falls Trailhead	tree/tree	-0.0786	-0.0451	-0.2511	-0.1993			-0.0679	-0.0619

Table 3.12 (cont'd)

Switzer Picnic Area	tree/tree	-0.0724	-0.0414	-0.2340	-0.1851			-0.0624	-0.0569
Three Points Trailhead	tree/tree	-0.0711	-0.0406	-0.2304	-0.1821			-0.0613	-0.0558
Vista Picnic Area	tree/tree	-0.0711	-0.0406	-0.2304	-0.1821			-0.0613	-0.0558
Windy Gap Trail	tree/tree	-0.0711	-0.0406	-0.2303	-0.1820			-0.0612	-0.0558

Table 3.13 Estimates of Per-trip Value Lost for All Sites and Fire Scenarios

Site	Vegetation	Old, all, far	Old, all, near	Recent, all, far	Recent, all, near	Recent, far, shrub	Recent, near, shrub	Recent, some, far	Recent, some, near
East Fork Trailhead	shrub/shrub					$ 24.99	$ 25.03		
Elizabeth Lake Canyon Road	shrub/shrub					$ 24.00	$ 24.00		
Josephine/Col by Road Trailhead	shrub/shrub					$ 23.96	$ 23.96		
Upper Bear Creek Trailhead	shrub/shrub					$ 23.95	$ 23.95		
Barrett Stoddard Road	tree/shrub		$ 23.98		$ 23.97	$ 23.98			$ 23.98
Bear Divide Vista Picnic Area	tree/shrub		$ 24.09		$ 24.07	$ 24.09			$ 24.09
Elizabeth Lake Picnic Area	tree/shrub		$ 24.04		$ 24.02	$ 24.04			$ 24.04
Frenchman's Flat	tree/shrub		$ 24.17		$ 24.14	$ 24.17			$ 24.17
Hidden Springs Picnic Area	tree/shrub		$ 23.95		$ 23.95	$ 23.95			$ 23.95
Stonyvale Picnic Area	tree/shrub		$ 24.03		$ 24.02	$ 24.03			$ 24.03
West Fork	tree/shrub		$ 25.31		$ 25.11	$ 25.29			$ 25.29
Wildwood Picnic Area	tree/shrub		$ 24.41		$ 24.34	$ 24.40			$ 24.40

Table 3.13 (cont'd)

Buckhorn Picnic Area	tree/tree	$ 23.96	$ 23.96	$ 23.96	$ 23.96			$ 23.96	$ 23.96
Chantry Flat Picnic Area	tree/tree	$ 32.48	$ 32.75	$ 31.36	$ 31.69			$ 32.56	$ 32.62
Charlton Flat Picnic Area	tree/tree	$ 24.02	$ 24.03	$ 24.01	$ 24.01			$ 24.03	$ 24.03
Chilao Visitor Center	tree/tree	$ 23.97	$ 23.97	$ 23.97	$ 23.97			$ 23.97	$ 23.97
Devil's Canyon Trailhead	tree/tree	$ 23.95	$ 23.95	$ 23.95	$ 23.95			$ 23.95	$ 23.95
Eagle Roost Picnic Area	tree/tree	$ 23.96	$ 23.96	$ 23.96	$ 23.96			$ 23.96	$ 23.96
Grassy Hollow Visitor Center	tree/tree	$ 24.27	$ 24.28	$ 24.22	$ 24.23			$ 24.27	$ 24.28
Icehouse Canyon Trailhead	tree/tree	$ 26.31	$ 26.39	$ 25.97	$ 26.06			$ 26.33	$ 26.35
Inspiration Point	tree/tree	$ 24.16	$ 24.17	$ 24.13	$ 24.14			$ 24.16	$ 24.17
Islip Saddle Trailhead	tree/tree	$ 24.10	$ 24.11	$ 24.08	$ 24.08			$ 24.10	$ 24.10
Jackson Lake Picnic Area	tree/tree	$ 24.08	$ 24.08	$ 24.06	$ 24.06			$ 24.08	$ 24.08
Mt. Wilson Observatory	tree/tree	$ 24.05	$ 24.05	$ 24.03	$ 24.03			$ 24.05	$ 24.05
Vincent Gap	tree/tree	$ 23.97	$ 23.97	$ 23.96	$ 23.96			$ 23.97	$ 23.97
Red Box Picnic Area	tree/tree	$ 24.19	$ 24.20	$ 24.15	$ 24.16			$ 24.19	$ 24.19
San Antonio Falls Trailhead	tree/tree	$ 26.49	$ 26.58	$ 26.12	$ 26.23			$ 26.52	$ 26.54

Table 3.13 (cont'd)

Switzer Picnic Area	tree/tree	$ 24.40	$ 24.42	$ 24.33	$ 24.35			$ 24.41	$ 24.41
Three Points Trailhead	tree/tree	$ 23.96	$ 23.96	$ 23.96	$ 23.96			$ 23.96	$ 23.96
Vista Picnic Area	tree/tree	$ 23.96	$ 23.96	$ 23.96	$ 23.96			$ 23.96	$ 23.96
Windy Gap Trail	tree/tree	$ 23.95	$ 23.95	$ 23.95	$ 23.95			$ 23.95	$ 23.95

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