ESSAYS IN NONMARKET VALUATION

by

WILLIAM P. WHEELER

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Student: William P. Wheeler

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This dissertation has been accepted and approved in partial fulfillment of the requirements for the Doctor of Philosophy degree in the Department of Economics by:

Trudy Ann Cameron	Chair
Wesley W. Wilson	Core Member
Grant McDermott	Core Member
Grant Jacobson	Institutional Representative

and

Janet Woodruff-Borden	Vice Provost and Dean of the Graduate School

Original approval signatures are on file with the University of Oregon Graduate School.

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DISSERTATION ABSTRACT

William P. Wheeler

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This dissertation focuses on the valuation of nonmarket goods using travel cost models of recreation demand. An accurate and up-to-date understanding of the value of public lands and nonmarket environmental goods is integral to benefit-cost analyses of public lands policies and policies that affect environmental amenities. The present work is motivated by the importance of these benefit-cost analyses and the methods used to value nonmarket amenities. In Chapter II, I examine demand for federally-managed campgrounds in California and consider how changes in campsite attributes or availability would affect consumer welfare. I develop a novel definition of the consideration set to include available sites at different available times over the course of the remaining season to capture the role that intertemporal substitution plays in these nonmarket valuation estimates. In Chapter III, I use campground demand to estimate the value of environmental amenities in the locality of the campgrounds people choose to visit. I use the fitted model to calculate the welfare impact of weather changes associated with projected climate change under two emissions scenarios and find that the lower emissions scenario results in 40% smaller welfare losses on average. In Chapter IV, I use remotely-sensed historical wildfire data to explore the relationship between campground demand and the effects of wildfire. Consistent with other research, I find that recent wildfires increase the utility associated with a particular recreational trip; though, this positive effect is attenuated if the burns were particularly severe.

CURRICULUM VITAE

NAME OF AUTHOR: William P. Wheeler

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:
University of Oregon, Eugene, OR
Colorado State University, Fort Collins, CO

DEGREES AWARDED:
Doctor of Philosophy, Economics, 2019, University of Oregon
Master of Science, Economics, 2015, University of Oregon
Bachelor of Arts, Economics and Political Science, 2014, Colorado State University

AREAS OF SPECIAL INTEREST:
Environmental Economics
Applied Mircoeconomics
Econometrics

GRANTS, AWARDS AND HONORS:

Graduate Employee Teaching Award, University of Oregon, 2018

Kleinsorge Summer Research Award, University of Oregon, 2018

Best First-Year Econometrics Performance Award, University of Oregon, 2018

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On a personal note, I would like to thank my parents, Bill and Suzanne Wheeler, for their love, support, and guidance throughout my life. Last but certainly not least, I would like to thank Jean Falconer, whose love and support I have been so lucky to enjoy during my years at the University of Oregon.

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CHAPTER I

INTRODUCTION

The dominant theme of my dissertation is the use of recreation demand models to estimate people's willingness to pay for environmental amenities and to construct welfare measures associated with hypothetical changes in the availability or quality of the sites people visit. Chapter II explores the determinants of demand for federally managed campgrounds in California by estimating willingness to pay for site amenities and the activities available at or nearby the site. Chapter III incorporates additional environmental amenities in the locality of the campgrounds and considers the welfare effects of weather changes associated with projected climate change. Chapter IV explores how wildfires impact the recreational use value of camping and how more severe or more frequent fires would affect campers.

All chapters use data from the Recreation Information Database (RIDB), which is part of the Recreation One Stop (Rec1Stop) project, a web-based single point of access for recreational opportunities including camping on federal lands. This dissertation is the first use of this expansive dataset to estimate utility-theoretic choice models. In Chapter II, I introduce a novel way of defining an individual's consideration set as consisting of campground-weekend pairs as opposed to the more traditional definition as a choice between different sites on a particular day. This allows me to capture the role that intertemporal substitution plays in a camper's decision making process. Within the context of this new framework, I focus on the role that nearby activities and campground amenities play in the customer's decision. I calculate equivalent variation (EV) measures for hypothetical changes in site availability and site quality that provide insight into the recreational use values derived from camping.

Chapter III places a larger focus on environmental amenities, examining how individuals' campground decisions reveal their value for attributes like temperature, precipitation, land cover, and light pollution. For time-varying amenities like temperature and precipitation, allowing for intertemporal substitution is particularly important because individuals may decide to change when they visit a site as opposed to substituting across sites. I find that an individual's utility is reduced by light pollution and high temperatures, and that many types of land cover are preferable to the most common type at California campgrounds (evergreen forests). To demonstrate the types of analysis that this specification can allow, I calculate the EV for temperature and precipitation changes associated with projected climate change under high-emissions and low-emissions scenarios.

In Chapter IV, I consider how the severity and frequency of recent wildfires affect the recreational use value derived from camping. I splice in historical data on remotely sensed wildfires in the locality of the campgrounds in my sample. These historical wildfire observations are matched to the area immediately around campgrounds to capture the direct effect that wildfires have on the scenery around a campground, as well as matched to the wider area around campgrounds to capture beliefs about the risk or frequency of wildfires in an area. To evaluate how wildfires affect camper utility, I calculate EV measures for increases in the severity of nearby fires and the frequency of severe fires in the general area.

CHAPTER II

CAMPGROUND RECREATIONAL USE VALUE: A RANDOM-UTILITY SITE CHOICE MODEL WITH ENDOGENOUS TRIP TIMING

Introduction

For public lands in the United States, the question of how to allocate vast resources across competing uses is a topic of ongoing debate. The relative priority assigned to commercial exploration versus recreation or preservation is a matter of growing concern in some quarters (Press (2017a); Turkewitz and Friedman (2017)). In 2017, the U.S. Interior Secretary at that time, Ryan Zinke, proposed turning over national park campsites to private businesses (Hood, 2017). The Executive Branch has expressed a desire to cut \$375 million from the National Parks Service's \$3 billion budget, and the agency is reportedly already facing a maintenance backlog of more than \$11 billion (Barnes (2017); Press (2017b)). Zinke has been quoted as saying "As the secretary, I don't want to be in the business of running campgrounds."[1]

A different set of campground management incentives might result in significant changes in the attributes of campgrounds on public lands. In December of 2017, President Trump ordered the reduction of Bears Ears and Grand Staircase Escalante National Monuments by roughly two million acres, and Secretary Zinke proposed changing the boundaries of four other monuments (Turkewitz, 2017). Such changes to the designated uses and levels of protection for public lands could potentially affect the availability of camping recreation. For these reasons,

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[1] This quote was reported from a speech to members of the Recreational Vehicle Industry Association, in Cama (2017)

it seems prudent to undertake an updated analysis of the determinants of value for campgrounds on public lands.

Travel cost models of recreation demand have been used widely to value nonmarket environmental goods and services. Hedonic models using house prices are useful for valuing such nonmarket goods located in urban areas, but travel cost models are better suited to the task of valuing environmental amenities located in rural areas. This research demonstrates the use of a travel-cost-based approach to estimate marginal willingness to pay (MWTP) by campers for amenities in and around campgrounds. Central to this estimation is a novel and richer specification of the consideration set—I assume that individuals choose between all available sites *at all available future dates* on each choice occasion. In this way, I endogenize the timing of trip the individual takes, explicitly accounting for intertemporal substitution across alternatives. This modeling choice is made possible by the structure of the campsite reservation data in the Recreation Information Database (RIDB), which records when each individual made their camping reservation and which campgrounds were then available at which times over the coming season. This time dimension to reservations is made more interesting by the fact that each individual's choice set varies over the course of the season—both because there is less time remaining until the season closes, and because certain sites may be unavailable because they reach their reservation limits.

Much research in the recreation demand literature does not fully account for intertemporal substitution across alternatives. In many cases, the estimation relies on only cross-sectional data, preventing an analysis of intertemporal substitution patterns. When repeated trip data are available, the decisions made on each choice occasion are often assumed to be independent. Realistically, and particularly in the case of camping reservations, individuals decide both when to go, and where to go, based on the expected seasonal attributes associated which each possible destination. My specification allows for this, and does not assume that the decision of *when* to recreate comes before the decision of *where* to recreate, or *vice versa*. I believe this specification more closely models the true decision making process.

Intertemporal substitution is particularly important when destination attributes can vary significantly over time, as is the case with expected temperature and expected precipitation, two important determinants of a camper's expected utility. Allowing for substitution across sites and over time will help me estimate more-reliable values for the MWTP for these time-varying amenities. Intertemporal substitution is also important to welfare assessments of different policy scenarios, particularly for scenarios involving seasonal changes to site quality or availability. Allowing for intertemporal substitution means that individuals have more flexibility in their responses to a given within-season change in expected site quality. For example, a site closure may cause people to change the date of their trip, leading to a smaller welfare loss than if I assumed that their alternatives were limited only to different sites on the same day. By comparing my estimates from models that do, and do not, account for intertemporal substitution, this research will contribute to an understanding of the importance of allowing for intertemporal substitution, and how choice models that overlook these alternatives may need to be employed with caution.

Section 2 reviews some of the relevant literature on the demand for campsites and the incorporation of intertemporal substitution into recreation demand models. Section 3 discusses the data I use. Section 4 discusses the empirical strategy for my analysis. Section 5 presents estimation results. Section 6 puts the estimated model through its paces with some welfare calculations that illustrate the implied total value of camping trips and the marginal values of campsite attributes. This section also demonstrates the calculation of measures of the equivalent variation associated with hypothetical campground closures or quality upgrades. Section 7 discusses directions for future research opportunities related to this analysis and Section 8 concludes.

Relevant Literature

One of the most relevant prior research studies is a study by Swait (2009), which focuses on innovations in methodology for the analysis of discrete choices. The recreational campsite selection application is just one of two empirical illustrations for the methodologies developed in the paper. The campsite data are drawn from a stated preference mail survey with 1776 respondents, and concern the choice of a campsite at a destination identified only as "a Western North American National Park." Each unnamed campsite is characterized in terms of 10 attributes with 2, 3, or 4 levels each. Price is a key attribute; one site is "primitive" and the choice sets include an option to stay at a motel, hotel, lodge or cabin in a town within the park, or to stay home (an opt-out alternative). The site attributes employed in Swait's analysis include types of hook-ups available, fees, visual separation between sites, security patrols, shower availability and toilet types, park staff presence, drinking water availability, cultural programs, and distance to nearest town.

Richards and Brown (1992) use registration fee envelopes for visitors to ten national forest campgrounds in Arizona, as well as on-site interviews with visitors. The information on the envelopes makes it possible to specify a basic travel cost model and to estimate consumer surplus for these sites. This study demonstrates the usefulness of fee-envelope data for fitting travel cost models. The modern online RIDB reservation system, exploited in my analysis, is the direct descendant of this early strategy for data-gathering.

Some of the previous economic research concerning the non-market value of camping opportunities has employed count data for camping trips. For example, Boxall et al. (1996) use trip counts during 1994, aggregated to the postal code of the trip origin. They exploit a camping fee collection permit which allowed a census of users. Their per-trip estimates of consumer surplus suggest that Land and Forest Service recreation areas in Alberta, Canada, were valued in the aggregate by about $750,000 in Canadian currency in 1994.

Brox and Kumar (1997) employ a multi-site count-data zonal travel cost model to characterize demand for 48 provincial parks in Ontario, Canada, using 14,000 survey responses for the year 1990. Their model uses travel distance between origin zone and the destination as the cost of travel, the population of the origin zone, and the average income of the origin zone, and controls in a simple fashion for whether the destination is a final destination or merely a stopover en route to somewhere else. They also control for a measure of the travel cost to substitute sites, arbitrarily using twice the average distance from the trip origin zone to all parks other than the park in question. Their campsite characteristics include an indicator for whether the park allows group camping, the number of developed campsites, the number of campsites providing electricity, the number of interior (undeveloped) camping sites, an indicator for whether the site is classified as a wilderness or scenic park, and an indicator for whether there is a ban on the use of alcohol during the high season. They report distinct sets of demand parameters for each of the 48 parks. In contrast to earlier studies, they find that camping in these parks is an inferior good, with demand by people in higher-income origin zones being statistically significantly lower.

Hunt et al. (2005) consider the demand for fly-in fishing vacations in Ontario. Camping *per se* is not a specific consideration, but their destination attributes include forest harvesting, forest fires, angling quality and fish-camp improvements. My current analysis includes only whether fishing is an activity that is supported at a particular destination. In future analyses, it may be possible also to control for the quality of the fishing (species, expected catch rates, etc.).

Congestion is often considered as a relevant (and endogenous) attribute for recreational destinations. Cole et al. (1997) report on an exit survey of visitors to three different wildernesses in Washington and Oregon states. They find that encounter rates were generally extremely high, “clearly exceeding those preferred by most visitors,” but that only about 10 to 23 percent of respondents favored reductions in use levels.

McFarlane and Boxall (1996) use on-site and mail surveys to collect data from campers at managed sites in the Rocky-Clearwater Forest of Alberta in 1994, exploring people’s management preferences. Campers who were most familiar with the area, and those with the greatest amount of camping experience, were the least supportive of traditional timber management (i.e. commercial harvesting) and campground development. Overall, across their sample, these researchers find that campers did not support increased facility development at campgrounds. Their findings suggests that campers may prefer an ecosystem approach to wilderness management that takes explicit account of non-timber values.

Limitations on use (i.e. restrictions placed on campsites in particular locations or at particular times) may be important determinants of the demand for those campsites. An unpublished thesis by Ramtahal (2012) emphasizes the degradation of environmental quality due to excessive human recreational use of campsites. Total visitation to a given campground prior to any given choice date, or cumulatively across recent years, might proxy for the amount of wear-and-tear on the ecosystem at that site by that point in the year.

A small number of economic/psychometric studies have considered the non-market recreational value derived from recreational destinations (including camping). Hailu et al. (2005) combine some of the typical variables used in travel cost models with psychological measures of "place attachment" (an attitudinal construct). They argue that "exposure and repeated visits to a site are generally considered to be prerequisites to the development of an emotional bond." They postulate that as people visit a site many times, they become dependent upon it and develop "emotional-symbolic meanings" for the site. Kyle et al. (2004a) also consider place attachment, identifying two dimensions of this concept: place identity and place dependence. In other work, Kyle et al. (2004b) study people's motivations to interact with natural settings, and the relationship of these motivations to their level of attachment to those settings.[2]

In a more-recent study, Smith et al. (2010) incorporate place attachment dimensions into a travel cost model based on stated preference data. These researchers find that place identity is significantly related to intended trip

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[2] Another (earlier) paper about place attachment, place dependence, and place identity is Williams and Vaske (2003).

behavior, but place dependence is not. They argue that travel cost models can employ psychometric scaling to provide helpful information for resource managers.[3]

From an economic perspective, these psychometric concepts would be most closely related to the economic issue of whether recreationists engage in either "variety-seeking" behavior or "habit formation." The U.S. Forest Service has conducted some research about whether a potential camper is specifically looking for new sites to visit. Lucas (1990) studies the Bob Marshall Wilderness complex in Montana, examining the ways in which wilderness visitors choose entry points and campsites. The analysis takes account of site attributes and how demands for these attributes vary with visitor characteristics. Among a wide variety of findings, it is interesting to note that hikers and horse users respond differently to campsite conditions. Some campers prefer secluded sites; others reject campsites that are "too far from water." Others prefer diverse trail systems. However, the presence of a fire ring has little effect on campsite acceptability.[4]

A handful of very specialized studies in the literature can suggest potentially interesting campground or campsite attributes that should be considered in a thorough analysis. Daniel et al. (1989) undertake an in-person open-ended contingent valuation survey of the importance of scenic beauty to recreational values. Their study areas included 20 timber stands and 12 USDA Forest Service campgrounds located in four National Forests in northern Arizona. Unfortunately, the statistical analysis in their paper does not seek to explain the incremental value of scenic beauty in addition to other campsite attributes. They focus on

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[3] Econometrically, of course, it is challenging to allow preference parameters to depend on an alternative measure of preferences/attitudes without raising concerns about endogeneity.

[4] The vintage of this study stands out, given its concerns about making information about campsites available to potential users. The internet has obviated most of these concerns.

the resulting 0.96 pairwise correlation between the mean scenic beauty assessments and the mean contingent value across the 35 photos used to elicit both measures.

According to Lillywhite et al. (2013), the opportunity to have a campfire at one's campsite is an important determinant of demand for campsites. In a 2011 online stated-preference survey of recent national forest visitors in the western U.S., these authors found that the ability to have a campfire dominated five other developed campsite attributes, including whether there was an on-site campground host, the cost of the campsite, the availability of picnic tables, restroom facilities, and recreational vehicle hookups. All of these campground/campsite attributes are candidates for inclusion, to the extent possible, in any new model of demand for camping based on revealed-preference data.

In a related vein, Smith et al. (2012) consider whether the provision of firewood at campsites serves to prevent the removal of woody debris in the surrounding area by campers. Scavenging for campfire fuel around campgrounds has ecological impacts including loss of habitat for small animals, removal of nutrients from the nutrient cycle, compaction of the soil, and damage to (or death of) trees and trampled vegetation. Thus the availability of firewood can indirectly affect the quality of the ecosystem around a campsite. Firewood availability might also be an attribute that affects campsite demand. Wolf et al. (2012) also mention "the number of fireplaces" along with campground size as relevant attributes of camping destinations.

Campbell (2012) explore the increasing number of negative interactions between humans and bears, focusing on a number of programs that have been devised to make recreational visitors more aware of how to avoid attracting bears to their cabins or campsites. Depending upon the availability of data on human-bear interactions at campsites in different areas (perhaps records on the transport or euthanization of “problem bears”), this may be a new attribute of campgrounds that could be worth exploring.

Mattsson and Li (1993) find that on-site consumptive use in Swedish forests (e.g. berry-picking and mushroom-harvesting) was more valuable to rural people than to urban-dwellers. In contrast, non-consumptive uses (e.g. hiking, camping, etc.) were more valuable to urban visitors. The urban/rural character of the origin zone for campground visitors may be a significant source of heterogeneity in the marginal utilities of some attributes of these destinations.

In a more-recent study, Dickinson et al. (2016) explore the desire for digital connection or disconnection during camping trips. They compile data based on interviews and a survey and report that up to 50% of such tourists have some desire to disconnect. This study suggests that it may be important to control for whether a campground offers wifi to its visitors, at least somewhere within the campground.

Moore et al. (2012) constitutes a non-economic study of the preferences of hiking-trail users, but this research may suggest some site attributes that may be relevant for a study of camping. Trail quality attributes include exposed roots, parallel trails, soil erosion, litter, mud, standing water. While it is unlikely that the quality of hiking opportunities is fully documented at this level of specificity in the data available for the present paper, it is possible that the demand for some campgrounds is derived from demand for the local hiking opportunities, which may also vary in their characteristics.

My initial analysis considers only summer-season camping, but it is possible that future analyses might be able to model winter demand for camping opportunities. Should that be the case, research by Englin and Moeltner (2004) suggests that it may be important to distinguish between skiing and snowboarding preferences, interacted with the availability of runs dedicated to one or the other type of use of snow parks.

Other studies have focused more on the regional economic impact created by visitors to camping sites as opposed to the measurement of consumer surplus. Bel et al. (2015) use a national tourism survey in France to explore what types of "rural tourism" create the greatest local revenue. Haener and Adamowicz (2000) consider camping as one type of recreational nonmarket service derived from public forestlands in northern Alberta. Their case study offers a framework for tracking the sustainability of income flows from the region which are related to such uses.

Intertemporal substitution in recreation demand models has received surprisingly little attention in the literature. Many recreation demand models use cross-sectional data and so simply cannot address intertemporal substitution. Even many papers that use panel data detailing a number of trips taken over the course of the season do not address interdependence in intertemporal substitution. Instead, many researchers model each choice occasion during the season as an independent choice between sites (and potentially a "no-trip" alternative capturing the participation decision). As Parsons (2003) points out, this is largely for two reasons: more limited availability of data, and the inherent endogeneity in trip choices over time. Specifically, unobserved factors that affect the utility of visiting particular sites are almost certainly correlated from one time period to the next, leading to bias into the parameters on past behavior variables.

For multi-site recreation demand models, the standard practice for estimating seasonal demand is the repeated random utility maximization framework. This is very similar to the RUM model of site choice, just repeated for each choice occasion for the season and allowing for a no-trip alternative to account for differing frequencies of trips. This allows for a simple form of inter-temporal substitution functioning through the participation decision, but does not account for temporal interdependence of choices. In a seminal paper, Morey et al. (1993) estimate a repeated three-level nested logit of participation and site choice for recreational fishers in Maine and Canada. They model individuals as first deciding whether to participate, then in which region, and then at which site within that region. They account for income effects (allowing income to enter nonlineraly into the indirect utility function) and compare their specification to a variety of simpler models. However, as is relatively common in many repeated RUM models, they assume no interdependence between trips taken over time. In a more recent example, Lew and Larson (2008) estimate a similar type of repeated nested logit model for beach users in southern California. They pay special attention to the way in which individuals' opportunity costs of time differ. However, they too do not account for interdependence of beach-going decisions over time either.

Adamowicz (1994) is one the first to incorporate a measure of state dependence in a RUM model of recreational fishing demand. When including measures of state dependence, he stresses the importance of including all relevant site attribute information in order to avoid bias in the state dependence parameters. He estimates four different models, taking care to differentiate between naive and rational state dependence, with the latter assuming that individuals are aware of the way in which past and future decisions impact their trip utility today.In order to estimate whether anglers display habit-forming or variety seeking behavior, he includes the count of past trips to each location in a repeated RUM model with a no-trip alternative. In a separate specification, he interacts the count of past trips with a set of alternative specific constants to see how state dependent behavior varies across alternatives. He finds that anglers have habit-forming preferences for most sites and variety seeking preferences for the no-trip alternative, indicating that individuals are more likely to go fishing after a long hiatus.

Moeltner and Englin (2004) examine how past choices affect decision making in the context of skiing recreation trips. Their findings suggest "play-it-by-ear" preferences: those that are not habit forming or variety seeking but shift across sites in search of the highest quality. This is in the context of recreation goods with high time variation in quality attributes, e.g. snowpack. If I believe temperature and precipitation also play a large role in camping quality then I may find similar results in this analysis. Estimates of state dependence will be inflated if time varying exogenous variables are omitted or consumer preferences are erroneously assumed to be homogeneous. To measure state dependence, they use total number and consecutive number of past trips. They find that high quality seeking individuals are less affected by state dependence.

Parsons and Stefanova (2011) use a combination of stated preference and revealed preference data to explore how intertemporal substitution impacts welfare losses associated with temporary closure. They have panel data on trips taken to beaches on the Gulf Coast of Texas in addition to on-site survey data taken from beaches on Padre Island in which beach goers were asked if they make a future trip if Padre Island was temporarily closed. They find that a large portion of individuals would choose to merely delay the trip the Padre Island if it were temporarily closed. They find that estimates of the compensating variation for a temporary closure of padre island are 70% smaller in magnitude when allowing for the intertemporal substitution implied by their survey responses.

Data

The RIDB dataset contains the universe of reservations for campgrounds that are available for reservation at *www.recreation.gov*. These campgrounds are located on federal land and are managed by a variety of agencies—the National Park Service and the U.S. Forest Service chief among them. Figure 1 displays a map of RIDB campgrounds across the United States. Federally managed campgrounds can be reserved online only through *www.recreation.gov*, meaning that RIDB contains all reservations for federally managed campgrounds.[5] Note that RIDB does not contain data for campsites that are available for walk-up use only. While RIDB does have a record linking individual users to reservations, allowing me to estimate how past visits affect a customer's choices, the publicly available data does not contain customer's addresses. This research thus relies on just the customer's zip code to connect the trip origin and the location of each campground in the camper's choice set.

RIDB contains millions of campsite reservations annually across the United States. To ease the computational burden for this initial analysis, I use just a sample of reservations made. I focus on campers in the Bay Area of California traveling to campgrounds in the state of California because camping destinations in CA have rich variation in attributes, allowing me to identify more precisely the factors that affect campground demand (as compared to a smaller or less

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[5] Other sites, such as the USFS website or *www.reserveamerica.com* can advertise the sites as being available, but the reservation transaction is always conducted through *www.recreation.gov* and is recorded in RIDB.

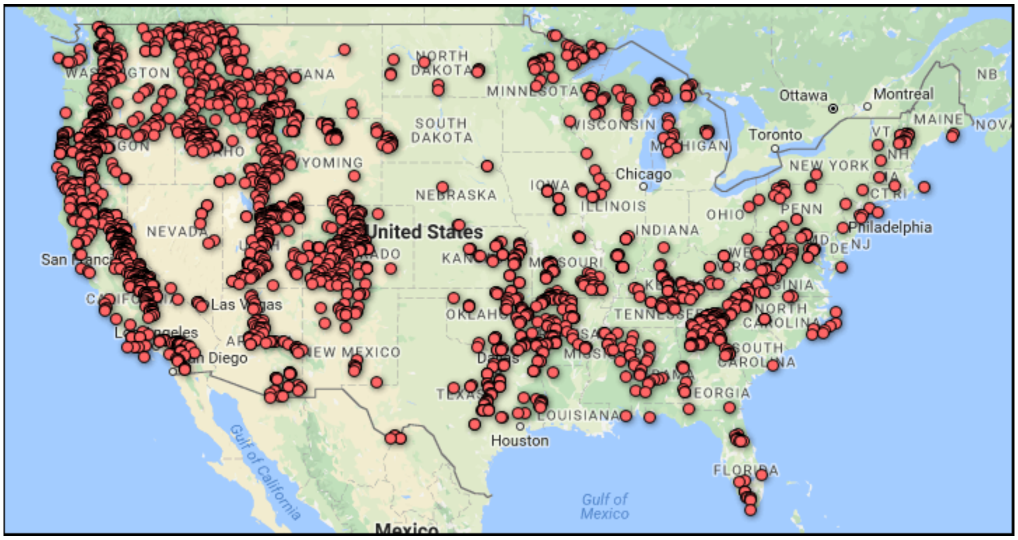

FIGURE 1.
RIDB Campgrounds in the Conterminous United States

geographically diverse state). Figure 2 is a map showing how RIDB campgrounds are spatially distributed in California. I consider reservations from campers originating in Bay Area of California for one- and two-night stays on Fridays during the 2014 summer season (June through August).

Consideration sets. The novel contribution of my estimation strategy is the incorporation of trip timing endogenously in the consideration set. In most travel cost models, the date at which the trip was planned is not known, so researchers assume that the choice occasion occurs on the date of the trip. This ignores the realities of people substituting across time in addition to across sites in order to maximize utility. In this case, the choice decision is represented as in Figure 3: choices across sites conditional on taking a trip that day. Even when the model also includes a choice of whether or not to participate on each choice occasion, each choice occasion is often assumed to be independent, failing to fully capture intertemporal substitution patterns.I benefit from having a highly detailed data set which informs me both when the reservation for a future camping trip was

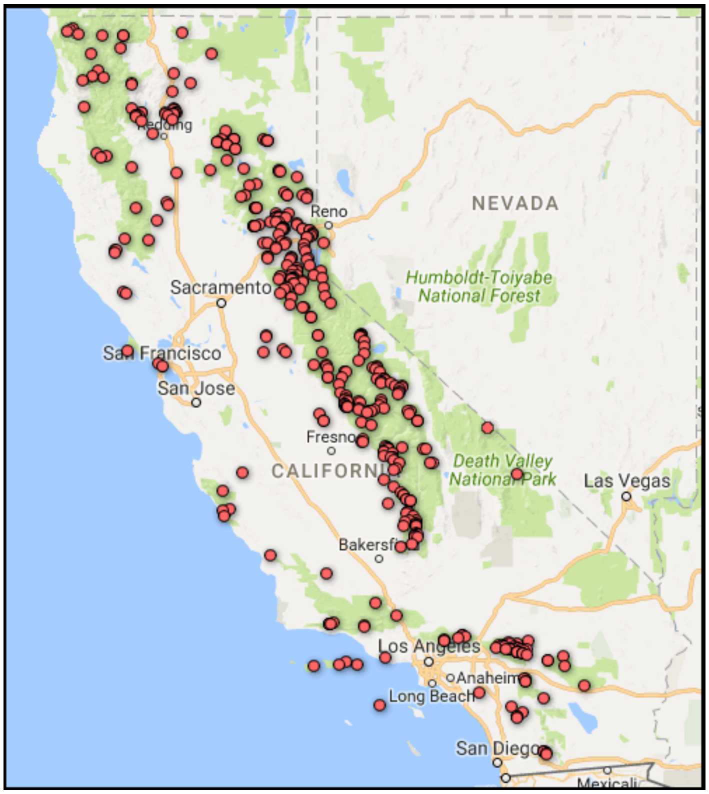

FIGURE 2.
RIDB Campgrounds in the State of California

made and what campgrounds were available at what times on the date of that reservation. This information allows me to define the consideration set on each choice occasion (date the reservation was made) as the set of all alternatives at all available times over the course of the remaining season.[6] This choice occasion is represented in Figure 4. The alternatives that fall into each individual's consideration set vary dynamically over the course of the season for two reasons. Reservations made later in the season will have less opportunity for intertemporal substitution because there are fewer available dates before the season ends. In addition to this, there are reservation limits at each campground. This is because

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[6] Due to a 6-month limit on how far in advance reservations can be made, I do not need to worry about reservations for future seasons for summer-season campgrounds.

there are only so many campsites available for reservation on any given date (some campgrounds reserve a proportion of sites for walk-up use, other campgrounds have all of the campsites available for reservation). This means that certain sites will be unavailable at certain times during the season, falling out of the choice set, as represented by the red X's in Figures 3 and 4. In Section 7, I compare my estimates of EV from this specification to the more standard assumption that the decision to make a trip occurs on the date of the trip to explore how endogenous trip timing affects EV estimates.

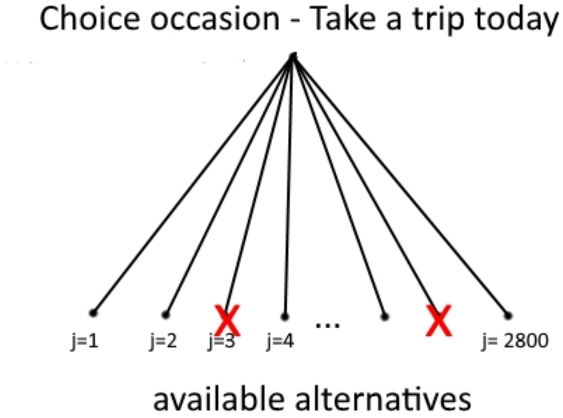

FIGURE 3.
Choice Structure without Intertemporal Substitution

Defining the consideration set in this way greatly increases the number of available alternatives for each individual (to over 3000 alternatives). This greatly increases the computational burden, so for this initial analysis I sample from the available alternatives. For each individual reservation, I sample 100 of the available sites and sample four weekends for each of those sites. In this sampling process, the chosen alternative and the three sites closed in the hypothetical analysis in Section 6 are included. In the future, this sampling can be expanded as I move the estimation to cloud computing services. I also plan to explore methods of

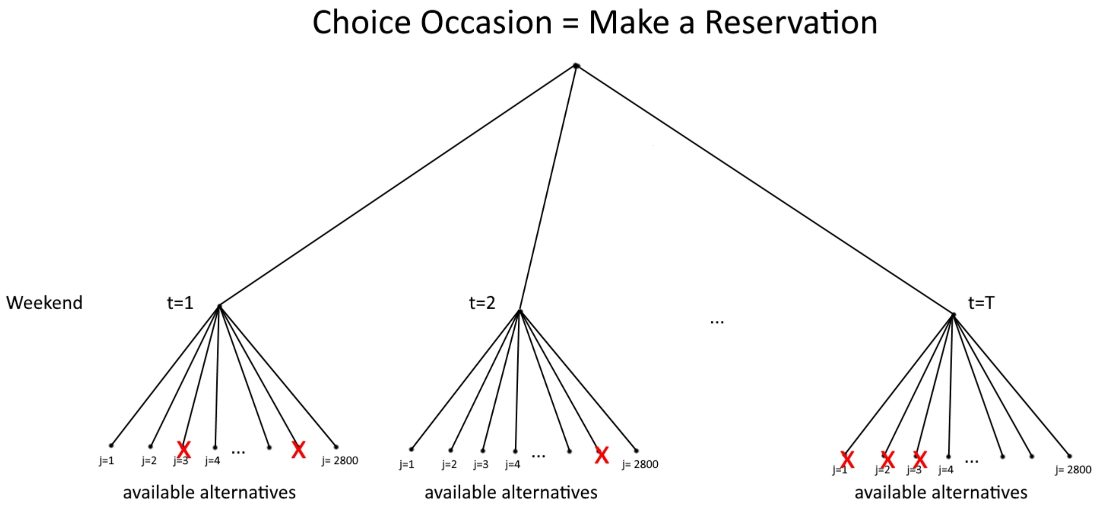

FIGURE 4.
Choice Structure with Intertemporal Substitution

endogenous consideration set formation, which may be particularly relevant in a situation with so many alternatives.

Campground activities. The key variables of interest are indicators for the activities available at (or within ten miles of) each destination. These activities include hiking, swimming, boating, horseback riding, and wildlife viewing, to name a few. The presence of these activities at each campground is recorded in RIDB database. These activities are advertised to potential campers when they view the campground description at *www.recreation.gov.* Additionally, these activities can be used to search over sites and to filter searches for other text. The easily accessible nature of this information makes it reasonable to assume that the advertised presence of these activities can readily affect the choices of campers, even those who have not previously visited a particular campground and thus have no first hand experience to draw upon.

Travel costs. Travel distance and travel time are calculated using the "best route" method.[7] In considering the travel cost faced by campers, I need to account for both the monetary cost of driving to the location (gasoline, maintenance costs, etc.) and the opportunity cost of forgone wages during the time spent traveling. To calculate the monetary cost, I multiply the travel distance in miles by the cost per mile for driving a sedan as reported by AAA.[8] I do not have access to individual-specific income, wage, or vehicle information. As a consequence, I use the American Community Survey (ACS) five-year estimates for zip code median household income. I convert this into an hourly wage and multiply travel time by a third of that wage to determine the opportunity cost of travel—an approximation that is common in the literature. Finally, I add the use fee for reserving the campsite as specified in RIDB data.

Congestion Measure and Past Visitation Indicator. A measure of how many other users are at a site is an important attribute in any recreation demand model. In many previous studies, having more other people at a recreation site lowers the utility associated with that site because the activity in question suffers from the negative effects of congestion. In rarer cases, such as Kolstoe and Cameron (2017), other users at a site can confer positive utility, or agglomeration benefits. Regardless of whether camping activities experience congestion or agglomeration effects, contemporaneous measures of site-use are known to be endogenous (Timmins and Murdock, 2007; Phaneuf et al., 2009) because they would be

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[7] The best route is found using the Open Source Routing Machine (OSRM). This is activated by the Stata osrmtime.ado utility by Huber and Rust (2016).

[8] I use the 2014 composite average (over the three size classes of sedan) cost per mile for drivers that drive 15,000 miles per year. The U.S. Department of Transportation Federal Highway Administration reports that the average American driver logs 13,476 miles per year. This, combined with the fact that sedans have a lower cost per mile than SUVs, vans, and RVs, indicate that this is a conservative estimate of cost.

correlated with any unobservables that influence site demand. I benefit from having many years of trip data, and can at least construct a measure of “expected” congestion based on trips taken in previous years.[9] While not exogenous, this measure is at least predetermined. In measuring expected congestion, I choose to use the average share of campsites that were reserved on the same weekend over the previous five years as a proportion of total campsites available for reservation. In this way, I am measuring congestion *density* as opposed to participation shares as is more commonly done in the literature. This choice follows from Bujosa et al. (2015) who find statistically significant results when using a density measure rather than using shares of total trips. This makes intuitive sense, given that a measure of participation shares measures only intensity of use, while a measure of site density also accounts for heterogeneity in site size. To be able to estimate whether past visits to a site affect the utility associated with a camping trip, I construct an indicator for whether each individual has visited that particular site at any time over the past five years. This information comes from the historical RIDB data.

Expected campground weather. Daily frequency temperature and precipitation data at a 4 km spatial resolution has been obtained from PRISM Climate Group at Oregon State University. These data are not directly from monitoring stations but are interpolated from monitoring station data using a Climatology-Aided Interpolation (CAI) process. These interpolated measures allows me to observe (approximated) temperature and precipitation at much finer spatial and temporal scales than monitor data would allow. To ease interpretation of the estimated models, weather variables are differenced from the sample mean over all weekend-

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[9] Another option that came to mind would be to use the fraction of reserved sites as of the date that the reservation was made. However, for reservations made far in advance, this seems unlikely to be considered by the individual as an expectation of how crowded the campground would be.

site pairs. I use the average values of the previous five-year period because historical weather information can be assumed to be a part of the information set of the potential camper, while date-of-stay weather information typically would not be available at the time of reservation (note that many reservations are made far in advance, by up to six months, meaning short term weather predictions would be unavailable for the camper).

Other campground attributes. Other campground attributes that vary across sites can be included as variables that shift total willingness to pay. These attributes include campground amenity information, such as the presence and type of toilets, availability of drinking water, proximity to a boat ramp, and whether or not trash collection is performed. These amenity variables were scraped from the campground descriptions shown on the web page for each campground at *www.recreation.gov.*[10] These variables are included primarily as controls, although the information on how they affect willingness to pay is also of interest. Indicator variables for which federal agency manages the campground are also used as controls, where this management information has also been collected from RIDB database.

Zip code fishing and hunting licenses. Information from the California Department of Fish and Wildlife on zip-code-level fishing and hunting licenses per household in 2010 were readily available, so I use these data in my current specifications. Future revisions of this paper will employ contemporaneous license information, but it is unlikely that the general preferences (over fishing and hunting) within a zip code vary greatly from year to year. To ease interpretation,

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[10] These facility descriptions are contained within RIDB database. To determine if particular amenities were present at the site, I used the Microsoft Excel FIND function to determine if this text contained mention of the amenity being available. Special care was taken to ensure that the description did not list the amenity as *not* available.

TABLE 1.
Selected descriptive statistics for trips taken

Variable	Brief Description	Mean	Std. Dev.
One-way travel distance (miles)	From zip code centroid to campground	144.58	70.96
One-way travel time (hours)	From zip code centroid to campground	3.02	1.31
Roundtrip travel cost (including time cost)	Using 1/3 imputed wage from ACS zip code data, in 2014 dollars	290.88	126.94
$1(\text{Past\_Visit})_{ji}$	Customer i visited the site in the past 5 years	0.21	0.41
Expected Campground Fullness	Average share of sites reserved over the past 5 years	0.69	0.3
$1(\text{One Week Lead Time})_{iw}$	Trip made within one week of the choice occasion	0.25	0.43
$1(\text{One Month Lead Time})_{iw}$	Trip made between one week and one month of the choice occasion	0.29	0.45
$1(\text{Five Month Lead Time})_{iw}$	Trip made more than 5 months from the choice occasion	0.1	0.31
$1(\text{Fishing})_j$	Fishing is listed as an activity near the site	0.72	0.45
$1(\text{Hiking})_j$	Hiking is listed as an activity near the site	0.74	0.44
$1(\text{Boating})_j$	Boating is listed as an activity near the site	0.57	0.5
$1(\text{Horseback Riding})_j$	Horseback riding is listed as an activity near the site	0.08	0.27
$1(\text{Hunting})_j$	Hunting is listed as an activity near the site	0.16	0.36
$1(\text{Swimming})_j$	Swimming is listed as an activity near the site	0.55	0.5
$1(\text{Flush Toilets})_j$	Availability of flush toilets are mentioned within the campground's description	0.47	0.5
$1(\text{Agency: NPS})_j$	Managed by the National Park Service	0.28	0.45
$1(\text{Agency: USFS})_j$	Managed by the US Forest Service	0.6	0.49

these values have also been differenced from the sample mean (over zip codes). These variables act as a zip-code-level approximation of expected camper avidity for one of these two activities. As these zip-code-level license data describe the origin zip code, they do not vary across alternatives on a given choice occasion, they cannot be included independently in the model but are interacted with the relevant activity. These interactions permit me to see whether the marginal utility from these two activities varies based on this (crude measure of) neighborhood avidity for each activity.

Table 1 presents descriptive statistics for selected site attributes for trips chosen.

Empirical Framework

To explain demand for camping in California, I estimate both conditional logit and mixed logit random utility models (RUMs). For these specifications, I assume that camper i's utility associated with a camping trip to site j on weekend w on choice occasion t, namely U^i_{jwt}, has a systematic component, V^i_{jwt}, that depends (linearly, for convenience) on income net of the full cost of round-trip travel to that site, $(Y^i - C^i_j)$. Note that this travel cost includes both the monetary costs associated with the trip as well as the opportunity cost of time spent traveling. The marginal utility of net income (i.e. consumption of other goods) is given by the coefficient α. Utility also depends on a vector of campground activities, A_j, with the marginal utility of elements of A_j perhaps depending upon the season, as captured by a vector of variables represented as W_w, on the values of other attributes Q_{jw}, or on the values of zip code attributes Z^i. Utility is also likely to depend upon on the values of Q_{jw} independent of their effect on the marginal utility of A_j. Omitting these other attributes could therefore bias the estimated effects of changes in A_j if these other attributes remain unchanged. In addition to the deterministic V^i_{jwt}, there is a stochastic component of utility, ϵ^i_{jwt}, that is considered known to the camper but unobserved by the researcher:

$$\begin{aligned} U^i_{jwt} &= V^i_{jwt} + \epsilon^i_{jwt} \\ &= \alpha(Y^i - C^i_j) + (\beta_0 + W_w\beta_1 + Q_{jw}\beta_2 + Z^i\beta_3)A_j + Q_{jw}\gamma_1 + \epsilon^i_{jwt} \qquad (2.1) \end{aligned}$$

Some elements of the A_j vector are specified as conferring a level of marginal utility that depends systematically on other factors. The error term ϵ^i_{jt} for the conditional logit specification is assumed to be independently and identically distributed according to a Type I Extreme Value distribution. To capture the effect of time preferences, I assume that a customer's indirect utility is also affected by set of variables D_{tw} that indicate how far in advance the reservation is made. Indicators are included for reservations made within a week of the trip, one month of the trip, five months of the trip, and six months of the trip (the earliest that a reservation can be made). These variables are interacted with an indicator for management by the National Park Service, to capture the role of a site's iconic status in encouraging early reservation (so as to secure a spot). [11] I also include an indicator P^i_j for whether the customer had visited the site in the past in order to capture whether customers make a habit of visiting the same site or instead seek variety. With these additions, a customer's utility is given by:

$$\begin{aligned} U^i_{jwt} = \alpha(Y^i - C^i_j) + (\beta_0 + W_w\beta_1 + Q_{jw}\beta_2 + Z^i\beta_3)A_j \\ + Q_{jw}\gamma_1 + D_{tw}\gamma_2 + \gamma_3 P^i_j + \epsilon^i_{jwt} \end{aligned} \tag{2.2}$$

Preferences across individuals most likely vary in more dimensions than I can capture in the systematic portion of the utility function. For this reason, I also estimate a mixed logit specification, allowing preferences over some activities A_j to vary randomly randomly according to an error term μ_i:

$$\begin{aligned} U^i_{jwt} = \alpha(Y^i - C^i_j) + [(\beta_0 + \mu^i) + W_w\beta_1 + Q_{jw}\beta_2 + Z^i\beta_3]A_j \\ + Q_{jw}\gamma_1 + D_{tw}\gamma_2 + \gamma_3 P^i_j + \epsilon^i_{jwt} \end{aligned} \tag{2.3}$$

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[11] I also explored whether utility could be assumed to follow exponential discounting over the lead time between making a reservation and the weekend of the trip. This produced models with worse overall fit, so the alternative method for capturing time preferences presented here was adopted.

Here μ^i is distributed normally with mean zero and variance σ_μ^2 and captures unobserved preference heterogeneity across individuals.

Campers are assumed to compare the utility to be gained from a trip to each destination in the consideration set, U_{jwt}^i, with the utility to be gained from no trip, U_{0t}^i, so I model the choice to visit this destination as a function of utility differences, $U_{jwt}^i - U_{0t}^i$:

$$
\begin{aligned}
U_{jwt}^i &= \alpha(Y^i - C_j^i) + [(\beta_0 + \mu^i) + W_w\beta_1 + Q_{jw}\beta_2 + Z^i\beta_3]A_j \\
&\qquad + Q_{jw}\gamma_1 + D_{tw}\gamma_2 + \gamma_3 P_j^i + \epsilon_{jwt}^i \\
U_{0t}^i &= \alpha(Y^i) + \epsilon_{0t}^i \\
U_{jwt}^i - U_{0t}^i &= \alpha(-C_{jt}^i) + (\beta_0 + W_w\beta_1 + Q_{jw}\beta_2 + Z^i\beta_3)A_j \\
&\qquad + Q_{jw}\gamma_1 + D_{tw}\gamma_2 + \gamma_3 P_j^i + (\mu^i A_j + \epsilon_{jwt}^i - \epsilon_{0t}^i)
\end{aligned}
$$

In RIDB database, however, the choice of any particular campground is conditioned on the decision to visit some campground on that choice occasion. As a consequence, choices among alternative trips are based on the utility differences *between* these trips. On any given choice occasion, t, the choice to make a reservation at campground j in weekend w rather than an alternative campground k or weekend x implies $U_{jwt}^i > U_{kxt}^i$ for all $kx \neq jw$.

Estimation and Inference: WTP and EV measures

The first step of my analysis is to estimate the conditional and mixed logit preference parameters in my model, as described above. Next, I am interested in calculating estimates of total willingness to pay (TWTP) for single trips to specific types of camping sites—sites that have the activities or amenities that I consider as possible determinants of demand. In addition to TWTP calculations, I also calculate marginal willingness to pay (MWTP) for the availability of a particular activity at or near a campground. Gaining an understanding of the WTP from marginal changes is important, but many potential changes are non-marginal—such as closures of sites or widespread changes in site quality. Such changes would most likely result in individuals substituting across sites or over time in order to maximize utility over an altered set of options. To assess the impact of these larger changes, I calculate the Equivalent Variation (EV) for these changes, allowing substitution between alternatives.

Assuming that individual i maximizes their utility by the choice over the $j = 1, ..., J$ sites and $w = 1, ..., W$ weekends, I can estimate TWTP by individual i for a trip to destination j on weekend w by setting the utility difference $U^i_{jwt} - U^i_{0t}$ equal to zero. I can then solve for the implied level of travel cost that would make the individual just indifferent between incurring the cost of access to that trip and enjoying the camping opportunity it represents, or avoiding this cost but missing out on this camping opportunity. Solving for this implied travel cost, my measure of TWTP is given by:

$$\begin{aligned} TWTP = C^{i*}_{jw} = \frac{1}{\alpha}\Bigg(&(\beta_0 + W_w\beta_1 + Q_{jw}\beta_2 + Z^i\beta_3)A_j \\ &+ Q_{jw}\gamma_1 + D_{tw}\gamma_2 + \gamma_3 P^i_j + (\mu^i A_j + \epsilon^i_{jwt} - \epsilon^i_{0t})\Bigg) \end{aligned}$$

I opt to evaluate this TWTP at the zero mean of all three error terms. TWTP for a reservation for a particular campground j on a particular weekend w thus depends upon observable site attributes (A_j and Q_{jw}), the observable seasonal indicators (W_w), customer past trip and zip code sociodemographic information

(P_j^i and Z^i), reservation lead time indicators (D_{tw}) and a vector of asymptotically joint-normally distributed maximum likelihood parameter estimates.[12]

A measure of the marginal willingness to pay (MWTP) for the availability of a particular activity A_1, evaluated at the mean of the random component μ^i, and variations in this MWTP over the season and as a function of the values of other attributes, can be calculated as:

$$\widehat{MWTP} = \frac{\partial C_j^i}{\partial A_j} = \frac{\hat{\beta}_0}{\hat{\alpha}} + T_t \frac{\hat{\beta}_1}{\hat{\alpha}} + Q_j \frac{\hat{\beta}_2}{\hat{\alpha}} + Z_i \frac{\hat{\beta}_3}{\hat{\alpha}}; \tag{2.4}$$

where:

$$\frac{\partial}{\partial T_t}(\widehat{MWTP}) = \frac{\partial}{\partial T_t}\left(\frac{\partial C_j^i}{\partial A_1}\right) = \frac{\hat{\beta}_1}{\hat{\alpha}} \tag{2.5}$$

$$\frac{\partial}{\partial Q_j}(\widehat{MWTP}) = \frac{\partial}{\partial Q_j}\left(\frac{\partial C_j^i}{\partial A_1}\right) = \frac{\hat{\beta}_2}{\hat{\alpha}}; \tag{2.6}$$

$$\frac{\partial}{\partial Z_i}(\widehat{MWTP}) = \frac{\partial}{\partial Z_i}\left(\frac{\partial C_j^i}{\partial A_1}\right) = \frac{\hat{\beta}_3}{\hat{\alpha}} \tag{2.7}$$

I recognize that a ratio of jointly asymptotically normally distributed maximum likelihood parameters has an undefined mean. I make 5,000 random draws from the joint parameter distribution to build up an approximate sampling distribution for each TWTP and MWTP estimate that I calculate. These simulated distributions based on the estimated covariance matrix for the model's parameters yield approximate confidence interval estimates for these TWTP and MWTP estimates, allowing me to determine whether zero values can be rejected.

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[12] Income is not included here as a determinant of TWTP because of the assumption that utility is linear in net income. This allows the individual's income to drop out of the choice model, which is convenient because I only have zip code median income and not individual household income in my data.

The MWTP estimates are interesting as an intellectual curiosity and policy-useful for small changes in site quality. But I am also interested in forecasting the per-trip welfare changes that would occur if large changes to site quality or availability caused individuals to re-sort across alternatives, substituting their choice to maximize utility. To do so, I use the fitted point estimates of the model to calculate the maximum attainable systematic utility over the consideration set that consumers actually face and compare this to the maximum attainable utility over some hypothetical modification to the alternatives that individuals face. In this paper, I consider a change to the consideration set stemming from the closure of three popular sites in Yosemite and also a change to site quality in the form of a statewide program to upgrade all sites to have flush toilets. These maximum attainable utilities are calculated using the "log-sum-exp" transformation which approximates the maximum value of V^i_{jwt} for each individual:

$$ln\Big(\sum_{j=1,w=1}^{J,W}[exp(V^i_{jwt})]\Big) \tag{2.8}$$

To calculate the equivalent variation (EV) for a hypothetical scenario, I calculate the maximum systematic utility for the actual case and do the same for the modified attributes, calling the result V^{*i}_{jwt}. I can monetize these utilities by dividing by the marginal utility of income α. Taking the difference of these monetized maximum utilities yields the individual-specific EV for the hypothetical change:

$$EV^i_t = \frac{1}{\alpha}\Big[ln\Big(\sum_{j=1,w=1}^{J,W}[exp(V^{*i}_{jwt})]\Big) - ln\Big(\sum_{j=1,w=1}^{J,W}[exp(V^i_{jwt})]\Big)\Big] \tag{2.9}$$

In the case that site availability changes instead of site quality, such that the number of sites becomes J^* or number of weekends W^*, the EV would be given by:

$$EV_t^i = \frac{1}{\alpha}\left[ln\left(\sum_{j=1,w=1}^{J^*,W^*}[exp(V_{jwt}^i)]\right) - ln\left(\sum_{j=1,w=1}^{J,W}[exp(V_{jwt}^i)]\right)\right] \tag{2.10}$$

Results

Table 2 presents selected parameter estimates and standard errors for both the conditional logit and mixed logit models estimated. First note that the coefficient on the round trip travel cost, the negative of the marginal utility of income, is negative and highly significant across both specifications. This is as expected—travel cost should be one of the primary determinants of trip choice. Note also that the parameter estimates vary little between the conditional logit and mixed logit specification. The particularly notable exceptions are the parameter estimates on hiking availability and rock climbing availability. Both of these parameters also have significant standard deviations under the mixed logit specification. This indicates that there is significant unobserved preference heterogeneity for hiking and rock climbing opportunities near campgrounds. This is intuitively plausible—both hiking and rock climbing are not universally enjoyed activities and individuals who are less physically able to hike would understandably derive little benefit from their availability. The other activity indicators have standard deviations that are not significantly different from zero. The two specifications have similar log likelihood values, reported at the bottom of the table, as well as nearly equal Akaike information criterion (AIC), indicating that the mixed logit specification provides little new information about the customers' choices. In fact, this information criteria favors the conditional logit model because it is more parsimonious. Given the small difference in model fit, I elected to move forward with just conditional logit analyses in Chapters III and IV of this dissertation.

Past visitation and expected fullness. Note the very large and highly significant coefficient on the indicator for past visitation. Whether an individual has visited a particular campground in the past plays a key role in whether they will travel there again in the future. This result suggests that customers are habit forming in regard to their demand for campgrounds—they are much more likely to visit a campground if they have visited that same campground in the past. This could be because they are certain of its quality, whereas other sites have uncertain quality, or it could be that camping is a type of recreational activity that is heavily influenced by tradition—think of the annual family camping trip. Future analyses could explore this in more detail, including the count of times visited in the past or the number of months since the most recent visit. The coefficient on expected share of campsites reserved is also positive and significant indicating that people like to go to popular sites. Beyond that, I am wary to interpret that coefficient, as it can represent agglomeration benefits associated with having many other campers there (e.g. socializing) as well as the negative congestion affects associated with having too many campers (e.g. noise, lack of isolation). As pointed out earlier, this variable would also be correlated with unobserved attributes that affect trip utility, making any thorough interpretation dubious without first correcting for that endogeneity.

TABLE 2.
Conditional and Mixed Logit Estimation Results, Selected Coefficients

Variable	Model 1 - Conditional Logit	Model 2 - Mixed Logit
Roundtrip Travel Cost	-0.0108***	-0.0108***
	(0.000149)	(.000153)
$1(\text{Past Visit})_{ji}$	3.945***	4.006***
	(0.0458)	(0.0528)
Expected Campground Fullness	0.403***	0.404***
	(0.0273)	(0.0276)
$1(\text{One Week Lead Time})_{iw}$	2.066***	2.066***
	(0.0525)	(0.0529)
$1(\text{One Month Lead Time})_{iw}$	1.223***	1.224***
	(0.0447)	(0.0449)
$1(\text{Five Month Lead Time})_{iw}$	0.0889	0.0856
	(0.0715)	(0.0719)
$1(\text{One Week Lead Time})_{iw} \times 1(\text{Agency: NPS})_j$	-0.294***	-0.293***
	(0.068)	(0.0689)
$1(\text{One Month Lead Time})_{iw} \times 1(\text{Agency: NPS})_j$	-0.642***	-0.644***
	(0.0667)	(0.0673)

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Table 2 : Conditional and Mixed Logit Estimation Results, Selected Coefficients – *Continued from previous page*

Variable	Model 1 - Conditional Logit	Model 2 - Mixed Logit
1(Five Month Lead Time)$_{iw}$ × 1(Agency: NPS)$_j$	0.200**	0.2012**
	(0.0882)	(0.0892)
1(Boating)$_j$ Mean	-0.239***	-0.241***
	(0.0375)	(0.0377)
1(Boating)$_j$ Std.Dev.	-	0.00457
		(0.195)
1(Boating)$_j$ × 1(Boat Ramp)$_j$	0.132	0.137
	(0.0858)	(0.0862)
1(Hiking)$_j$ Mean	0.447***	0.535***
	(0.041)	(0.0595)
1(Hiking)$_j$ Std. Dev.	-	0.623***
		(0.162)
1(Hiking)$_j$ × dev. Temp.$_{jw}$	0.0866***	0.0877***
	(0.00871)	(0.00877)
1(Hiking)$_j$ × dev. Precip.$_{jw}$	-0.0535	-0.0548
	(0.0423)	(0.0425)
1(Fishing)$_j$ Mean	-0.307***	-0.294**
	(0.115)	(0.122)

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Table 2 : Conditional and Mixed Logit Estimation Results, Selected Coefficients – *Continued from previous page*

Variable	Model 1 - Conditional Logit	Model 2 - Mixed Logit
1(Fishing)$_j$ Std. Dev.	-	0.263
		(0.291)
1(Fishing)$_j$ × dev. Fish. Licenses p.c. $_i$	0.664***	0.690***
	(0.204)	(0.210)
1(Fishing)$_j$ × 1(June 6)$_w$	0.732***	0.738***
	(0.114)	(0.115)
1(Fishing)$_j$ × 1(June 27)$_w$	1.214***	1.221***
	(0.103)	(0.104)
1(Fishing)$_j$ × 1(July 18)$_w$	1.379***	1.387***
	(0.0922)	(0.0930)
1(Fishing)$_j$ × 1(August 8)$_w$	0.906***	0.912***
	(0.0896)	(0.0902)
1(Hunting)$_j$ Mean	-0.431***	-0.430***
	(0.0796)	(0.0797)
1(Hunting)$_j$ Std. Dev.	-	0.0467
		(0.156)
1(Hunting)$_j$ × dev. Hunt. Licenses p.c.$_i$	-0.385	-0.370
	(0.519)	(0.518)

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Table 2 : Conditional and Mixed Logit Estimation Results, Selected Coefficients – *Continued from previous page*

Variable	Model 1 - Conditional Logit	Model 2 - Mixed Logit
1(Swimming)$_j$ Mean	0.144***	0.142***
	(0.0345)	(0.0347)
1(Swimming)$_j$ Std. Dev.	-	0.00386
		(0.129)
1(Swimming)$_j$ × dev. Temp.$_j$	-0.00279	-0.00246
	(0.00689)	(0.00692)
1(Swimming)$_j$ × dev. Precip.$_j$	0.00938	0.00952
	(0.0398)	(0.0398)
1(Biking)$_j$ Mean	0.221***	0.218***
	(0.03)	(0.0302)
1(Biking)$_j$ Std. Dev.	-	0.0306
		(0.184)
1(Horseback Riding)$_j$ Mean	0.0705	0.0706
	(0.0513)	(0.0515)
1(Horseback Riding)$_j$ Std. Dev.	-	0.00529
		(0.167)
1(Rock Climbing)$_j$ Mean	0.588***	0.398***
	(0.0675)	(0.128)

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Table 2 : Conditional and Mixed Logit Estimation Results, Selected Coefficients – *Continued from previous page*

Variable	Model 1 - Conditional Logit	Model 2 - Mixed Logit
1(Rock Climbing)$_j$ Std. Dev.	-	0.727***
		(0.220)
1(Vault Toilets)$_j$	0.476***	0.484***
	(0.0537)	(0.0540)
1(Flush Toilets)$_j$	0.991***	0.998***
	(0.052)	(0.0524)
1(Vault Toilets)$_j$ × 1(Flush Toilets)$_j$	-1.8***	-1.815***
	(0.107)	(0.108)
1(Drinking Water)$_j$	0.378***	0.374***
	(0.0373)	(0.0375)
1(Trash Collection)$_j$	-0.668***	-0.670***
	(0.0594)	(0.0595)
1(Boat Ramp)$_j$	-0.242***	-0.243***
	(0.08)	(0.0803)
1(Agency: BOR)$_j$	0.0192	0.0189
	(0.102)	(0.102)
1(Agency: NPS)$_j$	0.761***	0.773***
	(0.058)	(0.0585)

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Table 2 : Conditional and Mixed Logit Estimation Results, Selected Coefficients – *Continued from previous page*

Variable	Model 1 - Conditional Logit	Model 2 - Mixed Logit
$1(\text{Agency: USACE})_j$	0.4***	0.394***
	(0.0572)	(0.0575)
Trips Taken	8,744	8,744
Total Alternatives	3,283,654	3,283,654
Log Likelihood	-37,030	-37,026
AIC	74,161	74,168

Lead time variables. The time between the reservation choice occasion and the weekend the trip is actually made could plausibly affect utility for a variety of reasons. My prior is that people would prefer to take the trip sooner, all else equal, as there is less uncertainty about the quality of the trip (weather changes, wildfire, etc.) and they get to consume the recreational opportunity sooner. Sure enough, this pattern is displayed in the marginal utility coefficients for the lead time variables. Relative to the omitted group, reservations made between one and five months in advance, people get much higher utility out of taking a trip within a week of making the reservation. Individuals would also prefer taking the trip within a month of the choice occasion, though to a lesser extent. The coefficient on the five months or more indicator is insignificant, meaning that this pattern does not continue past five months. I also wanted to capture the role that reservation limits might play in encouraging individuals to reserve early, even if they otherwise might prefer not to. The interactions with the NPS indicator, representing sites with iconic status among US public lands, serves to capture this effect. As expected, individuals who choose to camp in National Parks display a lessened desire for immediate trips.

Activities available nearby. Camping demand is a particularly interesting type of recreation demand in part because camping is complementary with many other types of recreational activities. Camping can allow easier access to desirable hikes, hard-to-reach fishing holes, scenic swimming opportunities, and remote rock climbing routes, for example. Including indicators for different activities nearby the alternative campgrounds in an individuals consideration set reveals the degree of this complementarity, or, in rarer cases, that having these activities might actually detract from the overall camping experience for the average individual.

The availability of boating near the site is one example, as it is a associated with a negative and significant estimated marginal utility. This could be because motor boats trolling the waters near a campground might detract from the experience.

Hiking opportunities near the campground are desirable on average, and the marginal utility of hiking availability increases with higher temperatures. Hiking desirability does not appear to vary with precipitation even though it varies with temperature. Swimming opportunities nearby also confer a positive marginal utility, though this does not vary systematically with temperature or precipitation. Bicycling opportunities and rock climbing opportunities both increase the probability that a campground is chosen, indicating customers' value for those attributes. The estimated parameter on horseback riding availability is statistically insignificant. This particular activity is a candidate for future exploration of random or systematic preference heterogeneity, as it seems quite likely that horse owners would highly value this activity while non horse owners might prefer to avoid the sights, sounds, and smells that accompany horses.

While the coefficient on the fishing indicator is negative and statistically significant, all of the seasonal interactions with fishing availability are positive, statistically significant, and of a larger magnitude. This indicates that fishing availability is in general desirable, with that desirability peaking in the middle of the summer and falling off by the end of the summer (the omitted seasonal interaction is the last week of the summer, during which fishing availability would confer a negative shock to utility on average). Further, fishing availability is more desirable for individuals traveling from zip codes with a higher number of fishing licenses per capita, showing that individuals who are more likely avid fishers benefit more from fishing opportunities near their campsites. When hunting is listed as an activity near the site, this decreases the likelihood that an individual picks that campground. Further, there is no significant change in the marginal utility of hunting availability for customers from zip codes with higher per capita hunting licenses. While this might at first seem counterintuitive, it is important to recognize that the sample time period is not open season for most types of game in California. So it makes sense that hunters would not additionally value these campgrounds at this time of year.

Campground amenities and managing agency. Having either vault of flush toilets at a site increases the utility of visiting a campground. One odd result, though, is that having *both* vault and flush toilets actually results in a loss to utility. There are relatively few alternatives that have both types of toilets, so this result could be coming from omitted attributes of those sites that negatively affect utility. It is also worth noting that these variables were generated from data scraped from the facility descriptions, meaning that there could be measurement error. The availability of drinking water increases the utility of visiting a site, while the presence of trash collection activities or boat ramps confer a negative utility shock. The result for boat ramps is intuitive and similar to that of the availability of the boating activity. The trash collection result is more perplexing, though it could stem from sites that are more heavily developed reducing the sense of outdoors exploration. Finally, note that campgrounds managed by the National Park Service or the Army Corps of Engineers confer a higher utility than sites managed by the Forest Service or the Bureau of Reclamation. This result is most noticeable for the National Park sites and could represent the fact that these sites tend to have higher budgets and allow access to some of the more iconic public lands in the United States.

Welfare Analysis

Table 3 presents MWTP estimates and their simulated 95% confidence intervals for selected site attributes. The MWTP to visit a site that an individual has visited in the past is massive at $370. This indicates that an individual would be willing to travel much further to visit an otherwise observably identical site if they had visited that site in the past. Clearly, past visitation plays a pretty dominant role in the welfare gains associated with camping trips. Taking the camping trip within one week of reservation is associated with a MWTP of $191. This is understandable—when choosing to go camping in the coming weekend, people are much more certain of the conditions at that campground and so are willing to incur a higher travel cost. When thinking about these two results in combination, it appears that individuals would be much more willing to reserve a site for the far future if they have visited it before, further suggesting that uncertainty plays a role in the reservation decision.

In examining the marginal willingness to pay estimates for the different activities nearby campgrounds, that fishing, at the right time in the season, is one of the most highly valued activities associated with the camping decision. Assuming that an individual comes from a zip code with average fishing licenses per capita, fishing availability is worth $94 for the last weekend in June. Hiking availability is worth $50 for the average individual and rock climbing opportunities are worth $54. Swimming and biking availability seem to matter less, valued at $13 and $20, respectively. Hunting availability and boating availability reduce total willingness to pay to visit a site, by $40 and $22 respectively. All else equal, people won't travel as far to go to a campground that advertises boating or hunting.

TABLE 3.
Marginal Willingness to Pay for Selected Amenities

Variable	MWTP ($)
1(Past Visit)$_{ji}$	370
	(356, 384)
Expected Campground Fullness	37
	(32, 42)
1(One Week Lead Time)$_{iw}$	191
	(181, 202)
1(Boating)$_{j}$	-22
	(-29, -16)
1(Hiking)$_{j}$	50
	(39, 60)
1(Fishing)$_{j}$	-29
	(-50, -8)
1(Fishing)$_{j}$ × 1(June 27)$_{w}$	113
	(94, 131)
1(Hunting)$_{j}$	-40
	(-54, -25)
1(Swimming)$_{j}$	13
	(7, 20)
1(Biking)$_{j}$	20
	(15, 26)
1(Rock Climbing)$_{j}$	54

Continued on next page

Table 3 : Marginal Willingness to Pay for Selected Amenities – *Continued from previous page*

Variable	MWTP ($)
	(41, 67)
$1(\text{Vault Toilets})_j$	44
	(35, 54)
$1(\text{Flush Toilets})_j$	92
	(83, 101)
$1(\text{Drinking Water})_j$	35
	(28, 42)
$1(\text{Agency: NPS})_j$	71
	(60, 82)

95% simulated confidence interval in parentheses.

Individuals are willing to pay $44 dollars for vault toilets or $92 if the campground has flush toilets, and $25 if the site has drinking water—amenities that would make their stay more comfortable. If the campground is in a National Park, people are willing to pay an additional $71 dollars to camp there, relative to the same type of site in a National Forest location.

To put these estimated WTPs to the test, I consider two hypothetical changes to customers consideration sets. Table 4 presents Equivalent Variation (EV) calculations for these two changes, both when intertemporal substitution is allowed and when individuals are constrained to substitute to a site on the same day of their original trip. I consider the hypothetical closure of three campgrounds at the heart of Yosemite National Park— North Pines, Upper Pines, and Lower Pines campgrounds. This results in an average per-trip EV of -$10 when allowing for intertemporal substitution or an average per-tip EV of -$11 when only allowing same-day substitution. The difference in these average EVs has the expected sign—that fewer opportunities for substitution results in a greater welfare loss, but is smaller than I would have expected. Figure 5 presents the distribution of EV across individuals for the closure of these three prominent sites in Yosemite National Park when allowing for intertemporal substitution.

TABLE 4.
Per-trip Equivalent Variation ($) for Hypothetical Changes in Site Quality and Site Availability; when allowing for intertemporal substitution and when restricted to same-day substitution only

Simulated Site Change	Intertemporal Substitution	Same-Day Substitution
Site Closures	-10	-11
	(22)	(30)
	[-57, 0]	[-46, 0]
Toilet Upgrades	39	38
	(16)	(19)
	[9, 65]	[5, 74]

The mean EV across individuals is presented. The standard deviation is in parentheses. 5^{th} and 95^{th} percentiles are in square brackets.

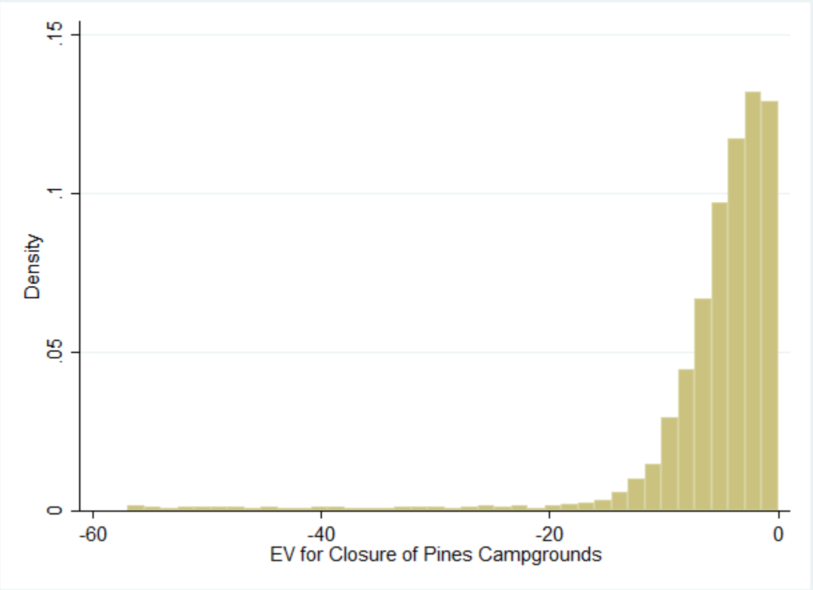

FIGURE 5.
Equivalent Variation across individuals for closure of three Yosemite campgrounds

The other hypothetical policy change I consider is the upgrading of every site to have flush toilets (and only flush toilets). This is an example of an improvement to site quality that we expect would have a positive per-trip EV. Indeed, the average per-trip Ev for this change is $39 in the intertemporal substitution case and $38 in the same-day substitution case. Again, the difference across these alternative consideration set definitions is not quite as large as I would expect. This could be because the upgrades are happening at every site, and so provide similar welfare benefits under either type of substitution. Figure 6 presents the distribution of these per-trip EVs across individuals.

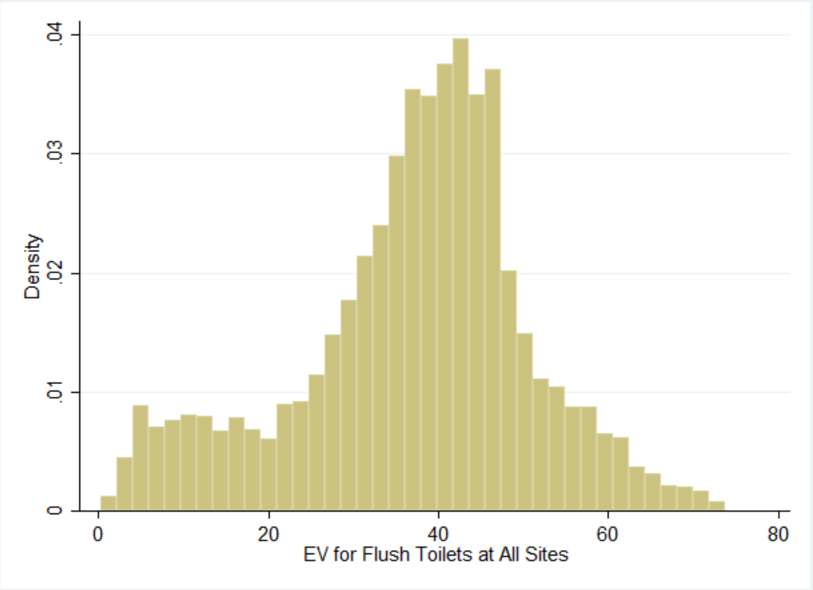

FIGURE 6.
Equivalent Variation across individuals for upgrading all sites to have only flush toilets

Directions for Future Research

The work presented here is an example of the utility of a previously unused, nationally representative dataset. While I used only a sample of the available data due to computational constraints, I have been able to estimate a detailed model of campground demand. These results give policy makers a better idea of what type of campground upgrades might be most beneficial, what sites might be best to shut down in the case of a budget shortfall, and how to allocate funding based on the revealed-preference use value estimates I present. The size and scope of this dataset and the framework I have set up in this paper also provide ample directions for future research. Possible directions for future research are outlined below:

Upgrade the estimation process. While the mixed logit model presented in this chapter was estimated on the University of Oregon's Talapas computing cluster, it still took over a day to converge. I plan to shift estimation to the cloud to further ease computational constraints and allow for greater flexibility in model specification. While I showed that a mixed logit model with preference heterogeneity over a handful of attributes had little effect on model fit, it is possible that a more robust mixed logit model, or a latent class model, would produce greater model fit and provide more accurate estimates of marginal utility and WTP. Before this paper is submitted for publication, I plan to shift the estimation to R and use cloud computing resources to ease to constraints that I have experienced so far.

Additional systematic preference heterogeneity. I plan to incorporate additional zip code-level characteristics to capture systematic preference heterogeneity. Including information on horse ownership or RV ownership could help differentiate between different types of consumers. I could also consider differences in demographic variables like race, age, and family size. Another dimension to consider is the urban/rural divide. Consumers coming from urban areas as opposed to suburban or rural areas might have different preferences over the campgrounds they visit

Explore different policy scenarios and their welfare effects. It was quite surprising that restricting the individuals consideration set to be across same-day alternatives did not have a larger effect on the EV measures. It could be that the policy changes I considered were not severe enough to cause substantial difference across these different specifications. I could, for instance, consider the closure of all sites in the vicinity of Yosemite as opposed to just the closure of three sites—which was shown to produce relatively small welfare effects. I also plan to consider changes that affect just one part of the season. In such cases, one would expect that allowing for intertemporal substitution will have a greater impact on welfare estimates.

Expand the analysis to beyond California. I have spent a significant amount of time understanding and tidying RIDB data—a substantial fixed cost investment that will allow me to consider camper preferences on a larger geographic scale. When combined with cloud computing resources, I will be able to estimate recreation demand models for other areas of the country or the country as a whole. This could reveal preference and WTP differences across different states that might imply different optimal policy in different areas of the United States.

Conclusions

It has been many years since anyone has undertaken a comprehensive assessment of the demand for campgrounds based on revealed preference data. One main contribution of this research is to demonstrate the use of RIDB campground reservation data to estimate a detailed random utility model of destination site-choice for these campers. The historical RIDB reservation data provides me with a dataset for trips taken from a given zip code to a wide variety of destinations over a large spatial extent in California. This model allows me to infer the trade-offs made by campers based upon their revealed preferences. When campers are willing to travel farther to reach a more-desirable campground, they reveal their total willingness to pay for different types of trips as well as their marginal willingness to pay for the presence of activities or amenities associated with each campground. Another key contribution of this research is my novel definition of the consideration set as over site-time pairs. While this change was not shown to greatly affect welfare measures in this paper, it is possible that other policy scenarios might produce larger differences.

I have shown that the time between the reservation choice occasion and the weekend of the trip plays a large role in an individual's WTP to make a trip. Having visited the site in the past is an even more important factor in determining whether an individual picks a particular campground. These results suggest that uncertainty about the quality of a future trip plays a large role in an individual's decision to go camping and the resulting welfare from that decision. Fishing over most of the season, hiking, bicycling, rock climbing, and swimming were all shown to be complementary activities to camping; boating and hunting on the other hand were associated with utility reductions. The closure of 3 sites in Yosemite produced an average per-trip welfare loss of $10. Upgrading all CA campgrounds would result in an average $39 increase in per-trip welfare. These two welfare analysis scenarios are just two examples of the types of benefit-cost analysis that this research can contribute to.

CHAPTER III

VALUING ENVIRONMENTAL AMENITIES USING A RECREATION DEMAND MODEL FOR CAMPGROUNDS IN CALIFORNIA

Introduction

One of the most valuable uses of recreation demand models is the valuation of nonmarket environmental amenities. While campground demand itself is important (it is a major recreational activity), I can use the campground demand revealed by the choices within the RIDB data as a way to value indirectly the important environmental amenities in the locality of campgrounds. If an individual is willing to travel further to an otherwise identical site that has, for example, more moderate temperatures or an appealing ecosystem, that choice reveals something about the value for that environmental amenity. These estimated valuations can then be used to help evaluate the benefits of polices or the welfare effects of natural events that impact the quality of the environmental amenities near campgrounds. Recreation demand models are uniquely powerful among revealed-preference methods for estimating the values of nonmarket goods that are far from urban centers. This paper estimates the values of different types of land cover (one component of the ecosystem), welfare losses due to light pollution, and how weather affects recreational use values. As an example of the types of welfare analysis this model is capable of performing, equivalent variation measures are calculated for weather changes associated with projected climate change under different emissions scenarios.

This research will also contribute to an updated understanding of recreational demand for camping opportunities. Swait (2009) and Richards and Brown (1992) estimate Random Utility Models of campground choice, using stated preference and revealed preference data, respectively. Other researchers, such as Boxall et al. (1996) and Brox and Kumar (1997), have used count data models to estimate campground demand. Brown et al. (2008) examine the effect of wildfire on camping demand. Rausch et al. (2010) also consider wildfire, specifically to examine how fire damage affects demand as the forest stand regrows. Cole et al. (1997) examine encounter rates in Oregon and Washington state wilderness areas, finding that encounter rates exceed those preferred by most visitors. I include expected congestion as site attribute in the current model, though this can be observationally equivalent to site popularity, such that it may appear to confer positive utility. [1]

Section 2 of this paper details the additional data incorporated and the modifications to model specification from Chapter II. Section 3 presents the model estimation results. Section 4 presents MWTP for variations in environmental amenities as well as equivalent variation for weather changes associated with projected climate change. Section 5 brings up directions for future research and Section 6 concludes.

Data and Methodology

Environmental attributes of the campgrounds will include temperature, precipitation, type of land cover (e.g. deciduous forest, mixed forest, grassland, wetland), percent tree cover, and degree of nighttime light pollution. Daily

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[1] See the Chapter II of this dissertation for a more detailed literature review of recreation demand models using camping data.

frequency temperature and precipitation data at a 4 km spatial resolution has been obtained from PRISM Climate Group at Oregon State University. These data are not directly from monitoring stations but are interpolated from monitoring station data using a Climatology-Aided Interpolation (CAI) process. These interpolated measures allows me to observe (approximated) temperature and precipitation at much finer spatial and temporal scales. Because RIDB contains reservation data, the actual weather on the date of the trip is not known. To construct a measure of expected weather, I calculate the mean daily values for each weekend at each site, averaged over the five years leading up to the sample period.

Land cover information has been obtained from the National Land Cover Database (NLCD) maintained by USGS. The closest version of this dataset to the sample period was constructed in 2011, though it is unlikely there was much land cover change between 2011 and 2014. These values were merged with the lat/long point location of the campgrounds and a set of indicators were constructed to signify what type of land cover is prevalent at the campground. The NLCD is raster data, so in rare cases the dominant land cover is something unintuitive for a campground, such as the land cover being primarily water. The percent of the area covered in tree canopy was also collected from the NLCD data. To capture the effects that light pollution may have on the camping experience, I gathered nighttime light data from NOAA's Defense Meteorological Program Operational Linescan System (DMSP OLS), which captures annual stable nighttime lights at a spacial resolution of 30 arc seconds (roughly 1 km). I use the data from 2013 to approximate a measure of expected light pollution.

The welfare analysis section incorporates additional data taken from the NASA Earth Exchange (NEX) Global Daily Downscaled Projections (GDDP)

(Thrasher et al., 2013). These data are downscaled from from coarse resolution projections of the Coupled Model Intercomparison Project Phase 5 (CMIP5) to be at a spatial resolution of 0.25 arc degrees (roughly 30 km). The NEX GDDP contains projections of daily temperature maximum, temperature minimum, and precipitation for each year from 1950 to 2100 (it includes retrospective projections). These projections come from 33 different General Circulation Model (GCM) runs conducted by a variety of climate scientist groups around the globe. The NEX GDDP contains these climate projections for two different emission scenarios known as Representative Concentration Pathways (RCP) 4.5 and 8.5 (listed in order of increasing greenhouse gas concentrations). I calculate welfare effects under both the RCP 4.5 and 8.5 scenarios. RCP 4.5 is consistent with large but reasonably obtainable reductions in emissions. RCP 8.5 is a fossil-fuel-intensive emissions scenario in which emissions continue to increase. Descriptive statistics for the additional variables introduced can be found in Table 5.

The methodology for estimating the recreation demand model and constructing measures of equivalent variation for changes in site quality is largely the same as the methodology described in Chapter II. I opt to use a conditional logit specification as the mixed logit specification in Chapter II made little difference in the conclusions of the model.[2] In Chapter II, individual i is assumed to choose across site-weekend pairs to maximize utility, given by:

$$\begin{aligned}U^i_{jwt} &= \alpha(Y^i - C^i_j) + (\beta_0 + W_w\beta_1 + Q_{jw}\beta_2 + Z^i\beta_3)A_j + Q_{jw}\gamma_1 + D_{tw}\gamma_2 + \gamma_3 P^i_j + \epsilon^i_{jwt} \\ &= X^i_{jwt}\zeta + \epsilon^i_{jwt}\end{aligned}$$

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[2] This decision was driven in part by the long estimation times necessary to estimate a mixed logit model. See section 5 for a discussion of modifying the specification to more generally capture preferences.

TABLE 5.

Selected descriptive statistics for trips taken

Variable	Brief Description	Mean	Std. Dev.
Night Lights	Measure of night time light level	2.59	4.83
Dev. Precip.	Expected daily precipitation, in mm, deviation from mean over alternatives	-0.01	0.7
Dev. Mean Temp.	Expected average temperature, in Celsius, deviation from mean over alternatives	-0.77	4.19
$1(\text{Water})_j$	Indicator for water being the primary land cover near the campground	0.08	0.27
$1(\text{Open Space})_j$	Indicator for developed open space being the primary land cover near the campground	0.13	0.34
$1(\text{Evergreen})_j$	Indicator for evergreen forests being the primary land cover near the campground	0.53	0.5
$1(\text{Mixed Forest})_j$	Indicator for mixed forests being the primary land cover near the campground	0.03	0.18
$1(\text{Shrubland})_j$	Indicator for shrubland being the primary land cover near the campground	0.14	0.35
$1(\text{Grassland})_j$	Indicator for grassland being the primary land cover near the campground	0.08	0.27
% Tree Cover	Percentage tree cover at the campground	42.91	24.29
Proj. Precip. Change (4.5)	Projected change in daily precipitation, in mm, under low emissions scenario	-0.22	0.68
Proj. Precip. Change (8.5)	Projected change in daily precipitation, in mm, under high emissions scenario	-0.16	0.65
Proj. Temp. Change (4.5)	Projected change in temperature midpoint, in Celsius, under low emissions scenario	2.41	2.5
Proj. Temp. Change (8.5)	Projected change in temperature midpoint, in Celsius, under high emissions scenario	3.9	2.55

where the weather information described above was included as controls and as systematic shifters over the preferences for different campground activities. In this paper, I pay special attention to the (expected) weather variables as they are the key coefficients associated with the welfare effects of the climate change projections. Additionally, to be able to indirectly value other environmental amenities in the locality of campgrounds, I include in the utility function a set of land cover indicators and percent tree cover L_j and expected nighttime light pollution N_j:

$$U^i_{jwt} = X^i_{jwt}\zeta + L_j\lambda_1 + \lambda_2 N_j + \epsilon^i_{jwt} \tag{3.1}$$

The marginal utilities of these environmental amenities, λ_1 and λ_2, can be monetized into MWTP for those amenities by dividing by the marginal utility of net income α.

Results

Table 6 presents selected coefficients from four increasingly general conditional logit estimations.[3] The first column includes only expected weather variables as environmental amenities of the campground weekend pairs (this specification also includes all other non-environmental attributes from Chapter II as controls). The second column adds the level of expected night time light pollution as an environmental amenity in the individual's utility function. The third specification, presented in the third column of Table 6, adds the percentage tree cover at the campground as reported in the NLCD. Column 4 of Table 6 presents a specification that includes the full set of NLCD land cover indicators, where the most common type of land cover, evergreen forests, is the omitted group.

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[3] See Table A1 in the appendix for a report of the estimates for all of the attributes included in the models.

TABLE 6.
Selected Conditional Logit Estimates, Environmental Amenities

	Weather only	Add night lights	Add tree cover	Add LC indicators
Full round-trip travel cost	-0.0108***	-0.0112***	-0.0113***	-0.0116***
	(0.000149)	(0.000156)	(0.000157)	(0.000158)
De-meaned precipitation	0.0938**	0.0579	0.0711	0.0937**
	(0.0458)	(0.0463)	(0.0466)	(0.0465)
De-meaned avg. temperatures	-0.160***	-0.172***	-0.170***	-0.163***
	(0.00758)	(0.00771)	(0.00770)	(0.00783)
× De-meaned precipitation	0.0224***	0.0218***	0.0231***	0.0240***
	(0.00498)	(0.00502)	(0.00502)	(0.00499)
(De-meaned avg. temp)^2	0.00158**	0.00124*	0.00211***	0.00205***
	(0.000681)	(0.000687)	(0.000694)	(0.000707)

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Table 6 : Selected Conditional Logit Estimates, Environmental Amenities

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	Weather only	Add night lights	Add tree cover	Add LC indicators
(De-meaned precipitation)^2	-0.0143	-0.0200	-0.0294*	-0.0326*
	(0.0170)	(0.0174)	(0.0177)	(0.0175)
Night-time lights		-0.0285***	-0.0276***	-0.0334***
		(0.00216)	(0.00216)	(0.00230)
% Tree cover			0.00479***	0.000532
			(0.000548)	(0.000908)
Land cover = water				-0.711***
				(0.0731)
Land cover = open space				0.201***
				(0.0430)

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Table 6 : Selected Conditional Logit Estimates, Environmental Amenities

– continued from previous page

	Weather only	Add night lights	Add tree cover	Add LC indicators
Land cover = low-density developed				-1.217***
				(0.146)
Land cover = med-density developed				2.522**
				(1.011)
Land cover = barren land				1.756***
				(0.321)
Land cover = deciduous forest				1.382***
				(0.346)
Land cover = mixed forest				1.025***
				(0.0889)

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Table 6 : Selected Conditional Logit Estimates, Environmental Amenities

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	Weather only	Add night lights	Add tree cover	Add LC indicators
Land cover = shrubs				-0.0860
				(0.0545)
Land cover = grassland				0.217**
				(0.108)
Land cover = cultivated land				0.571
				(0.514)
Land cover = woody wetland				-0.835
				(0.581)
Land cover = herbaceous wetland				2.075**
				(1.009)

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Table 6 : Selected Conditional Logit Estimates, Environmental Amenities

– *continued from previous page*

	Weather only	Add night lights	Add tree cover	Add LC indicators
Max. log-likelihood	-37030.62	-36928.96	-36890.38	-36697.48
No. choices	8748	8748	8748	8748
No. alternatives	3283654	3283654	3283654	3283654

Standard errors in parentheses

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

The coefficient on round-trip travel cost, interpreted as the negative of the marginal utility of net income, is negative and highly significant across all four specifications. It gets slightly larger in magnitude as environmental amenities are added to utility function, indicating that the coefficient on travel cost was previously picking up on some of the variation in environmental attributes. For the most part, the qualitative interpretations of the coefficients on the expected weather variables don't change across specifications. Precipitation becomes insignificant for the second and third specification, and the square of precipitation becomes marginal significant in the final two specifications. Night-time light pollution has a negative and statistically significant marginal utility across all specifications, indicating that people are willing to travel further to avoid this dis-amenity. Percentage tree cover is significant and positive when included in the third specification, but appears to have only been picking up on the effect of the land cover attributes. In the final specification, percentage tree cover, conditional on a given type of land cover, has no significant effect on a recreationist's utility. For the rest of the analysis in this chapter, I focus on the final specification presented in Table 6, both because it allows me to explore how a greater variety of environmental amenities affect camper welfare and because it has the highest value of the maximized log likelihood function across the four specifications.

Consider the marginal utilities associated with the various expected weather attributes presented in column 4 of Table 6. They indicate that recreationists prefer to pick campgrounds on weekends when it has historically been more likely to rain. This positive marginal utility falls away as expectations of the amount of precipitation rise, indicated by the negative coefficient on the square of precipitation. These results are intuitively plausible— a light rain in the summertime might be a relief, whereas a downpour could put a damper on a camping experience. The results reveal that campers avoid hotter places and times, though at a decreasing rate as average daily temperatures rise above the mean over alternatives. The interaction term of de-meaned precipitation and temperature has a positive and statistically significant coefficient, reinforcing the story that rains can ameliorate the negative effects of high temperatures. These relationships play the integral role in my later analysis of projected weather changes associated with climate change.

Welfare Analysis

Table 7 presents the MWTP estimates and simulated 95% confidence intervals for night-time light pollution and the various land cover indicators. These results show that campers avoid high levels of ambient night-time lights. All else equal, individuals would be willing to incur \$21 in additional travel costs to avoid a site with night-time light levels one standard deviation above the mean over chosen sites. Many of the land cover indicators have positive MWTP estimates, indicating that they are preferable to the excluded group, evergreen forests. As evergreen forest is the most common type of land cover, this indicates that individuals have a taste for more unique land cover ecosystems in the vicinity of their campground. Both other types of forest land—mixed and deciduous—are more desirable than evergreen forests, with individuals willing to pay \$88 more to visit a mixed forest site or \$119 more to visit a deciduous forest site. Grassland and even barren landscapes are preferable to evergreen forests, to the tune of \$19 and \$151, respectively.

TABLE 7.

Marginal Willingness to Pay ($) for Environmental Attributes

Variable	MWTP ($)
Night-time lights	-3
	(-3, -3)
Land cover = water	-61
	(-73, -49)
Land cover = open space	17
	(10, 25)
Land cover = low-density developed	-105
	(-129, -80)
Land cover = med-density developed	217
	(45, 387)
Land cover = barren land	151
	(96, 205)
Land cover = deciduous forest	119
	(62, 177)
Land cover = mixed forest	88
	(73, 103)
Land cover = shrubs	-7
	(-16, 2)
Land cover = grassland	19
	(1, 37)
Land cover = cultivated land	49
	(-38, 138)
Land cover = woody wetland	-72
	(-167, 31)
Land cover = herbaceous wetland	179
	(15, 356)

95% simulated confidence interval in parentheses.

Some types of land cover appear to be less attractive to recreationists than evergreen forests. If water is the most common type of land cover near a site, WTP to visit that site is reduced by $61.[4] Campgrounds in low-density developed areas have a MWTP of -$105 while campgrounds in medium density developed areas have a MWTP of $217. There is a similar disconnect between different types of wetlands— woody wetlands decrease WTP by $72 while herbaceous wetlands increase WTP by $179, relative to evergreen forests.

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[4] It may seem strange that water is the dominant type of land cover near a site. These land cover indicators are constructed from raster (image) data spatially linked to the campground's point in space given by its latitude and longitude. Future analyses can consider the percentage of each type of land cover within a certain buffer of the point location of the campground.

By including environmental amenities as determinants of recreationist's utility, I create the opportunity to use the fitted model estimates to calculate welfare effects for policy scenarios or natural events that would affect those attributes. One prominent example of such a natural event is climate change, which I use as a proof-of-concept to show how the models I develop can be used for policy analysis. Table 8 presents summary statistics for the per-trip equivalent variation (EV) across individuals associated with projected weather changes associated with two different climate change scenarios—RCP 4.5, a relatively low-emissions scenario, and RCP 8.5, a high-emissions scenario. The difference in per-trip EV between these two scenarios can help give policy makers an idea of the benefits of climate change mitigation, even if it is just a small portion of the total damages of projected climate change. I calculate the EV for changes under these scenarios leading up to 2075, and calculate EVs both when allowing individuals to substitute intertemporally and when restricting their substitution decisions to the original weekend they chose.

The mean EVs are similar when allowing for substitution over time versus restricting substitution to same-day choices. But the standard deviation in EVs is noticeably larger when individuals can only substitute between campgrounds on the same weekend. This pattern holds true across both considered emissions scenarios. Figure 7 presents the distribution of per-trip EV resulting from temperature and precipitation changes leading up to 2075 projected as part of the low-emissions RCP 4.5 scenario, and Figure 8 presents the same except for the RCP 8.5, high emissions scenario. Under both emissions scenarios, some individuals are projected to experience welfare gains. But in both cases, the large majority of individuals experience welfare losses, with those losses being

TABLE 8.
Per-trip Equivalent Variation ($) for projected weather changes; when allowing for intertemporal substitution and when restricted to same-day substitution only

	Intertemporal Substitution	Same-Day Substitution
RCP 4.5 (Low Emissions)	-31	-32
Projected Changes, 2075	(16)	(23)
	[-52, -4]	[-69, 3]
RCP 8.5 (High Emissions)	-50	-51
Projected Changes, 2075	(17)	(23)
	[-73, -23]	[-88, -14]

The mean EV across individuals is presented. The standard deviation is in parentheses. 5^{th} and 95^{th} percentiles are in square brackets. Distribution is not symmetric around the mean.

substantially greater under the high emissions scenario. The mean EV under the low emissions scenario is -$31, while under the high emissions scenario it is -$50.

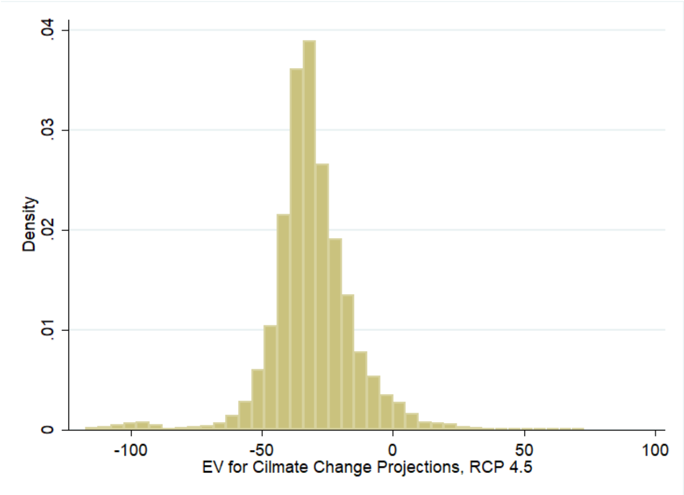

FIGURE 7.
Equivalent Variation across individuals for RCP 4.5 projected weather changes

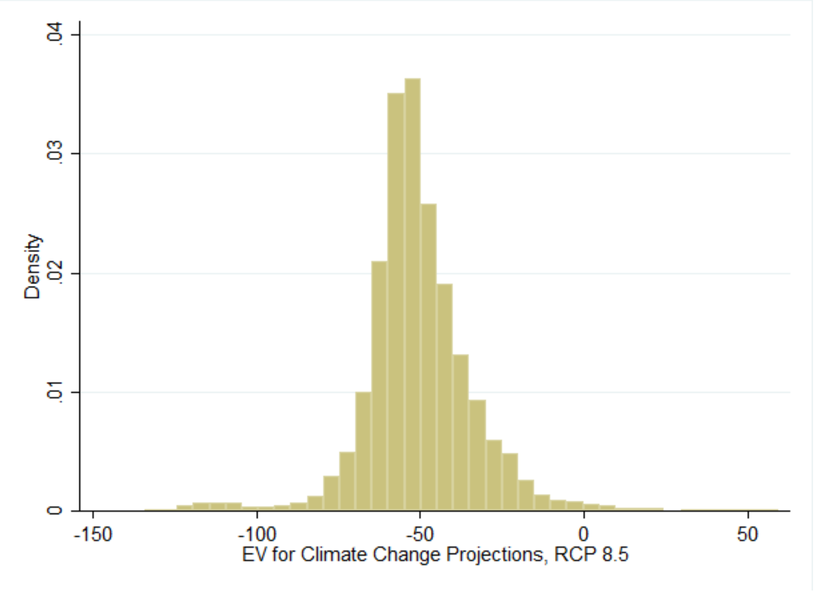

FIGURE 8.
Equivalent Variation across individuals for RCP 8.5 projected weather changes

Directions for Future Research

The analysis presented in this paper integrates a wide variety of data to indirectly value environmental amenities through demand for federally managed, reservable campgrounds. The analysis opens up some new questions and directions for future research, outlined below:

Upgrade the estimation process. I plan to consider a wider variety of model specifications once I move the estimation process to cloud computing services. I haven't completed this yet because of the additional fixed cost of learning new programming languages, but this step will be necessary to bring to bear the most state-of-the-art estimation techniques. I can consider a variety of mixed logit specifications, allowing the marginal utility of different environmental attributes to vary randomly across individuals. I can also explore latent-class models which allow preferences to vary across different classes of customers, where the class of each customer is not explicitly observable.

WTP-space estimation. Future analyses could estimate MWTP values directly by parameterizing the model in WTP space. Cameron and James (1987) were among the first to parameterize a discrete choice model in this way, in the context of contingent valuation. Train and Weeks (2005) and Sonnier et al. (2007) extend the use of estimation in WTP space to multinomial models with random coefficients using Bayesian techniques. Both sets of authors compare estimates from preference-space models to estimates from WTP-space models in the context of stated preference data for car choice. Both studies found that WTP-space estimates did not produce the fat tails of the preference-space estimates (which indicate that some individuals favor or disfavor certain attributes to an unreasonable degree). However, they find that the preference-space estimates provide better in-sample fit. Scarpa et al. (2008) is the first extension of WTP-space estimation to a model of recreation demand and the first to use Maximum Simulated Likelihood with this type of parameterization. They compare preference-space and WTP-space estimates in the context of destination choice in the Italian Alps. Unlike earlier authors, Scarpa *et al.* find that their WTP-space estimates provide better in-sample fit in addition to WTP distributions without fat right tails. They also compare results from Hierarchical Bayes (HB) estimation and MSL, finding that MSL provides the best model fit.

Endogenous consideration sets. While my novel definition of the consideration set as all sites over all remaining weekends in the season allows my model to capture intertemporal substitution, it also results in extremely large consideration sets. In this paper, I dealt with this fact by sampling from individual's consideration sets. But I can also explore methods of endogenous consideration set formation, so that I am estimating not just the marginal utility parameters associated with choosing a camping alternative, but also the probability that a particular alternative is included in an individual's consideration set. Haab and Hicks (1997) and Von Haefen (2008) are two examples of papers that estimate recreation demand models with endogenous consideration sets. Haab and Hicks (1997) use data on beach visits in Massachusetts and the Chesapeake Bay area and find that allowing for endogenous consideration sets results in significantly different parameter estimates. In particular, they find that a basic multinomial logit underestimates the parameters on travel cost and water quality as compared to their model with endogenous consideration sets. Von Haefen (2008) allows for endogenous consideration set formation in a Kuhn-Tucker framework and finds that models with latent consideration sets fit the data better. Li et al. (2015) conduct a Monte Carlo experiment on simulated data and find that ignoring consideration set formation can bias welfare measures by 30% to 50%. I can build upon the results of the current paper and be the first to consider endogenous consideration set formation in the context of campground demand and in the context of these new site-time consideration sets.

Alternative temperature specifications. It is possible to include the minimum and maximum temperature instead of or in addition to average temperatures. I could also explore weather the temperature range (max-min) has a significant impact on camper utility. This last variable would partially capture the role that humidity has to play in recreational demand for campgrounds, as more humid places would on average have smaller temperature fluctuations over the course of the day. Dew point is another potential weather related variable that can be explored in future specifications.

Other impacts of climate change. In this paper, I consider the welfare impacts of weather changes that are projected to occur as a part of climate change under different emissions scenarios. But temperature and precipitation are just two examples of environmental attributes of campgrounds that will be affected by campgrounds. Future analysis can consider the additional impact of other climate-change-related impacts to campground attributes. One example would be the effects that climate change is projected to have on land cover. Unfortunately, land cover forecasts don't exist for the RCP scenarios. They do exist for the SRES scenarios, an earlier version of climate change projections, though they could not be compared directly with the RCP forecasts used in the current paper. Climate change has also been show to result in higher frequency extreme weather events and natural disasters like wildfires. The analysis in this paper could be combined with the analysis in Chapter IV of this dissertation to give a more more full picture of the negative welfare effects of climate change.

Conclusions

This paper demonstrates the capabilities of the RIDB data, when combined with a variety of environmental attribute data from other sources, to indirectly value environmental amenities near campgrounds. I found that light pollution reduces camper utility, as one would expect. Additionally, the type of land cover that dominates the area around a campground plays a large roll in an individuals willingness to pay to visit a particular campground. This dominates the effect of the percentage of tree cover in the area, which was found to have an insignificant effect on the individuals decision. People are willing to pay $88 more to go to a site that has a mixed forest as opposed to an evergreen forest, or $119 if the landscape is a deciduous forest. Indeed, most types of land cover present around the campgrounds in the sample were preferable to evergreen forests (the most common type), suggesting that people prefer variety in the ecosystem around where they camp.

I also estimated how the expected weather conditions at a campground affect individual utility. I found that utility falls (at a decreasing rate) with higher temperatures but rises (at a decreasing rate) with precipitation. At the highest levels of precipitation, rain has a negative effect on camper utility, a sensible result to anyone who has been stuck in a tent during a downpour. Rain is more preferable at higher temperatures, perhaps because it provides a respite from the heat or leads to greener plant life. I took the estimated marginal utilities associated with these weather variables and used them to construct measures of equivalent variation for climate change under different emissions scenarios. The low emissions scenario produced a per-trip EV of -$30 on average while the high emissions scenario reduced camper welfare by an average of $50 per trip.

CHAPTER IV

WILDFIRES AND RECREATIONAL USE VALUE: EVIDENCE FROM CAMPGROUND DEMAND IN CALIFORNIA

Introduction

Every year, significant wildfires occur in California and many other (especially Western) states. These wildfires receive the greatest media coverage when they threaten structures that have been built at the wildland-urban interface, but such fires can also interfere with the quality of outdoor recreation activities. Aside from the evacuation or closure of areas where wildfires are currently burning, or significant decreases in downwind air quality caused by drifting smoke from nearby active fires, visible wildfire burn scars can become a long-lived new attribute of recreational areas that can affect the values of these areas to recreational users for years to come.

Even many years after a wildfire in the vicinity of a campsite, burn scars can mar scenic vistas that campers may find less attractive than they were before the fire. However, it is also possible that burn scars, or the novelty of the ecological succession that takes place during the regrowth of a burned forest, may add new interest to a landscape. The smoke from even very distant fires in the broader region can still increase reduce air quality and visibility and produce negative health effects (where Kochi et al. (2012), Richardson et al. (2012), Moeltner et al. (2013) and Kochi et al. (2016) have explored the health effects of exposure to smoke from wildfires in Southern California, and Jones (2017) has considered the effects of wildfire smoke on “life satisfaction”). Furthermore, a history of wildfires in a region, in the driest months, can also increase people's uncertainty about the likely conditions around a recreational destination at different times of the year and may affect the timing of a planned excursion when reservations are being made in advance.

In this paper, I focus on the effects of nearby wildfires in prior years, and the history of seasonal wildfires in the broader region around a campground, on people's choices among possible campground reservations at different future times in the current camping season. The main data source is the set of campground reservation in the RIDB data for California in the summer of 2014.

The goal of the research is to quantify the role that wildfires play in an individual's decision about where and when to make a campground reservation. I use remotely sensed historical wildfire footprints to approximate people's expectations about future wildfire risks at the different destinations in their choice sets. This destination choice model permits inferences about the effects of both nearby and regional past wildfire events on choice among different destinations at different times during the rest of the camping season.

Intuitively, it might be expected that a past wildfire that has marred the natural beauty in the vicinity of a campsite would reduce that campsite's attractiveness. But if a fire has removed trees or foliage or underbrush to reveal new vistas that could not be seen previously, then perhaps the destination takes on a distinctly new set of attributes. Perhaps not all of these new attributes are bad. Burn scars may quickly sprout unexpected arrays of wildflowers or attract birds or other wildlife that did not frequent the original forest ecosystem, but are attracted to the new habitat.

Alternatively, if someone has visited a given campsite previously, and then a wildfire occurs, they may be intrigued to return to see what has happened to the local ecosystem. Curiosity might bring them back after the fire. After they have learned whether the fire has had a net positive or negative effect on the extent to which the destination remains attractive, they may find that the destination is now attractive for new reasons, or they may choose other destinations for may years until the forest is restored. It is thus difficult to predict, ex ante, whether wildfires near a given campsite will decrease or increase the utility to be derived from a prospective visit to that site.[1]

A history of significant wildfires in the wider region may have had no net adverse effect on the aesthetic value of a given campground, but it could increase the perceived risk associated with making an advance reservation at that campsite during the peak season for wildfires. People may be concerned that their reservation would be canceled if the area were to be evacuated, or perhaps heavy smoke in the region might render the experience very unpleasant. If potential substitute reservations would be booked by the time the trip was to be taken, perhaps no camping trip would be taken at all. To avoid this risk, people might make reservations in areas with lower seasonal risks of wildfire. Thapa et al. (2013) examine tourist risk perceptions concerning wildfires in Florida, surveying 771 non-resident overnight travelers that had visited Florida previously. They identify three segments of traveler perceptions and explore wildfire situations that could influence their future travel choices concerning fire-prone destinations.

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[1] The "recovery" period matters. Ryan and Hamin (2008) study stakeholder concerns in the aftermath of wildfire, taking into account "community economic, recreational, and emotional connection" to the forest by conducting key informant interviews with recreation groups, among others, in three wildfire-devastated communities. Their goal was to understand how the US Forest Service and affected stakeholders interact during forest restoration and rehabilitation.

The previous literature includes a number of papers that specifically explore the effect of wildfire on the value of camping experiences. Brown et al. (2008) use an on-site survey of about 220 visitors to a Wilderness Area in Oregon that was affected by the 2003 Bear Butte and Booth fires. These researchers ask respondents about their post-fire changes in use of the wilderness and their preferences for managing recreational use of the area after the fire. They find that recreational use did decline after the fires, but that the impact of these fires on visitation was actually less than the impact of the Recreation Fee Demonstration Program, which increased the monetary cost of access. These authors identify considerable heterogeneity in opinions about post-fire management of recreational use (with respect to use restrictions or camping regulations).

Of interest in the present paper will be the short-term versus longer-term effects of wildfire on people's willingness to pay for a trip to an affected destination. Hilger and Englin (2009) use a Poisson estimator to estimate demand for wilderness recreation and calculate welfare measures for a 40,000 acre wildfire in Washington state. Their results suggest that recent wildfires increase consumer welfare relative to before the fire. Similarly, Sanchez et al. (2016) they find that recreational users are attracted to sites with access to burn scars that can be viewed up close. Their welfare estimates increase for sites that were partially affected by wildfire, and the greatest gains are associated with the most-recent wildfires, although actual trail closures reduce welfare.

It seems, however, that the question of whether wildfires increase or reduce the value of a recreational destination may depend on the type of activity being pursued at that destination. Loomis et al. (2001) surveyed hikers and mountain bikers visiting National Forests in Colorado to explore whether wildfires had differential impacts on the two groups. They estimate a count-data travel cost model and find that years since a non-crown fire had a significantly positive effect on demand by hikers. They find that crown fires also increase trip value for hikers, but decrease trip value for bicyclists. Hesseln et al. (2003) also study the effects of wildfires and prescribed burns on hikers and mountain bikers in New Mexico, finding that both types of demands decrease with prescribed burning. Wildfire results in fewer visits by both groups, but only hikers exhibit an increase in per-trip benefits. Their results suggest that different types of recreational users will not react identically to fires of different types. In other work, Hesseln et al. (2004) find that hikers' demands decreased slightly for destinations recovering from crown fires but increased for destinations recovering from prescribed fires in western Montana. However, bikers decreased their annual trips to destinations recovering from prescribed fire. Both groups, though, seemed not to value individual trips by any more or less as a result of either wildfire or prescribed fire. To date, there seems to have been no published economic research concerning the effects of wildfires on the demand for camping.

Rausch et al. (2010) offer an intertemporal fire-damage function for forest-based recreational activities on the eastern slope of the Canadian Rocky Mountains. This analysis employs both revealed-preference and stated-preference data in models to explain the annual camping-trip frequencies by respondents. They find that fires initially decrease annual trips, but as the new stand of trees ages, the effect of the fire diminishes until trip frequencies begin to look like pre-fire frequencies after about 12 years. The authors note that this time profile differs from some others that have appeared in the literature. Simoes et al. (2013), however, use a combination of revealed-preference and stated-preference data to assess the predicted welfare effects of a hypothetical wildfire that damages a National Forest. In that case, the intended number of trips would be reduced and respondents would experience a welfare loss.

The persistence of wildfire effects on wildland recreation is thus also an important question, given that most forests take may years to attain anything like their former attributes. Boxall and Englin (2008) combine revealed-preference and stated-preference data to estimate the welfare effects of forest fires and how those effects change over the post-fire regrowth period. Similarly, my current analysis explores how the welfare effects of fire evolve over time by including among destination attributes the number of years since the most recent nearby fire.

Camping is certainly not the only recreational activity that can be affected by local or regional wildfire in the current period or in recent years. Recognizing the beneficial role that wildfires can have on forest health, Englin et al. (2000) explore the relationship between fire risks, timber values, and recreational amenities. They find that failing to account for back-country recreation in multiple-use wilderness areas can lead to sub-optimal fire management program. Englin et al. (2006) consider the value of ancient forests for recreational users, with specific concerns about the persistent effects of crown fires on recreational values. Hesseln et al. (2002) compare the effects of wildfire on recreation demand in Colorado and Montana.

There also exists a small but growing literature on wildfire and recreational use in international settings outside the U.S. and Canada. Climate change seems to be increasing wildfire risks at many locations in the northern hemisphere. Bestard and Font (2010) estimate the value of forest recreation at a regional level using a discrete count model linking forest areas in Spain. Gadaud and Rambonilaza (2010) estimate the willingness-to-accept of private forest owners in France to allow public wilderness recreation in their forests. Allowing public recreational use increases fire risk perceptions which in turn reduces the timber value of the forest. Mavsar et al. (2013) explore the relative importance of different ecosystem services of forest lands—recreation, water purification, and biodiversity— in Slovenia. They find that fire prevention is less important than the provision of other ecosystem services. Likewise, Rodriguez y Silva et al. (2014) consider the implications of the value of forests for recreation and ecosystems service on how agencies should prioritize the use of wildland forest management and protection budgets in Cordoba Province, Spain.

It is, of course, relevant to note that the economics of wildfire extends beyond just recreational values. A significant share of the literature that concerns wildfire emphasizes the challenges of managing wildfires that threaten the wildland-urban interface. A number of papers in that literature use hedonic property value models to infer the value of reduced wildfire risks, and much of the policy discussion concerns incentives and market failures that affect homeowners' decisions to undertake fuel-reduction activities around their houses. I do not review the entirety of that literature for this paper because most camping areas are well-removed from this interface.

Wildfire also affects other types of ecosystems services besides recreational uses. Hallema et al. (2018) discuss the effects of wildfires, in many different parts of the world, on ecohydrological systems and sociohydrosystems. In simpler terms, they survey wildfire threats to water supplies, especially freshwater availability and water supply resilience. Loomis and Gonzalez-Caban (2010) review US Forest

Service use of non-market valuation in the economics of wildfire, focusing on fire suppression in critical species habitat (i.e. spotted owl old-growth forests).

It is worth mentioning, however, that sociodemographics and wildfire have been considered specifically by Gonzalez-Caban et al. (2007), who assess the difference in willingness to pay for wildfire mitigation between Native American communities and the general population in Montana, while Gaither et al. (2011) focus on the relationship between wildfire risk and socially vulnerable rural communities in the Southeast U.S. Loomis et al. (2009) consider the different preferences White households and Hispanic households in California, Montana and Florida in the context of willingness to pay to reduce acres burned by wildfire. The segments of the U.S. population that select into camping as a recreational activity are not representative of the U.S. population as a whole, so the environmental justice dimensions of wildfire effects on the non-market values of campgrounds seem not yet to be on many research agendas.

For completeness, I will also acknowledge that numerous researchers focus on the loss of commercial value of forests due to wildfire. Alcasena et al. (2016) have studied post-fire tree mortality in southern European commercial conifer forests where the main natural hazard is wildfire. Amacher et al. (2005) consider stand management decisions by non-industrial forest owners as they undertake fire prevention without perfect knowledge of wildfire probabilities. Other research, for example Barbour et al. (2008a), considers fire-hazard reduction by removal of merchantable timber, and Barbour et al. (2008b) the use of mechanical fuel treatments to reduce fire risks on public timberland in the western U.S. Calkin et al. (2011) review progress in wildfire risk management strategies for federal lands concerns both the prevention of fires and management of those wildfires which do break out in a manner that acknowledges the multiple-use values of forests. Fuel reduction to reduce wildfire risks requires the allocation of scarce resources, and some economic incentives for these activities are considered by Becker et al. (2009). There are many more such papers in the wider literature on forest economics and policy.

Not all economic analyses relating to wildfire seek to measure net benefits or welfare changes. Nielsen-Pincus et al. (2014) consider the economic impact of wildfires in the western U.S., noting that there are winners and losers across sectors, including the leisure and hospitality industries (which would include campgrounds). Likewise, Starbuck et al. (2006) also seek to measure regional economic impacts from wildfire, and they use pooled travel cost and stated-behavior survey data to quantify the effects of wildfire on recreational demands as one component of their analysis of alternative fire and fuel-management strategies in New Mexico.

The paper proceeds as follows: Section 2 discusses data and methodology. Section 3 presents the marginal utilities that are the results of the conditional logit model used to estimate campground demand. Section 4 discusses welfare impacts, both in terms of the MWTP for changes in expected wildfire conditions and measures of equivalent variation for larger changes in the pattern of wildfires. Section 5 discusses directions for future research, and Section 6 concludes.

Data and Methodology

This paper builds upon the data and model used in Chapter III of this dissertation. I merge in historical wildfire data from the MODIS Burned Area Monthly Global 500m dataset provided by NASA and the USGS EROS Center.

This data is remotely sensed by NASA's Terra and Aqua satellites and contains monthly observations of burn area at a 500 meter spatial resolution. I join the fire observations to the lat/long point locations of the campgrounds in my sample using both a 5 km buffer and a 50 km buffer. My intention is to capture direct/scenic effect of recent fires using the 5 km buffer and approximate a measure of fire-proneness with the 50 km buffer. For the small buffer, I construct three variables to provide information on the direct effect of recent wildfires: an indicator for whether a fire has occurred within 10 years, how long ago the most recent fire occurred, and the square kilometers burned by the most recent fire within 5 km of the campground. For the larger buffer, I construct three variables to capture the general severity and frequency of fires in the area: a count of all years over the past 10 years for which there was a fire that burned more than 5 square km, a similar count that considers only fires larger than 50 square km in burn area, and finally a variable containing the total amount of square kilometers burned within 50 km of the campground over the 10 years preceding my sample period. Table 9 presents descriptive statistics for the wildfire attributes for trips chosen. Figure 9 maps historical wildfire areas and their proximity to RIDB campgrounds in northern California.

TABLE 9.
Descriptive statistics for trips taken, wildfire attributes

Variable	Brief Description	Mean	Std. Dev.
Wildfire within 5 km	Indicator for whether there was a wildfire within 5 km of the campground in the previous 10 years	0.26	0.44
Size of burn scar (km^2)	Square kilometers burned within 5 km by the most recent fire	4.05	11.62
Years since wildfire	Number of years since the most recent fire within 5 km	1.58	3.15
Number of wildfires w/in 50 km	Count of years that a fire burned within 50 km of the campground over the past 10 years	6.05	2.14
Number of severe wildfires w/in 50 km	Count of years that a large fire (>50 sq. km) burned within 50 km of the campground over the past 10 years	2.27	1.25
Total burned w/in 50 km (km^2)	Total sq. km burned within 50 km of the campground over the past 10 years	556.88	461.97

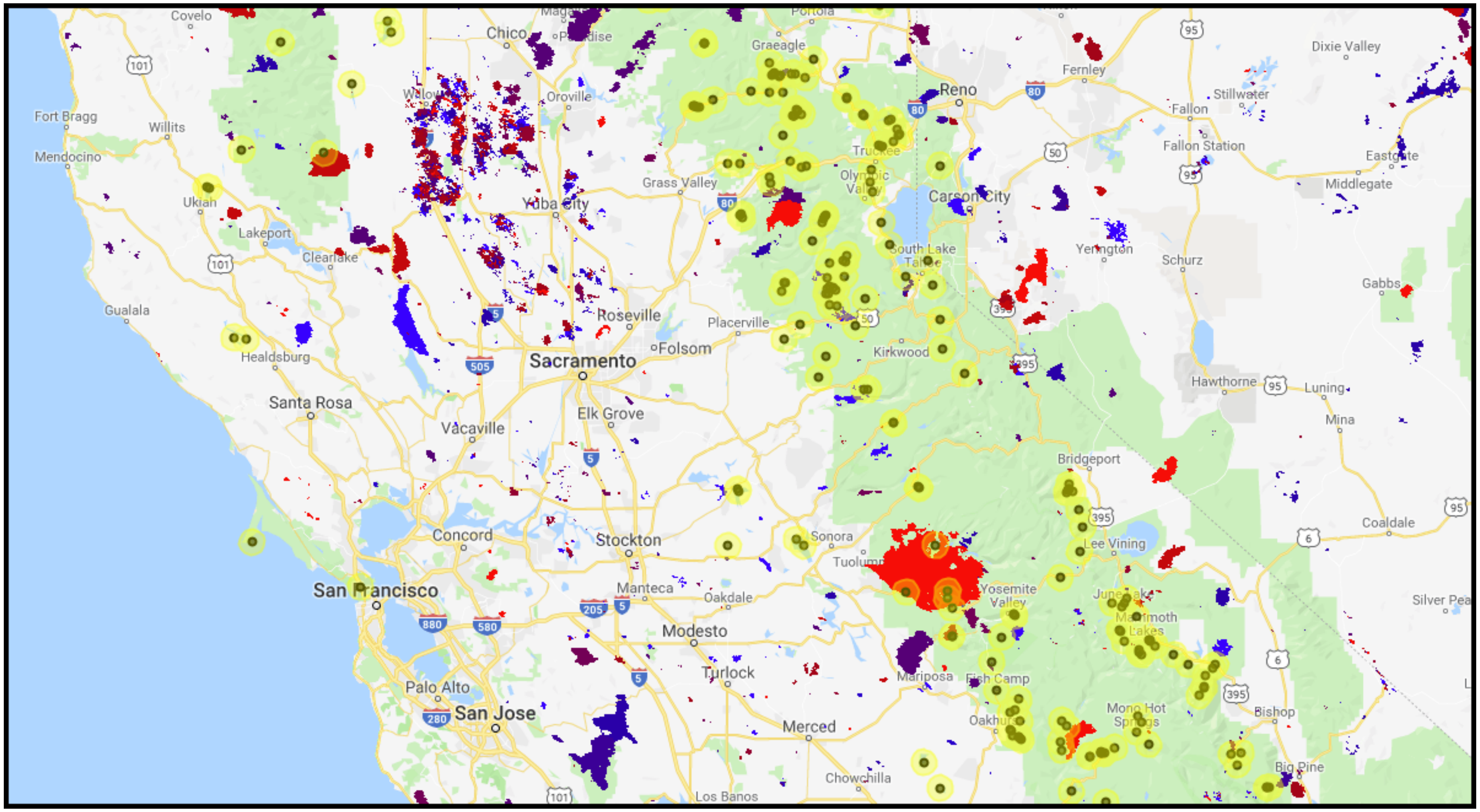

FIGURE 9.
Historical Fires near Northern CA RIDB Campgrounds

Fires displayed by recency on a scale from red (newest) to blue (oldest) over the 10 years prior to the sample. RIDB campgrounds displayed with a 5 km buffer.

The methodology for estimating the recreation demand model and constructing measures of equivalent variation for changes in site quality is largely the same as the methodology described in Chapter III. In Chapter III, individual i is assumed to choose across site-weekend pairs to maximize utility, given by:

$$\begin{aligned} U^i_{jwt} &= X^i_{jwt}\zeta + L_j\lambda_1 + \lambda_2 N_j + \epsilon^i_{jwt} \\ &= X^{*i}_{jwt}\xi + \epsilon^i_{jwt} \end{aligned}$$

In this paper, I also include the measures of historical wildfires described above. So I include fire indicators that might have a direct effect on camper welfare F^D_j as well as indicators designed to capture the risks that fire prone areas entail F^R_j:

$$U^i_{jwt} = X^{*i}_{jwt}\xi + F^D_j\eta_1 + F^R_j\eta_2 + \epsilon^i_{jwt} \tag{4.1}$$

MWTP and EV measures in this framework are calculated in the same way as in Chapter III.

Results

Table 10 presents selected conditional logit estimates from of five increasingly general specifications.[2] The estimated parameters can be interpreted as the marginal utility of a change in the associated attribute. As I would expect, the coefficient on travel costs is negative and highly significant across all model specifications, and changes relatively little in magnitude. It is plausible to think that the expected weather variables might pick up on the effect of expected

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[2] See Table A.2 in the appendix for a report of the estimates for all of the attributes included in the models.

wildfire conditions, but note that the marginal utilities associated with the expected weather attributes change relatively little across all specifications.

The first column of Table 10 presents the results of a specification with none of the expected wildfire attributes included (the final specification presented in Chapter III). The second column presents results from a specification in which just an indicator for a nearby fire occurring within the past 10 years is included as a determinant of utility. The associated marginal utility is relatively small, significant, and positive, indicating that individuals are more likely to go to a campground that has experienced a wildfire. This result is reinforced by the third specification, presented in column 3, that also includes the frequency of fires in a larger area near the campground. The results indicate that individuals are willing to travel further to campgrounds in areas that have experienced more fires in recent years. The fourth column of Table 10 presents results from a specification that includes more details about the most recent nearby fire, including how long ago the fire occurred and how large of an area near the campground was burned. Both of these attributes have negative and significant marginal utilities, indicating that customers prefer sites that have been burned more recently but are less likely to go to campgrounds that experienced large burns, all else equal. The final specification presented, in the fifth column of Table 10, includes additional information about historical wildfires in the general area of campgrounds. The results suggest that individuals prefer sites in areas that have burned more frequently and experienced a greater total area burned.

TABLE 10.
Selected Conditional Logit Estimates, Historical Wildfires

	No fire	Add base fire	Add freq	Add burn details	All variables
Full round-trip travel cost	-0.0116***	-0.0116***	-0.0117***	-0.0121***	-0.0121***
	(0.000158)	(0.000159)	(0.000164)	(0.000169)	(0.000169)
Wildfire within 5 km		0.114***	0.110***	1.090***	1.134***
		(0.0310)	(0.0311)	(0.0706)	(0.0709)
Years since wildfire				-0.106***	-0.112***
				(0.00863)	(0.00868)
Size of burn scar (km^2)				-0.0225***	-0.0255***
				(0.00139)	(0.00145)
Number of severe wildfires w/in 50 km			0.0234**	0.0364***	-0.0762***
			(0.0118)	(0.0121)	(0.0179)

Continued on next page

Table 10 : Selected Conditional Logit Estimates, Historical Wildfires – *continued from previous page*

	No fire	Add base fire	Add freq	Add burn details	All variables
Number of wildfires w/in 50 km					0.0701^{***}
					(0.0113)
Total burned w/in 50 km (km^2)					0.000263^{***}
					(0.0000550)
De-meaned precipitation	0.0937^{**}	0.0924^{**}	0.0870^{*}	0.0878^{*}	0.0962^{**}
	(0.0465)	(0.0466)	(0.0466)	(0.0464)	(0.0464)
De-meaned avg. temperatures	-0.163^{***}	-0.166^{***}	-0.167^{***}	-0.163^{***}	-0.166^{***}
	(0.00783)	(0.00789)	(0.00792)	(0.00781)	(0.00806)
Max. log-likelihood	-36697.48	-36690.82	-36688.88	-36548.43	-36511.26
No. choices	8748	8748	8748	8748	8748
No. alternatives	3283654	3283654	3283654	3283654	3283654

Standard errors in parentheses; stars indicate significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The estimated marginal utilities presented in Table 10 vary substantially across the different specifications presented. This is because the different expected wildfire variables are in some cases highly correlated. Table 11 presents a correlation matrix of the wildfire attributes. Unsurprisingly, the correlations are all positive—campgrounds in fire-prone areas are more likely to experience nearby burns as well as more burns in the general area. Note that the indicator for a nearby wildfire is highly correlated with the burn details of that wildfire. This helps explain the large increase in magnitude for the coefficient on the fire indicator that occurs when those burn detail attributes are included. Also note that there is a relatively large correlation between the three variables that capture the frequency and severity of wildfire in a larger area of the campground. These high correlations can explain why the coefficient on the number of severe wildfires within 50 km changes to become negative and statistically significant in the final specification presented. In earlier specifications, it had been picking up on the positive effects of the other two variables. For the rest of the analysis, I choose to focus on this final specification that includes all of the expected wildfire variables. I do so both because it is the most general and because it produces the greatest model fit, as evidenced by the maximized values of the log likelihood function presented across specifications in Table 10.

TABLE 11.
Correlations Between Fire Attributes

	Wildfire within 5 km	Years since wildfire	Size of burn scar (km^2)	# Severe wildfires within 50 km	# of wildfires within 50 km	Tot. burn w/in 50 km (km^2)
Wildfire within 5 km	1	-	-	-	-	-
Years since wildfire	0.84	1	-	-	-	-
Size of burn scar (km^2)	0.56	0.35	1	-	-	-
# Severe wildfires w/in 50 km	0.22	0.13	0.24	1	-	-
# of wildfires w/in 50 km	0.22	0.22	0.23	0.57	1	-
Tot. burn w/in 50 km (km^2)	0.31	0.15	0.36	0.67	0.44	1

Taken as a whole, the results of suggest that individuals in general prefer to visit sites that have had a wildfire nearby in recent years. The negative coefficient on the years since the fire attribute suggest that they also prefer for that fire to have occurred in the relatively recent past. If our prior belief is that burn scars mar the scenery of an outdoor recreational experience, this seems at first counterintuitive. However, this result is consistent with results of other papers in the wildfire literature that find positive effects from wildfires. One plausible explanation is that individuals are curious about how the fire affected the landscape. It is also possible that the burns offer an alternative type of scenery or open up views that were previously unavailable. Note that, all else equal, a larger burned area near the campground decreases the utility gained from visiting that site, so the positive effects of recent wildfire are reduced if the campground was particularly affected. The results also suggest that customers prefer to camp in areas that experience fires more frequently. Similar to the results for nearby fires, this positive effect on utility is mitigated when the area within 50 km of the campground has experienced a number of severe forest fires.

Welfare Analysis

Table 12 presents MWTP estimates and 95% simulated confidence intervals for changes in the historical wildfire variables. Individuals are willing to pay $93 more to visit a site that experienced a wildfire within 5 km over the past 10 years. This is consistent with a story of people being willing to drive further or longer to see an area that has been affected by wildfire. If the most recent fire near a site happened a year earlier, this then an individuals WTP to visit that site falls by $9.25, revealing people's preferences for more recently burned

TABLE 12.
Marginal Willingness to Pay ($) for Fire Attributes

Variable	MWTP
Wildfire within 5 km	93.36 (81.99, 104.55)
Years since wildfire	-9.25 (-10.6, -7.85)
Size of burn scar (km^2)	-2.1 (-2.33, -1.86)
Number of severe wildfires w/in 50 km	-6.28 (-9.17, -3.42)
Number of wildfires w/in 50 km	5.77 (3.99, 7.66)
Total burned w/in 50 km (km^2)	0.02 (0.01, 0.03)

95% simulated confidence interval in parentheses.

areas. Individuals are less willing to pay to visit campgrounds that had severe burn damage nearby, with their WTP falling by $2.10 for every additional sq. km burned. For campgrounds one standard deviation above the mean of area burned, this translates into a reduction in WTP of $32. Individuals are less willing to camp at sites in areas prone to severe fires—their WTP to visit a site decreases by $6.28 for each year over the past 10 years that the area experienced a fire that burned more than 50 sq. km. This effect would be at least partially offset by the apparent desire to camp in areas that frequently experience smaller wildfires, as the MWTP for the frequency of any-size wildfire within 50 km is $5.77. Further, people are willing to pay more to visit sites in regions that have had a greater total area burned over the past 10 years. While this MWTP is small at $0.02, this translates to an increase in WTP of $11 for the average chosen site.

The MWTP estimates discussed above are helpful for getting a more thorough understanding of how historical wildfires affect an individuals recreation

TABLE 13.
Per-trip Equivalent Variation ($) for hypothetical changes to historical fire attributes; when allowing for intertemporal substitution and when restricted to same-day substitution only

	Intertemporal Substitution	Same-Day Substitution
20% larger nearby wildfires	-1.56	-1.54
	(2.00)	(2.34)
	[-3.86, -0.17]	[-4.94, -0.04]
20% more frequent severe burns	-2.84	-2.82
	(0.74)	(0.87)
	[-4.06, -1.59]	[-4.19, -1.26]

The mean EV across individuals is presented. The standard deviation is in parentheses. 5^{th} and 95^{th} percentiles are in square brackets. Distribution is not symmetric around the mean.

decisions, but another major use of the models estimated in this paper is to calculate the welfare changes associated with non-marginal changes in site quality. To explore this dimension and provide a proof-of-concept analysis for the types of policies that this work can help evaluate, I consider two hypothetical changes in historical wildfire conditions. I calculate the per-trip equivalent variation (EV) for each individual under these changes; both when allowing the individual to substitute across sites and across weekends and also when allowing only for substitution across sites on the originally chosen weekend. Table 13 presents the mean EV for each of these changes.

As can be seen in Table 13, the welfare losses from a 20% increase in the burn area of nearby fires is relatively small, with a mean value of $1.56 per trip. This result is largely the same when restricting the individual's substitution opportunities to just those campgrounds on the same weekend of their original choice. The distribution of EV over individuals displays a left skew, as can be seen in Figure 10. Certain individuals, presumably those who highly favor sites that were close to substantial burns, suffer greater losses from this change. A 20% increase in the frequency of severe wildfires in the general area of the campground results in a mean EV of -$2.84. The EV when allowing for only same-day substitution is essentially the same, though has a slightly higher standard deviation, as was the case with the other hypothetical quality change. Figure 11 presents the distribution of equivalent variations across individuals. Both hypothetical changes to the wildfire attributes associated with a site produce relatively small welfare effects. This is partly because I consider relatively small changes in attributes, partly because substitution allows individuals to mitigate the negative effects by substituting to a less affected site, and partly because the estimated MWTP for these attributes are relatively small. In the next section, I discuss some alternative scenarios that could plausibly affect welfare in different and larger ways and that can be explored in future analyses.

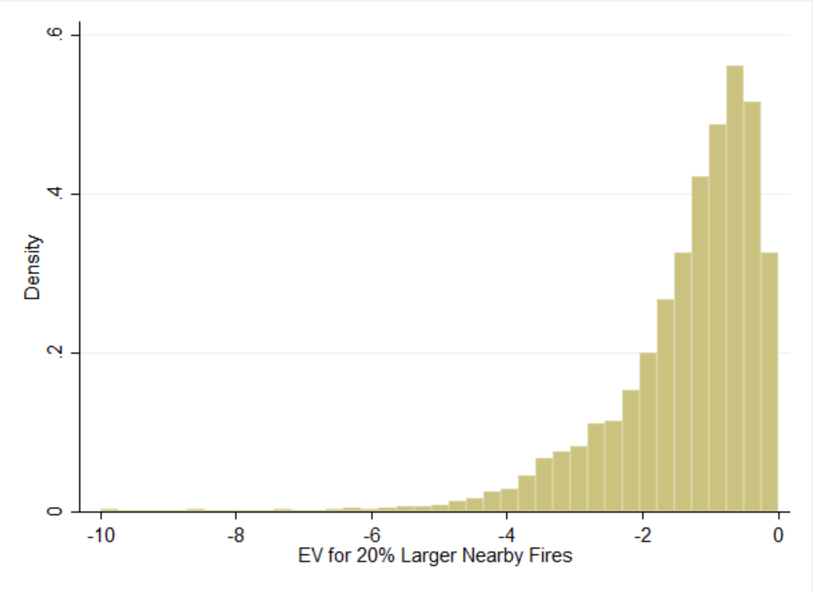

FIGURE 10.
Equivalent Variation across individuals for a 20% increase in burn area near campgrounds

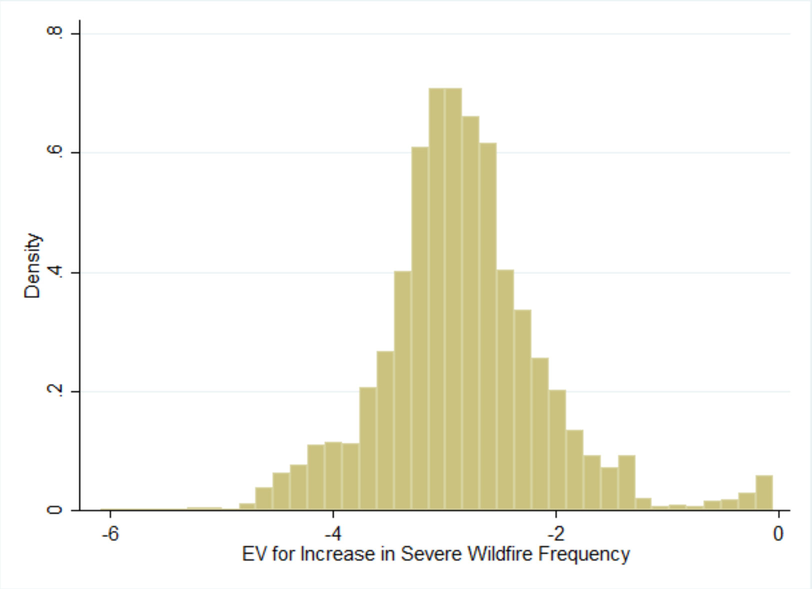

FIGURE 11.
Equivalent Variation across individuals for a 20% increase in the frequency of bad burns within 50 km of campgrounds

Directions for Future Research

The ambitious variety and complexity of the selection of wildfire-related variables employed in the final model in this analysis still does not necessarily produce the richest specification that could be considered with these data. A variety of additional questions remain for further research.

Upgrade the estimation process. It is apparent that greater computing capacity will be required, so that each model can be estimated in a much shorter amount of time. It will be appropriate to explore models with random parameters (i.e. mixed logit models) that have non-zero variances for each preference parameter as well as potential correlations between key utility parameters. It will be important also to consider latent-class specifications, where several market "segments" for camping participants can be identified and segment membership is not explicitly observable. These richer specifications are more likely to be tractable with faster estimation. This is likely to require that computation be transferred to cloud-based computing. This will necessitate changing to open-source, rather than proprietary software, for the estimation tasks. This change will require some significant fixed costs to be incurred, which is why the transition did not occur prior to this point.

Further exploration of alternative wildfire measures. There is more to be done with respect to the measures of wildfire effects on people's preferences for different types of campgrounds at different times of the year. The introduction to this paper described the variety of results that have been found in other empirical analyses of wildfire effects on recreational demands (for example, for hiking and mountain biking). Different short-term effects of wildfire on demand for wilderness recreation seem to have been found in different contexts. With the data available for this study, it may be possible to fit a model where demand for campgrounds near a recent burn is different if the destination is familiar to the camper because of other recent trips to that destination prior to the burn. Curiosity may bring visitors back. The question is whether they will visit again, having seen the effects of the burn. It would be reasonable, especially with multiple years of data, to examine how long it takes before any given individual returns to a burned area a second time after seeing what has happened to the site as a result of the wildfire event.

Consider alternative explanations for counterintuitive signs. It will be important to explore further some potential alternative explanations for counterintuitive signs on some of the fire-related variables. Certain variables (such as the years since the most recent fire) may be picking up some of the effects of unobservable attributes of sites that have had fires in recent years (since this paper uses only one year's worth of the available data). For example, Yosemite had a large fire in 2013, which could mean that estimates for the coefficient on years since a large burn might simultaneously be picking up some of the positive unobservable attributes of Yosemite as an iconic destination. These possibilities will need to be pursued, to produce greater confidence that the coefficients on the wildfire measures are conveying the true marginal effects of wildfires. With a small number of very big wildfires, specific fires at specific locations could be confounding the model's ability to reveal the average effects of typical wildfires on the demand for camping at these destinations.

Make use of remotely sensed data on smoke plumes. It may be possible to include remotely sensed data on smoke plumes associated with wildfires in the area. The presence of a smoke plume over a particular region could easily deter potential reservations, especially if someone is making their reservation very near the planned time of their trip. Smoke can travel far, depending on wind conditions. Destinations that lie even a considerable distance from an active wildfire could be affected by air pollution and a loss of visibility. These conditions could adversely affect demand for campgrounds over a wide area.

Fires at origins, as well as destinations. Do wildfires close to home, for a recreationist who is planning a camping trip, affect demand for camping trips? If a fire is currently burning in an area, does that affect how people choose where and when to go camping? Do residents of rural areas who are urged to evacuate choose to take a tent or a motor-home or trailer to a campground in a neighboring region, if they are required to leave their own homes?

Explore data on canceled reservations. The available data include information about cancellations of campground reservations, and this information has not yet been exploited in the current analysis. It may be possible to explore how contemporaneous wildfires affect cancellation behavior in the wider region, even outside of the immediate at-risk area where reservations are unilaterally revoked due to a temporary site closure.

Heterogeneous wildfire effects by type of activity. Given the evidence from prior studies that the effects of wildfire damage on recreational experiences can depend on the type of recreation in question, it may be possible to discern different effects for fire variables according to other attributes of each destination. Suppose that the types of activities near a one campground are very sensitive to wildfire damage, whereas the activities available near other campgrounds are less sensitive. Then the same amount of fire damage could easily have different effects at different campgrounds. Loomis et al. (2001) found that wildfires can affect hikers and mountain bikers in opposite ways—it is plausible that other types of heterogeneous effects might be apparent for campgrounds that provide access to different types of activities.

Include birding, along with hunting, fishing, etc. The citizen science data on bird biodiversity used in Kolstoe and Cameron (2017) could be acquired and processed in the same manner as it was for that paper (for California, rather than Washington State and Oregon). The availability of fishing opportunities makes destinations more attractive to people who come from zip codes with more per-capita fishing licenses, for example. The eBird citizen science data can reveal the level of birding participation in the origin area for each reservation, and the same data can help identify the locations of birding "hotspots" in the vicinity of each campground. If the amount of biodiversity in bird populations around some campgrounds make them more attractive to people who come from birding areas, there will be a richer story about the attraction of bird biodiversity at each destination, beyond just land cover information. Bird populations can change quickly and significantly in the wake of a wildfire. These species are highly mobile and opportunistic, and will readily move into a new ecological niche created by wildfire.

Other potential covariates. It was a substantial investment to wrangle the data for this analysis into usable form, but I am now poised to consider a wide variety of extensions and improvements that will be possible simply by merging other new variables into the dataset by location and time. With additional computing power from migrating this project to a cloud-computing environment, the time cost to consider richer models will also be substantially reduced.

Conclusions

This paper explores how historical wildfires and expectations of wildfires, an increasingly common type of natural disaster, affect the utility of people who choose to camp on federally managed public lands in California. The results I find are in part counterintuitive: individuals prefer when a campground has been burned in recent years, so long as it has not burned too intensely. Areas where wildfires are more frequent also appear to confer a positive marginal utility. Still, some results are as expected: severe burns in the locality of campgrounds reduce consumer welfare. These results fall in line with other wildfire research that has shown positive effects of recent wildfires for certain outdoor activities. But these results also open the door to new analyses. How might wildfires near origin locations affect recreation decisions? How do wildfires affect cancellation decisions of campsite reservations made far in advance? The present analysis is an important step on the way to understanding how wildfires affect the recreational use values of public lands.

CHAPTER V

CONCLUSIONS

This dissertation focuses on using utility-theoretic discrete choice models to explore the value of nonmarket goods associated with federally managed public lands in the United States. Chapter II focuses on non-environmental determinants of campground demand—exploring the complementarity with other recreational activities and how different site amenities affect welfare. Chapter III turns to focus on using campground demand as a way to indirectly value environmental public goods in the locality of campgrounds, demonstrating the importance of weather, land cover, and light pollution to the camper's decision making process. Chapter IV uses historical wildfire data to explore how a common type of natural disaster affects recreational use value and what that can mean for the value of wildfire mitigation policies. In all three chapters, I used a novel definition of the consideration set to help capture the role that intertemporal substitution plays in the individual's decision.

This is the first use of a wealth of data representing all reservations to federally managed campgrounds across the United States in the construction of utility-theoretic models of recreation demand. The analysis presented in these three chapters sheds light on the role that intertemporal substitution plays in estimating campground demand, how activities and campsite amenities affect individual welfare, and how campground demand can be used as a way to indirectly value non-market environmental amenities. This analysis is of use to policy makers considering public policies that affect camping directly as well as a much larger set of policies—such as wildfire mitigation, ecosystem preservation, and climate change policies—that play a role in individuals' decisions of where and when to go camping.

APPENDIX

FULL SET OF MODEL ESTIMATES

In the main body of this dissertation, I elected to only present selected coefficients from the models run for the sake of brevity. This appendix presents the full set of estimated parameters for the conditional logit models presented throughout this dissertation. The first column of Table A1 is the full set of estimated parameters from the conditional logit model estimated in Chapter II. The remaining columns of Table A1 present the full set of results for the specifications presented in Chapter III. Table A2 presents the full set of estimated parameters for the specifications in Chapter IV, where the first column is the same as the final specification adopted in Chapter III. Outside of the specific examples addressed in the body of this dissertation, the qualitative interpretation of most of the marginal utilities presented in these tables remains the same across models.

TABLE A1.

All Conditional Logit Estimates from Chapter III Models

	Weather only	Add night lights	Add tree cover	Add LC indicators
Full round-trip travel cost	-0.0108***	-0.0112***	-0.0113***	-0.0116***
	(0.000149)	(0.000156)	(0.000157)	(0.000158)
De-meaned precipitation	0.0938**	0.0579	0.0711	0.0937**
	(0.0458)	(0.0463)	(0.0466)	(0.0465)
De-meaned avg. temperatures	-0.160***	-0.172***	-0.170***	-0.163***
	(0.00758)	(0.00771)	(0.00770)	(0.00783)
× De-meaned precipitation	0.0224***	0.0218***	0.0231***	0.0240***
	(0.00498)	(0.00502)	(0.00502)	(0.00499)
(De-meaned avg. temp)^2	0.00158**	0.00124*	0.00211***	0.00205***
	(0.000681)	(0.000687)	(0.000694)	(0.000707)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
(De-meaned precipitation)^2	-0.0143	-0.0200	-0.0294*	-0.0326*
	(0.0170)	(0.0174)	(0.0177)	(0.0175)
Night-time lights		-0.0285***	-0.0276***	-0.0334***
		(0.00216)	(0.00216)	(0.00230)
% Tree cover			0.00479***	0.000532
			(0.000548)	(0.000908)
Land cover = water				-0.711***
				(0.0731)
Land cover = open space				0.201***
				(0.0430)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
Land cover = low-density developed				-1.217***
				(0.146)
Land cover = med-density developed				2.522**
				(1.011)
Land cover = barren land				1.756***
				(0.321)
Land cover = deciduous forest				1.382***
				(0.346)
Land cover = mixed				1.025***
				(0.0889)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
Land cover = shrubs				-0.0860
				(0.0545)
Land cover = grassland				0.217**
				(0.108)
Land cover = cultivated land				0.571
				(0.514)
Land cover = woody wetland				-0.835
				(0.581)
Land cover = herbacious wetland				2.075**
				(1.009)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
Visited site previously	3.945***	3.925***	3.898***	3.882***
	(0.0458)	(0.0459)	(0.0461)	(0.0461)
Congestion/popularity	0.403***	0.435***	0.443***	0.410***
	(0.0273)	(0.0265)	(0.0273)	(0.0278)
Less than one week from reserve date	2.066***	2.064***	2.060***	2.058***
	(0.0525)	(0.0525)	(0.0525)	(0.0525)
× Nat'l Park Service land	-0.294***	-0.296***	-0.298***	-0.296***
	(0.0680)	(0.0681)	(0.0681)	(0.0681)
One week to one month from reserve date	1.223***	1.222***	1.221***	1.221***
	(0.0447)	(0.0447)	(0.0447)	(0.0447)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
× Nat'l Park Service land	-0.642***	-0.645***	-0.647***	-0.647***
	(0.0667)	(0.0668)	(0.0668)	(0.0668)
More than one month from reserve date	0.0889	0.0971	0.102	0.0901
	(0.0715)	(0.0715)	(0.0715)	(0.0715)
× Nat'l Park Service land	0.200**	0.188**	0.186**	0.201**
	(0.0882)	(0.0884)	(0.0883)	(0.0883)
Boat ramp	-0.242***	-0.297***	-0.203**	-0.233***
	(0.0800)	(0.0801)	(0.0806)	(0.0814)
Boating nearby	-0.239***	-0.276***	-0.284***	-0.204***
	(0.0375)	(0.0378)	(0.0379)	(0.0382)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
× Boat ramp	0.132	0.247***	0.186**	0.179**
	(0.0858)	(0.0864)	(0.0864)	(0.0867)
Fishing nearby	-0.307***	-0.240**	-0.253**	-0.218*
	(0.115)	(0.117)	(0.117)	(0.117)
× Fishing licenses	0.664***	0.748***	0.773***	0.749***
	(0.204)	(0.211)	(0.213)	(0.212)
× Weekend 1	0.732***	0.707***	0.691***	0.687***
	(0.114)	(0.114)	(0.114)	(0.113)
× Weekend 2	0.982***	0.987***	0.956***	0.933***
	(0.0985)	(0.0984)	(0.0985)	(0.0986)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
× Weekend 3	1.067***	1.064***	1.037***	1.011***
	(0.0965)	(0.0965)	(0.0966)	(0.0967)
× Weekend 4	1.214***	1.217***	1.220***	1.228***
	(0.103)	(0.103)	(0.104)	(0.103)
× Weekend 5	1.471***	1.493***	1.498***	1.504***
	(0.0956)	(0.0956)	(0.0957)	(0.0957)
× Weekend 6	1.263***	1.271***	1.280***	1.286***
	(0.0941)	(0.0941)	(0.0941)	(0.0941)
× Weekend 7	1.379***	1.385***	1.393***	1.401***
	(0.0922)	(0.0922)	(0.0922)	(0.0923)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
× Weekend 8	1.203***	1.220***	1.234***	1.265***
	(0.0927)	(0.0927)	(0.0927)	(0.0927)
× Weekend 9	1.171***	1.175***	1.181***	1.210***
	(0.0904)	(0.0903)	(0.0904)	(0.0904)
× Weekend 10	0.906***	0.908***	0.905***	0.910***
	(0.0896)	(0.0895)	(0.0895)	(0.0895)
× Weekend 11	0.926***	0.931***	0.933***	0.950***
	(0.0894)	(0.0894)	(0.0894)	(0.0895)
× Weekend 12	0.934***	0.938***	0.939***	0.949***
	(0.0878)	(0.0877)	(0.0877)	(0.0877)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
Hunting nearby	-0.431***	-0.451***	-0.463***	-0.538***
	(0.0796)	(0.0801)	(0.0805)	(0.0791)
× hunting licenses	-0.385	-0.364	-0.413	-0.261
	(0.519)	(0.522)	(0.526)	(0.506)
Swimming nearby	0.144***	0.0942***	0.0971***	0.116***
	(0.0345)	(0.0347)	(0.0346)	(0.0345)
× Mean temperatures	-0.00279	-0.00215	-0.0146**	-0.0263***
	(0.00689)	(0.00688)	(0.00704)	(0.00725)
× Mean precipitation	0.00938	0.0326	0.0340	-0.00960
	(0.0398)	(0.0396)	(0.0397)	(0.0400)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
Bicycling nearby	0.221***	0.237***	0.261***	0.282***
	(0.0300)	(0.0301)	(0.0301)	(0.0314)
Hiking nearby	0.447***	0.404***	0.413***	0.334***
	(0.0410)	(0.0407)	(0.0410)	(0.0423)
× Mean temperatures	0.0866***	0.0920***	0.0931***	0.0873***
	(0.00870)	(0.00870)	(0.00871)	(0.00872)
× Mean precipitation	-0.0535	-0.0159	-0.0180	-0.00648
	(0.0423)	(0.0422)	(0.0424)	(0.0423)
Horse-riding nearby	0.0705	0.136***	0.166***	0.0892*
	(0.0513)	(0.0510)	(0.0513)	(0.0528)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
Climbing nearby	0.588***	0.485***	0.580***	0.479***
	(0.0675)	(0.0679)	(0.0678)	(0.0732)
Vault toilets	0.476***	0.451***	0.421***	0.298***
	(0.0537)	(0.0528)	(0.0530)	(0.0542)
Flush toilets	0.991***	1.003***	0.972***	0.835***
	(0.0520)	(0.0515)	(0.0518)	(0.0530)
Both vault and flush toilets	-1.800***	-1.893***	-1.880***	-2.220***
	(0.107)	(0.107)	(0.107)	(0.114)
Drinking water available	0.378***	0.247***	0.245***	0.223***
	(0.0373)	(0.0380)	(0.0381)	(0.0389)

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators
Trash collection	-0.668***	-0.673***	-0.598***	-0.529***
	(0.0594)	(0.0595)	(0.0600)	(0.0615)
Bureau of Reclamation land	0.0192	-0.0156	0.111	-0.267**
	(0.102)	(0.102)	(0.102)	(0.125)
National Park Service land	0.761***	0.781***	0.812***	0.962***
	(0.0580)	(0.0578)	(0.0580)	(0.0602)
US Army Corps of Engineers land	0.400***	0.357***	0.415***	0.0756
	(0.0572)	(0.0578)	(0.0579)	(0.0735)
Max. log-likelihood	-37030.62	-36928.96	-36890.38	-36697.48
No. choices	8748	8748	8748	8748
No. alternatives	3283654	3283654	3283654	3283654

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Table A1 : All Conditional Logit Estimates from Chapter III Models

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	Weather only	Add night lights	Add tree cover	Add LC indicators

Standard errors in parentheses

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

TABLE A2.

All Conditional Logit Estimates from Chapter IV Models

	No fire	Add base fire	Add freq	Add burn details	All variables
Full round-trip travel cost	-0.0116***	-0.0116***	-0.0117***	-0.0121***	-0.0121***
	(0.000158)	(0.000159)	(0.000164)	(0.000169)	(0.000169)
Wildfire within 5 km		0.114***	0.110***	1.090***	1.134***
		(0.0310)	(0.0311)	(0.0706)	(0.0709)
Years since wildfire				-0.106***	-0.112***
				(0.00863)	(0.00868)
Size of burn scar (km^2)				-0.0225***	-0.0255***
				(0.00139)	(0.00145)
Number of severe wildfires w/in 50 km			0.0234**	0.0364***	-0.0762***
			(0.0118)	(0.0121)	(0.0179)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
Number of wildfires w/in 50 km					0.0701***
					(0.0113)
Total burned w/in 50 km (km^2)					0.000263***
					(0.0000550)
Night-time lights	-0.0334***	-0.0322***	-0.0319***	-0.0352***	-0.0315***
	(0.00230)	(0.00232)	(0.00233)	(0.00239)	(0.00247)
% Tree cover	0.000532	0.000607	0.000660	0.00220**	0.00249***
	(0.000908)	(0.000907)	(0.000908)	(0.000928)	(0.000934)
Land cover = water	-0.711***	-0.672***	-0.655***	-0.703***	-0.660***
	(0.0731)	(0.0736)	(0.0739)	(0.0743)	(0.0741)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
Land cover = open space	0.201***	0.207***	0.215***	0.256***	0.239***
	(0.0430)	(0.0430)	(0.0431)	(0.0432)	(0.0436)
Land cover = low-density developed	-1.217***	-1.220***	-1.246***	-1.203***	-1.140***
	(0.146)	(0.146)	(0.147)	(0.147)	(0.147)
Land cover = med-density developed	2.522**	2.521**	2.488**	2.691***	2.554**
	(1.011)	(1.011)	(1.011)	(1.011)	(1.012)
Land cover = barren land	1.756***	1.662***	1.695***	2.007***	1.896***
	(0.321)	(0.322)	(0.322)	(0.323)	(0.324)
Land cover = deciduous forest	1.382***	1.426***	1.442***	1.265***	1.316***
	(0.346)	(0.346)	(0.346)	(0.346)	(0.347)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
Land cover = mixed	1.025***	1.010***	1.010***	1.209***	1.025***
	(0.0889)	(0.0889)	(0.0889)	(0.0887)	(0.0930)
Land cover = shrubs	-0.0860	-0.0853	-0.0787	-0.154***	-0.0983*
	(0.0545)	(0.0544)	(0.0545)	(0.0553)	(0.0560)
Land cover = grassland	0.217**	0.205*	0.214**	0.382***	0.387***
	(0.108)	(0.109)	(0.109)	(0.111)	(0.111)
Land cover = cultivated land	0.571	0.501	0.494	-0.296	-0.202
	(0.514)	(0.515)	(0.515)	(0.517)	(0.519)
Land cover = woody wetland	-0.835	-0.922	-0.855	-0.836	-1.123*
	(0.581)	(0.581)	(0.582)	(0.582)	(0.584)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
Land cover = herbacious wetland	2.075**	2.015**	2.035**	2.181**	2.146**
	(1.009)	(1.009)	(1.009)	(1.009)	(1.009)
Visited site previously	3.882***	3.877***	3.872***	3.857***	3.838***
	(0.0461)	(0.0461)	(0.0462)	(0.0466)	(0.0467)
Congestion/popularity	0.410***	0.407***	0.406***	0.436***	0.464***
	(0.0278)	(0.0279)	(0.0280)	(0.0279)	(0.0285)
Less than one week from reserve date	2.058***	2.053***	2.050***	2.052***	2.040***
	(0.0525)	(0.0525)	(0.0525)	(0.0526)	(0.0526)
× Nat'l Park Service land	-0.296***	-0.295***	-0.294***	-0.295***	-0.297***
	(0.0681)	(0.0681)	(0.0681)	(0.0682)	(0.0682)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
One week to one month from reserve date	1.221***	1.217***	1.214***	1.220***	1.212***
	(0.0447)	(0.0447)	(0.0448)	(0.0448)	(0.0448)
× Nat'l Park Service land	-0.647***	-0.646***	-0.645***	-0.649***	-0.652***
	(0.0668)	(0.0668)	(0.0668)	(0.0668)	(0.0668)
More than one month from reserve date	0.0901	0.0948	0.0965	0.0892	0.0984
	(0.0715)	(0.0715)	(0.0715)	(0.0715)	(0.0716)
× Nat'l Park Service land	0.201**	0.201**	0.201**	0.206**	0.209**
	(0.0883)	(0.0883)	(0.0883)	(0.0884)	(0.0884)
Boat ramp	-0.233***	-0.264***	-0.264***	-0.163**	-0.195**
	(0.0814)	(0.0819)	(0.0819)	(0.0825)	(0.0830)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
Boating nearby	-0.204***	-0.208***	-0.190***	-0.176***	-0.174***
	(0.0382)	(0.0382)	(0.0393)	(0.0392)	(0.0396)
× Boat ramp	0.179**	0.224**	0.208**	0.113	0.152*
	(0.0867)	(0.0876)	(0.0880)	(0.0885)	(0.0894)
Fishing nearby	-0.218*	-0.241**	-0.248**	-0.0994	-0.0815
	(0.117)	(0.118)	(0.118)	(0.118)	(0.118)
× Fishing licenses	0.749***	0.757***	0.756***	0.746***	0.720***
	(0.212)	(0.213)	(0.212)	(0.213)	(0.212)
× Weekend 1	0.687***	0.691***	0.697***	0.676***	0.630***
	(0.113)	(0.113)	(0.113)	(0.113)	(0.114)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
× Weekend 2	0.933***	0.930***	0.931***	0.930***	0.889***
	(0.0986)	(0.0986)	(0.0986)	(0.0988)	(0.0990)
× Weekend 3	1.011***	1.006***	1.007***	0.993***	0.950***
	(0.0967)	(0.0967)	(0.0967)	(0.0969)	(0.0971)
× Weekend 4	1.228***	1.234***	1.239***	1.236***	1.246***
	(0.103)	(0.104)	(0.104)	(0.104)	(0.104)
× Weekend 5	1.504***	1.510***	1.512***	1.520***	1.538***
	(0.0957)	(0.0957)	(0.0957)	(0.0958)	(0.0960)
× Weekend 6	1.286***	1.292***	1.293***	1.300***	1.316***
	(0.0941)	(0.0941)	(0.0941)	(0.0942)	(0.0943)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
× Weekend 7	1.401***	1.407***	1.408***	1.411***	1.430***
	(0.0923)	(0.0923)	(0.0923)	(0.0924)	(0.0925)
× Weekend 8	1.265***	1.271***	1.272***	1.281***	1.308***
	(0.0927)	(0.0928)	(0.0928)	(0.0929)	(0.0930)
× Weekend 9	1.210***	1.210***	1.213***	1.223***	1.229***
	(0.0904)	(0.0904)	(0.0904)	(0.0905)	(0.0905)
× Weekend 10	0.910***	0.912***	0.913***	0.909***	0.898***
	(0.0895)	(0.0895)	(0.0895)	(0.0896)	(0.0896)
× Weekend 11	0.950***	0.953***	0.955***	0.954***	0.964***
	(0.0895)	(0.0895)	(0.0895)	(0.0896)	(0.0896)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
× Weekend 12	0.949***	0.951***	0.952***	0.953***	0.963***
	(0.0877)	(0.0877)	(0.0877)	(0.0878)	(0.0878)
Hunting nearby	-0.538***	-0.556***	-0.540***	-0.554***	-0.588***
	(0.0791)	(0.0793)	(0.0794)	(0.0783)	(0.0776)
× hunting licenses	-0.261	-0.258	-0.255	-0.131	-0.0510
	(0.506)	(0.506)	(0.504)	(0.492)	(0.486)
Swimming nearby	0.116***	0.140***	0.144***	0.0394	0.0350
	(0.0345)	(0.0352)	(0.0352)	(0.0353)	(0.0356)
× Mean temperatures	-0.0263***	-0.0267***	-0.0263***	-0.0346***	-0.0463***
	(0.00725)	(0.00724)	(0.00724)	(0.00732)	(0.00749)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
× Mean precipitation	-0.00960	-0.00883	-0.00649	-0.00828	-0.0224
	(0.0400)	(0.0400)	(0.0401)	(0.0399)	(0.0404)
Bicycling nearby	0.282***	0.264***	0.258***	0.380***	0.373***
	(0.0314)	(0.0317)	(0.0319)	(0.0330)	(0.0329)
Hiking nearby	0.334***	0.353***	0.365***	0.173***	0.204***
	(0.0423)	(0.0426)	(0.0432)	(0.0441)	(0.0455)
× Mean temperatures	0.0873***	0.0901***	0.0907***	0.0878***	0.0835***
	(0.00872)	(0.00876)	(0.00876)	(0.00865)	(0.00872)
× Mean precipitation	-0.00648	-0.00509	-0.00810	-0.0129	-0.00881
	(0.0423)	(0.0423)	(0.0424)	(0.0420)	(0.0426)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
Horse-riding nearby	0.0892*	0.0979*	0.0850	-0.0167	-0.0768
	(0.0528)	(0.0527)	(0.0531)	(0.0532)	(0.0551)
Climbing nearby	0.479***	0.499***	0.509***	0.891***	0.819***
	(0.0732)	(0.0728)	(0.0727)	(0.0810)	(0.0825)
De-meaned precipitation	0.0937**	0.0924**	0.0870*	0.0878*	0.0962**
	(0.0465)	(0.0466)	(0.0466)	(0.0464)	(0.0464)
De-meaned avg. temperatures	-0.163***	-0.166***	-0.167***	-0.163***	-0.166***
	(0.00783)	(0.00789)	(0.00792)	(0.00781)	(0.00806)
× De-meaned precipitation	0.0240***	0.0251***	0.0254***	0.0256***	0.0271***
	(0.00499)	(0.00502)	(0.00501)	(0.00493)	(0.00498)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
(De-meaned avg. temp)^2	0.00205***	0.00237***	0.00236***	0.00193***	0.00224***
	(0.000707)	(0.000714)	(0.000714)	(0.000717)	(0.000725)
(De-meaned precipitation)^2	-0.0326*	-0.0336*	-0.0310*	-0.0226	-0.0224
	(0.0175)	(0.0176)	(0.0175)	(0.0171)	(0.0173)
Vault toilets	0.298***	0.300***	0.284***	0.306***	0.215***
	(0.0542)	(0.0543)	(0.0548)	(0.0540)	(0.0555)
Flush toilets	0.835***	0.831***	0.825***	0.847***	0.687***
	(0.0530)	(0.0530)	(0.0530)	(0.0529)	(0.0561)
Both vault and flush toilets	-2.220***	-2.233***	-2.222***	-2.295***	-2.241***
	(0.114)	(0.114)	(0.114)	(0.112)	(0.112)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
Drinking water available	0.223***	0.242***	0.250***	0.206***	0.227***
	(0.0389)	(0.0393)	(0.0395)	(0.0393)	(0.0397)
Trash collection	-0.529***	-0.499***	-0.496***	-0.517***	-0.620***
	(0.0615)	(0.0620)	(0.0620)	(0.0621)	(0.0636)
Bureau of Reclamation land	-0.267**	-0.199	-0.221*	-0.429***	-0.324**
	(0.125)	(0.126)	(0.127)	(0.128)	(0.129)
National Park Service land	0.962***	0.928***	0.917***	0.969***	0.873***
	(0.0602)	(0.0609)	(0.0611)	(0.0605)	(0.0627)
US Army Corps of Engineers land	0.0756	0.109	0.117	0.00572	0.144*
	(0.0735)	(0.0742)	(0.0744)	(0.0751)	(0.0768)

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Table A2 : All Conditional Logit Estimates from Chapter IV Models

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	No fire	Add base fire	Add freq	Add burn details	All variables
Max. log-likelihood	-36697.48	-36690.82	-36688.88	-36548.43	-36511.26
No. choices	8748	8748	8748	8748	8748
No. alternatives	3283654	3283654	3283654	3283654	3283654

Standard error in parentheses

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

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