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Essays in the Economics of Wildfire

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Essays in the Economics of Wildfire

A dissertation submitted in partial satisfaction
of the requirements for the degree

Doctor of Philosophy
in
Environmental Science and Management

by

Jacob Gellman

Committee in charge:

Professor Andrew Plantinga, Chair
Professor Olivier Deschênes
Professor Kelsey Jack
Professor Max Moritz

June 2023

The Dissertation of Jacob Gellman is approved.

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June 2023

Essays in the Economics of Wildfire

To my parents, Richard and Valerie Gellman, and my sister, Celia Gellman.

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Curriculum Vitæ
Jacob Gellman

Education

2023	Ph.D. in Environmental Science & Management, University of California, Santa Barbara.
2013	B.A. in Economics, University of Puget Sound, Tacoma, Washington.

Publications

Gellman, J., Walls, M., & Wibbenmeyer, M. (2022). "Wildfire, smoke, and outdoor recreation in the western United States." Forest Policy and Economics, 134, 102619.

Seto, D., Jones, C., Trugman, A. T., Varga, K., Plantinga, A. J., Carvalho, L. M., Thompson, C., Gellman, J., & Daum, K. (2022). "Simulating potential impacts of fuel treatments on fire behavior and evacuation time of the 2018 Camp Fire in Northern California." Fire, 5(2), 37.

Working Papers

Gellman, J., Walls, M., & Wibbenmeyer, M. "Non-market damages of wildfire smoke: evidence from administrative recreation data."

Daum, K. L. W., Hansen, W. D., Gellman, J., Plantinga, A., Jones, C., & Trugman, A. T. "Do vegetation fuel reduction treatments alter forest fire severity and carbon stability in California forests?"

Works in Progress

Boomhower, J., Fowlie, M., Gellman, J., & Plantinga, A. "Property insurance markets and climate change adaptation."

Gellman, J. "Spatial and dynamic natural disaster risk mitigation."

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Research Experience

2020 - 2023	Graduate Student Researcher, Earth Research Institute, University of California, Santa Barbara.
2019	Research Intern, Resources for the Future, Washington, District of Columbia.
2015 - 2017	Research Associate, McCullough Research, Portland, Oregon.
2014 - 2015	Research Assistant, Earth Economics, Tacoma, Washington.
2012 - 2013	Research Assistant, Earth Economics, Tacoma, Washington.

Teaching Experience

	Teaching Assistant, University of California, Santa Barbara.
2019 - 2020	Intermediate Microeconomic Theory, Undergrad (Prof. Sevgi Yuksel, Prof. Cheng-Zhong Qin).
2019	Statistics for Economics, Undergrad (Lect. Brian Wainwright).
2019	Introduction to Econometrics, Undergrad (Prof. Clément de Chaisemartin).
2018	Natural Resource Economics, Master's (Prof. Andrew Plantinga).
	Assistant de Langues, Académie de Rouen, Le Havre, France.
2013 - 2014	English, 4ème - 3ème (Prof. Paule Rocher-Ferchaud, Prof. Jean-Marc Cosseron).

Presentations and Workshops

2023	Occasional Workshop in Environmental Economics at UCSB, egg timer.
2023	AERE OSWEET, presenter.
2022	NBER Summer Institute, invited attendee.
2022	Santa Barbara County Fire Safe Council, flash talk.
2021	AERE Summer Conference, presenter.
2020	Berkeley Summer School in Environmental and Energy Economics, egg timer.
2020	UCSB EcoDataScience, presenter.

Honors and Awards

2021	UCSB Academic Senate Outstanding Teaching Assistant Award, nominee.
2019	UCSB Graduate Student Internship Fellowship.
2017 - 2019	Bren School Fellowship.
2013	Phi Beta Kappa.

Service

2020 - present	Bren School Antiracist Caucus, participant.
2019 ; 2023	Bren School Ph.D. Research Symposium, MC.
2021 - 2022	Bren School Seminar Speaker Committee.
2018 - 2022	UCSB Environmental Economics Reading Group, Participant (2018-21), Co-Organizer (2021-22).
2021 - 2021	UC Student Researchers United, UAW 2865, Department Organizer.
2019 - 2020	Bren School Ph.D. Events Committe ("GDC").

Membership

2020 - present	American Economic Association.
2020 - present	Association of Environmental and Resource Economists.
2019	Alliance Française de Washington DC.
2016 - 2018	Alliance Française de Portland.

Skills

R, Stata, Python, Matlab, SQL, LATEX, ArcGIS, QGIS, Google Cloud Platform.

Languages

English (native), French (advanced, C1). Citizenship: United States.

Permissions and Attributions

1. Chapter 1 was a collaboration with Margaret Walls and Matthew Wibbenmeyer. The content of Chapter 1 and Appendix A benefitted from gridded air quality data shared by Jude Bayham and coauthors. The work was supported by a United States Department of Agriculture (USDA), National Institute of Food and Agriculture (NIFA) Agriculture and Food Research Initiative (AFRI) grant, award number 2020-67023-33258.

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Abstract

Essays in the Economics of Wildfire

by

Jacob Gellman

This dissertation explores the economic consequences of wildfire and smoke in the United States. The third chapter, Wildfire smoke in the United States, is joint work with Matthew Wibbenmeyer, and examines regional and temporal trends in wildfire smoke impacts. It synthesizes research on health, economic, and behavioral impacts, proposing modifications to federal air quality regulations to address wildfire smoke. The second chapter, Wildfire, smoke, and outdoor recreation in the western United States, is a collaboration with Margaret Walls and Matthew Wibbenmeyer. It focuses on the effects of wildfire and smoke for outdoor recreation. The paper combines millions of administrative campground reservation records with daily satellite data on wildfire, smoke, and air pollution, finding that more than ten percent of available recreation days are affected by severe smoke in some regions. The first chapter, Non-market damages of wildfire smoke: evidence from administrative recreation data, is also a collaboration with Margaret Walls and Matthew Wibbenmeyer. This chapter exploits the dataset of the second chapter to provide among the first revealed preference estimates of smoke damages. A structural model of sequential recreation decisions finds that smoke reduces welfare by $107 per person per trip. Annually, more than 21.5 million outdoor visits in the western United States are affected by wildfire smoke, with welfare losses of $2.3 billion. These findings contribute to a growing body of evidence on the costs of wildfire smoke.

Contents

Chapter 1

Non-market damages of wildfire smoke: evidence from administrative recreation data

1.1 Introduction

Large wildfires have increased in frequency and severity in the western United States, and these trends are expected to continue as the climate warms (Abatzoglou and Williams 2016, Westerling 2016, Westerling 2018, Williams et al. 2019). Increased wildfire activity has also brought an increase in wildfire smoke, which can transport pollution hundreds of miles from the point of origin. The smoke produced by wildfires has large costs for society. Wildfire smoke now accounts for up to half of particulate matter pollution in some areas of the western United States (Burke et al. 2021a). Health damages from wildfire smoke are distinct from other air quality damages, as smoke harms health more severely than fine particles from other sources (Aguilera et al. 2021, Kochi et al. 2010). Negative health effects include increased morbidity, higher mortality, and reduced mental health (Cullen 2020, Heft-Neal et al. 2022, McCoy and Zhao 2020, Miller et al. 2021, Reid et al. 2016, Wen and Burke 2021).

While measures of health impacts are numerous, there are few revealed preference estimates for the welfare damages of smoke. In contrast to stated preference approaches such as surveys, revealed preference methods directly measure individuals' behavioral responses to an amenity or disamenity. Smoke is particularly challenging to study in a revealed preference setting because it is a transient environmental bad: it may blanket an area for several days before winds change or the fire is extinguished. Estimation of revealed preference values for wildfire smoke requires a context where individuals are both exposed to the environmental bad and where the researcher can observe their behavior at a high temporal resolution.

One setting where exposure is likely to be high is outdoor recreation. Researchers frequently use changes in outdoor recreation activity, such as camping and hiking, for revealed preference estimates of environmental amenities. Natural areas hold implicit non-market value due to the time and travel cost that people expend to visit them; the difference in a site's value across levels of an amenity identifies the amenity's value. Empirical measures of recreation value often form a large portion of natural resource appraisals or damage assessments (Phaneuf and Requate 2016). These estimates inform conservation decisions, natural resource management, and legal settlements for environmental accidents (English et al. 2018, Phaneuf and Requate 2016).

Wildfire smoke has numerous consequences for recreation. Wildfire season and peak outdoor recreation season tend to coincide, with more than 1 million National Park visitor-days per year taking place during hazardous smoke conditions (Gellman et al. 2022). This smoke puts visitors at an increased risk of respiratory health problems (Reid et al. 2016). Visitors to natural areas spend the majority of their trip outdoors, and vigorous activity such as hiking or rock climbing may exacerbate the effects of this direct exposure (Korrick et al. 1998, Richardson et al. 2012). Apart from health impacts, smoke may also reduce the visibility and amenity value from visitation. Visitors wary of air pollution and reduced site quality may avoid their trip altogether, with documented reductions in participation due to smoke (Cai 2021, Gellman et al. 2022). However, despite the numerous effects of wildfire smoke on outdoor visitation, most recreation data has not allowed for welfare estimation because it typically lacks the necessary temporal resolution to study avoidance behavior.

In this paper we provide the first revealed preference welfare estimates of the damage of wildfire smoke for outdoor recreation. We combine millions of administrative campground reservation records with satellite data on wildfire, smoke, and air pollution. These data are especially rich among most studies of recreation. The combined dataset features more than 16 million transactions from 2 million unique users, high frequency daily data over eight years, nearly 1,000 federally managed campgrounds across the west, and detailed records of individual-level behavior. The detail and variation afforded by this data are particularly necessary in our setting. Because wildfire smoke events affect large areas, campgrounds in a single region are often affected by smoke at exactly the same time, limiting the effectiveness of a region- or year-specific study. Our approach exploits daily variation across many years and many regions, which is necessary for proper identification of smoke effects.

We also account for the transient nature of wildfire smoke by measuring decisions both before and after visitors have knowledge of smoke conditions. Most visitors to campgrounds reserve their site several weeks or months in advance, before smoke conditions can be known. But, by the time smoke conditions are likely known, many campgrounds are either completely full or completely empty, which would limit the identifying variation from measuring new visitors. Our setting allows us to study one decision where visitors both have knowledge of site conditions and where they are unconstrained by congestion: cancellations of existing reservations due to smoke.

We consider visitors' cancellation decisions with a unique two stage discrete choice. In a first stage, a visitor chooses to reserve ahead of time based on expected site conditions; in a second stage, they decide whether to cancel or follow through with the reservation based on realized site conditions. A key feature of this setting is the correlation of preferences between the two decisions. A visitor can only cancel a trip if they previously made a reservation, meaning they have already demonstrated a taste for the site. Using a numerical example we show how failure to account for this form of sample selection would bias welfare estimates of wildfire smoke damages. The bias operates by attenuating estimates of visitors' marginal disutility in expenditure, a key input for welfare calculation. To correct for this bias we develop a novel control function approach to link preferences across choices (Wooldridge 2015), and demonstrate its effectiveness through numerical simulations.

There are several main findings of this paper. First, we estimate that wildfire smoke reduces welfare by \$107 per person per trip. This estimate uses the aforementioned control function to account for sample selection. Without accounting for sample selection, the analysis would have implied damages of \$154 per person per trip, which would overstate welfare damages by 44%. Inclusion of the control function increases the estimated magnitude of the marginal disutility in expenditure, as the numerical example predicts.

In further analyses we explore how welfare losses vary by the duration of smoke events. When a campground was affected by smoke on only one day in the week of arrival, damages are as low as \$32 per person per trip; when affected by smoke on all seven days in the week of arrival, losses are as high as \$432 per person per trip. These damages increase at an increasing rate, implying convexity of losses in the duration of smoke events. In addition, damages vary by proximity to active wildfires. Previous research has found that visitors to natural areas are less avoidant of smoke that originates from distant fires (Cai 2021). We find results that are in line with this research, with 20% lower welfare damages for smoke-affected campgrounds that are far from active fires. In general, the estimates are robust to multiple specifications, including a placebo for wildfire smoke. The placebo reassigns smoke events to either one or two weeks after the scheduled arrival date, testing whether visitors actually respond to wildfire smoke. We indeed find null results for this placebo, building confidence that the main estimates measure smoke responses.

The scale of wildfire smoke impacts for outdoor recreation is large. We combine estimates of the proportion of smoke-affected campers in our dataset, at park-specific and forest-specific levels, with total visitation data from state and federal agencies to determine the total number of outdoor visits affected by smoke each year. As a back of the envelope calculation we multiply this total smoke-affected visitation by the empirical per trip welfare estimate to approximate the total annual welfare loss due to smoke in the west. This analysis carries the limitation that welfare estimates are derived from camping activity, which may not be representative of other forms of outdoor recreation such as swimming, fishing, or day hiking. In addition, it accounts for lost welfare to inframarginal visitors and does not include the value of lost trips due to smoke. However, it provides an approximation of the magnitude of total annual smoke damages for recreation in the west. We find that an average of 21.5 million outdoor recreation visits per year are affected by wildfire smoke on lands managed by the National Park Service, US Forest Service, Bureau of Land Management, US Army Corps of Engineers, and at state parks. A high proportion of outdoor trips are affected by smoke, at roughly 4.2% of the more than 511 million annual visits. Applying the empirical welfare estimate of $107 per person per trip, this figure implies welfare losses of roughly $2.3 billion per year due to wildfire smoke.

This paper makes several contributions. First, it adds to the literature on both market and non-market damages of wildfire smoke. To the best of our knowledge, this study is the first to directly value smoke damages using revealed preference methods and observational data. Existing non-market estimates have used survey methods, healthcare costs, or have applied the value of a statistical life (VSL) to changes in mortality. This paper's results complement these estimates. Richardson et al. (2012) surveyed individuals about self-protective expenditures following one fire in Los Angeles County. They found a willingness to pay (WTP) to reduce one wildfire smoke induced symptom day of $102.[1] We measure the value of an exposure day, rather than a symptom day; by comparison, this paper's estimate of $107 per trip roughly translates to $38 per day. The total cost of smoke for recreation, at $2.3 billion per year, is also informative for the literature. Miller et al. (2021) estimated the increase in mortality among elderly Medicare recipients in the United States, finding annual damages of $6 billion to $170 billion, depending on VSL assumptions. Borgschulte et al. (2022) found annual lost labor earnings of $125 billion per year due to wildfire smoke. Other studies have found costs of

[1]This figure is inflation-adjusted to 2020 dollars from the published estimate of $84 in 2009 dollars.

wildfire smoke for test scores, crime, and hospital visits (Burkhardt et al. 2019, Cullen 2020, Wen and Burke 2021). Aside from smoke, this paper complements the literature on the costs of wildfires more generally (Baylis and Boomhower 2021, Graff Zivin et al. 2020, Plantinga et al. 2022).

Measuring the cost of wildfire smoke is crucial to inform public policy. The federal government has spent an average of $2.8 billion per year on fire suppression over the period 2017 to 2021, while California has spent an average of $900 million per year from 2018 to 2022.[2,3] Proactively, California has proposed spending $1.2 billion over Fiscal Years 2022-23 and 2023-24 on fire mitigation measures including vegetation management, prescribed burns, home hardening, and related activities.[4] These activities are consistent with the state's recently declared goal to treat 1 million acres of hazardous fuels per year.[5] Understanding the averted costs of wildfire and smoke is critical to assess the benefit of these public expenditures.

This paper also contributes by using novel methods and data sources. We value a transient environmental good, wildfire smoke, in a setting where users make decisions under evolving sets of information. The two stage choice structure which links preferences across decisions is informed by literature on sample selection correction in non-linear models (Greene 2012, Terza 2009), as well as in recreation contexts (Cameron and DeShazo 2013, Cameron and Kolstoe 2022, Kolstoe and Cameron 2017, Lewis et al. 2019). Our framework could be used to model sample selection or sequential choices in other non-linear or discrete choice settings. It could also be applied to recreation studies valuing other transient environmental amenities such as temperature, rainfall, or acute pollution events. In addition to the modeling, our use of administrative data contributes to a recent literature using new, large, or innovative data to study recreation across broad areas (Cameron and Kolstoe 2022, Dundas and von Haefen 2020,

[2] National Interagency Fire Center. Suppression Costs. https://www.nifc.gov/fire-information/statistics/suppression-costs.

[3] California Department of Forestry and Fire Protection. Suppression Costs. https://www.fire.ca.gov/stats-events.

[4] California Legislative Analyst's Office. The 2022-23 Budget Wildfire and Forest Resilience Package. https://lao.ca.gov/Publications/Report/4495.

[5] Agreement for shared stewardship of California's forest and rangelands between the State of California and the USDA Forest Service, Pacific Southwest Region. https://www.gov.ca.gov/wp-content/uploads/2020/08/8.12.20-CA-Shared-Stewardship-MOU.pdf.

English et al. 2018).

The remainder of this paper is organized as follows. In Section 1.2 we describe the data sources for the study, including recreation, smoke, fire, and pollution data. We also discuss several descriptive features of the data. Section 1.3 describes the modeling approach, including a conceptual framework and a description of the estimating dataset. In Section 1.4 we turn to estimation, describing various sets of results. Section 1.5 appraises the total annual welfare damages of wildfire smoke in the west. Section 1.6 concludes.

1.2 Data

We combine data on recreation, wildfire smoke, air pollution, wildfire activity, and weather. We build three main datasets. The first is a daily panel of federally managed campgrounds in the western United States over the period 2010 to 2017. This panel includes daily smoke, wildfire activity, pollution, weather, and climate normals at each campground. The second dataset is a record of individual-level reservations for campgrounds, which we link to the daily campground panel to show site conditions for users' reservation dates. The last dataset aggregates the individual users into travel cost zones around each campground to show daily reservation activity at various distance radii.

1.2.1 Recreation

We obtained data on campground use from Recreation.gov.[6] Recreation.gov is the web portal used to make reservations for federally managed campgrounds, including those managed by the National Park Service, Bureau of Land Management, US Forest Service, US Army Corps of Engineers, and Bureau of Reclamation. Figure A.1 in Appendix A.1 displays the Recreation.gov web interface as a user would experience it. The website gives users information about campground amenities, prices, availability, and nearby points of interest.

The raw data include more than 90 million transactions from more than 7 million unique

[6] Recreation.gov. `https://www.recreation.gov`.

users. We limit attention to campgrounds in the eleven western states, during the months of May through September, and for the years 2010 to 2017, which leaves more than 16 million transactions from 2 million unique users at 999 campgrounds. Our analysis is primarily concerned with overnight camping and excludes, for instance, large group or equestrian facilities.

The data give detailed information on reservations, walk-ins, cancellations, no shows, transaction dates, payments, refunds, zip code of origin, group size, user identifiers, and other information. For every transaction in an order, such as a payment or cancellation, the exact time of the transaction is known. For the 999 campgrounds in our analysis, 84% of transactions were made online, 9% over the phone, and 7% on-site (such as walk-ins or early checkouts).

1.2.2 Travel costs

We calculate travel costs using the distance and travel time between an origin zip code and a destination campground. We use GraphHopper, an open source routing engine which calculates routes using Djikstra's algorithm and OpenStreetMap data.[7,8] In total, we calculate nearly 5.4 million routes representing 5,379 origin points and 999 destinations. Our estimates reflect the fastest routes by car between each origin and destination. Optimal routes generally match routes identified by Google Maps during periods of low traffic. To identify coordinates of each user's zip code, we matched zip codes to Census Zip Code Tabulation Areas (ZCTAs) and found the centroid of each ZCTA.[9,10] Figure A.2 in Appendix A.1 displays an example automobile route.

Following English et al. (2018), we calculate the per-person travel costs between ZCTA z and campground j as:

$$c_{zjt} = \frac{p_{zt}^{D} D_{zj}}{n} + p_{zt}^{T} T_{zj}, \tag{1.1}$$

[7] GraphHopper. `https://www.graphhopper.com`.

[8] GraphHopper GitHub. `https://github.com/crazycapivara/graphhopper-r`.

[9] Health Resources and Services Administration, John Snow, Inc., & American Academy of Family Physicians. Uniform Data System. `https://udsmapper.org/zip-code-to-zcta-crosswalk`.

[10] Because ZCTA centroids may not be located along roads, we snapped ZCTA centroids to the nearest road using Census TIGER/Line shapefiles, and used the nearest points along roads as origin points.

for travel distance D_{zj} and travel time T_{zj}. The per-kilometer cost of traveling between ZCTA z and campground j is given by p_{zt}^{D} and includes costs of gasoline, per-kilometer vehicle maintenance costs, and per-kilometer average vehicle depreciation. For gasoline costs we use state- and year-specific averages of per-kilometer gasoline costs during summer months, based on per-gallon gasoline costs from the Energy Information Administration and nationwide average fleet fuel economy.[11,12] We use per-kilometer average depreciation and vehicle maintenance costs from AAA data, as in English et al. (2018).[13] Lastly, we measure hourly costs of travel time p_{zt}^{T} as one third of the average household income in ZCTA z divided by 2,080 hours worked per year (English et al. 2018). All numbers are inflation-adjusted to 2020 US dollars.

1.2.3 Smoke and air pollution

For each day we record whether a campground was covered by wildfire smoke. We use daily observations of wildfire smoke from the National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) by Schroeder et al. (2008).[14] Each day NOAA analysts manually trace the perimeters of wildfire smoke plumes using satellite photography, producing daily shapefiles. These data have been used in studies examining the effect of smoke on air pollution, health, labor markets, self-protective behavior, and crime (Borgschulte et al. 2022, Burke et al. 2021a, Burke et al. 2021b, Burkhardt et al. 2019, Cullen 2020, Gellman et al. 2022, Heft-Neal et al. 2022, Miller et al. 2021, Preisler et al. 2015).

One challenge presented by this dataset is that satellite photography does not reveal where in the air column a smoke plume is: the smoke could be at the ground level or it could be high in the atmosphere. If the plume is located high in the atmosphere it might not reflect on-the-ground conditions. To address this challenge we code an area as smoke-affected only if it is both covered by a smoke plume and if its ground-level $PM_{2.5}$ is above at least 1.64 standard

[11] Energy Information Administration. Weekly Retail Gasoline and Diesel Prices. https://www.eia.gov/dnav/pet/pet_pri_gnd_a_epmr_pte_dpgal_m.htm.

[12] Bureau of Transportation Statistics. Average Fuel Efficiency of US Light Duty Vehicles. https://www.bts.gov/content/average-fuel-efficiency-us-light-duty-vehicles.

[13] For example: AAA. Your Driving Costs 2016. https://jacobgellman.github.io/files/aaa/aaa_your_driving_costs_2016.pdf.

[14] NOAA. Hazard Mapping System. https://www.ospo.noaa.gov/Products/land/hms.html.

deviations of the location-specific seasonal mean for non-smoke days, which represents the 95th percentile of a normal distribution (Burkhardt et al. 2019, Gellman et al. 2022).[15] Figure A.3 in Appendix A.1 displays an example of that restriction using kriged $PM_{2.5}$ data from Burkhardt et al. (2019). The map shows that while many areas were covered by smoke, only some had air quality poor enough to be coded as smoke-affected.

1.2.4 Wildfire activity

At each campground we measure the daily distance to an actively burning fire. To measure wildfire activity we combine NASA MODIS fire detection points with the United States Geological Survey Monitoring Trends in Burn Severity (MTBS) fire perimeter dataset.[16,17] The MODIS detection points record 1 km centroids of fire activity at a daily resolution, including agricultural and prescribed fires (Giglio et al. 2016). The MTBS data map the final perimeters for wildfires occurring in the United States. Combining these data has two advantages. First, the use of known wildfire perimeters filters out any MODIS points not associated with a large wildfire. Second, the MODIS detection points limit attention only to the portion of a wildfire that was burning on a given day. We use a 1 km buffer around the final perimeter of the fire, as well as the start and containment dates of the fire, to filter MODIS points. Figure A.4 in Appendix A.1 demonstrates an example of this process for the western United States.

1.2.5 Temperature and precipitation

To control for weather conditions we gather daily precipitation (mm), maximum temperature (°C), and minimum temperature (°C) for every campground. These data are published at a 4 km resolution by the PRISM Climate Group at Oregon State University.[18] In addition, at each campground we record 30-year climate normals which reflect average conditions over the period 1980 to 2010.

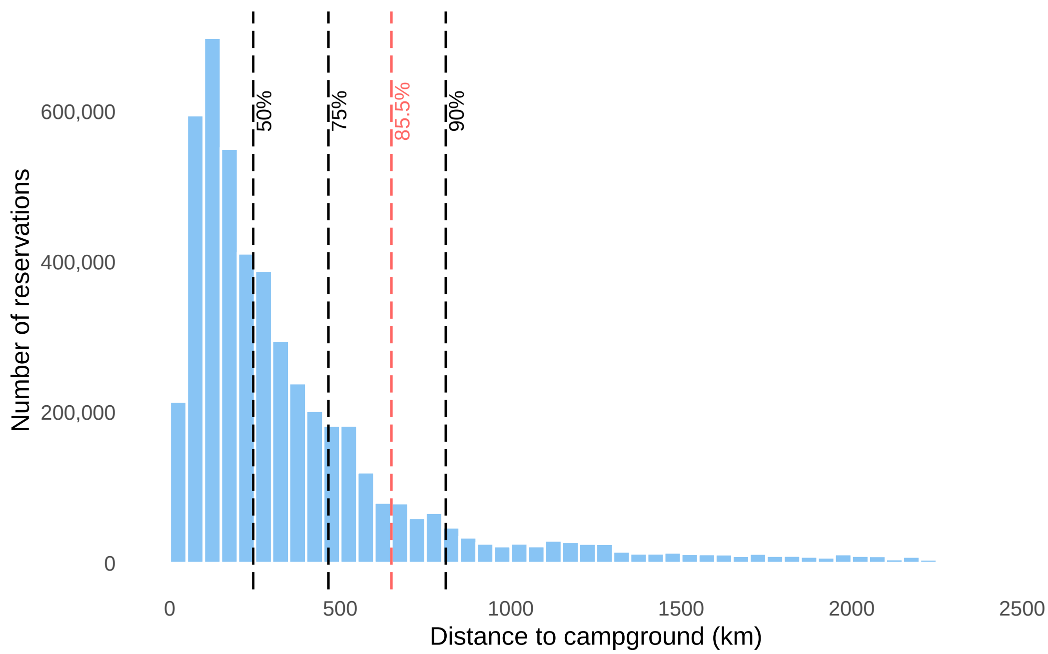
[15] A "season" is defined as fall, winter, spring, or summer.
[16] NASA. Earthdata. `https://earthdata.nasa.gov`.
[17] USGS. Monitoring Trends in Burn Severity. `https://www.mtbs.gov`.
[18] Northwest Alliance for Computational Science and Engineering, Oregon State University. PRISM Climate Data. `https://www.prism.oregonstate.edu`.

1.2.6 Descriptive features of the data

Of the 999 campgrounds in the analysis, 908 are managed by the US Forest Service, 50 by the National Park Service, 31 by the US Army Corps of Engineers, 5 by the Bureau of Land Management, and 5 by the Bureau of Reclamation. Figure A.5 in Appendix A.1 plots a map of the campgrounds in the analysis. While most of the campgrounds are managed by the Forest Service, the most-visited campgrounds tend to be National Parks. Table A.1 in Appendix A.1 reports the most-visited campgrounds in the dataset.

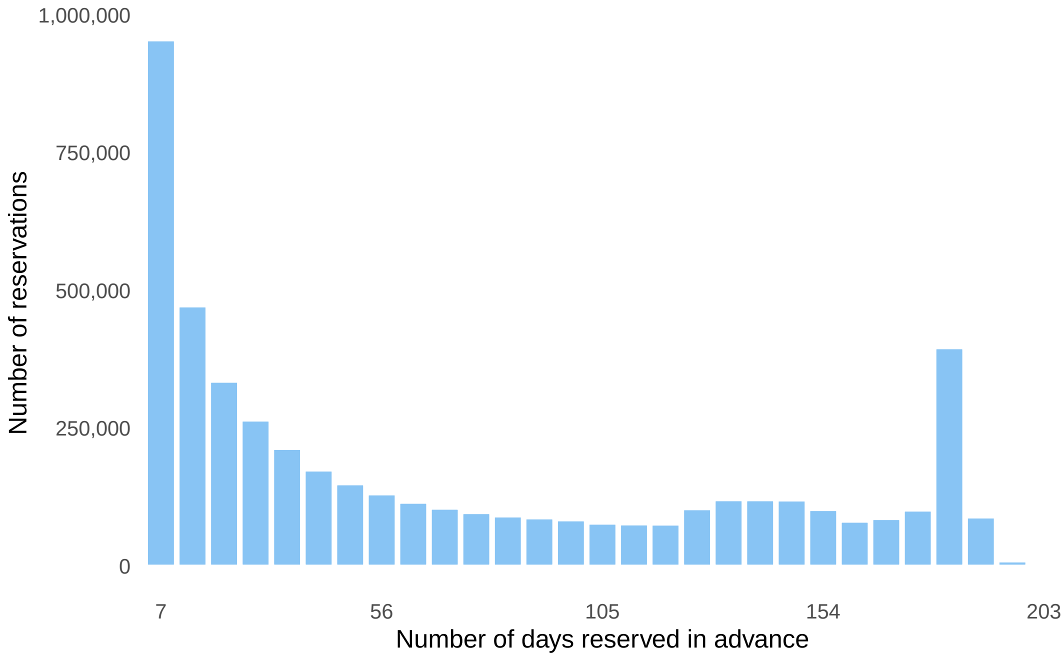
For the main analysis we restrict the set of potential reservers to residents living within one day's driving distance of a given campground. We set this restriction at 650 km (400 miles) of one-way driving distance. English et al. (2018) report survey results showing that, beyond 500 miles of driving distance, a substantial portion of recreation visitors are likely to have flown to their destination, which adds additional complications in the calculation of travel cost. Figure 1.1 shows that our 650 km restriction results in inclusion of more than 85% of reservations in the dataset. Half of our observed trips come from within 250 km (155 miles) and three quarters come from within 450 km (280 miles). Appendix A.7 reports the main results using alternative distance thresholds.

Figure 1.1: One-way driving distance of reservations from campground. Red line indicates 650 km cutoff.



The timing of a reservation is also key for our setting. Wildfire smoke is a random event, meaning that visitors who reserved far in advance could not have known that their chosen campground would be smoke-affected. Figure 1.2 shows that most visitors reserve far in advance of their arrival date, consistent with results in Walls et al. (2018). Although a plurality of visitors reserve within a week of arrival, a majority reserve early. In addition, there is significant mass around six months in advance, which is the earliest that some popular destinations allow reservations. In the following section we describe our modeling approach to study the cancellation decisions of visitors who reserved ahead of time.

Figure 1.2: Days reserved in advance of arrival date.



1.3 Modeling approach

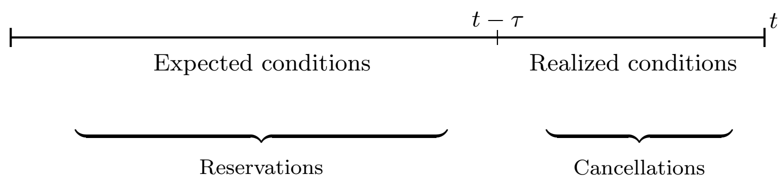
In this section we model an individual's decision to visit a campground under smoke and non-smoke conditions. A key feature for this setting is that smoke is ephemeral; it is a random event that may affect a site for several days before eventually disappearing. However, most campground reservations are made well in advance, before site conditions are known. But, by the time smoke conditions are likely known, many campgrounds are either completely full or completely empty, which would limit the identifying variation from measuring new visitors.[19] We therefore consider the cancellation decisions of visitors who reserved ahead of time.[20] We model a two part sequential process. In a first stage, visitors choose whether to reserve at a campground based on expected site conditions. In a second stage, close to the arrival date, they decide whether to cancel or follow through with the reservation based on realized site conditions.

[19]See Figure A.6 in Appendix A.1.

[20]We could have also considered new reservations close to arrival. For a discussion of late reservers, see Appendix A.2.

We allow for correlation of preferences across these decisions using a control function. For the reservation decision we use a pooled zonal travel cost model, which provides parameters for the control function in a trip-level model of cancellations. Figure 1.3 illustrates the timing of these decisions, where t gives the arrival date and τ denotes a bandwidth sufficiently close to the arrival date.

Figure 1.3: Timing of decisions.



1.3.1 Reservations

Define utility for the initial reservation decision as follows:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, \tag{1.2}$$

where V_{ijt} gives the indirect utility of person i for campground j on arrival date t. The variable ε_{ijt} represents preferences known to the individual but unobserved by the researcher. Define the observable portion of utility as:

$$V_{ijt} = \begin{cases} \delta c_{ijt} + \phi s_{jt} + X'_{jt}\gamma + \psi_j + \lambda_t, & j \in \{1, 2, ..., J\}; \\ 0, & j = 0. \end{cases} \tag{1.3}$$

The variable c_{ijt} gives the travel cost for person i to site j at time t, while s_{jt} is equal to 1 if there are smoke conditions at campground j on date t. The vector X_{jt} contains campground-level conditions including precipitation, temperature, and proximity to an active wildfire.

Additional variables include the alternative-specific constant ψ_j, which denotes campground-specific, time-invariant traits such as the quality of a campground. The variable λ_t similarly captures time-specific factors including seasonality and yearly trends. The parameter of interest is the willingness to pay (WTP) to avoid smoke, which is found by taking the ratio of marginal disutility of smoke ϕ to the marginal disutility of expenditure δ, WTP $= \phi/\delta$.

To operationalize our model, we estimate the reservation decision using a pooled zonal travel cost model. For each campground j and each day t, we sum the number of reservers and non-reservers in concentric zones z around a campground. Consider a representative agent in zone z. Because the agent reserves in advance, before site conditions are known, they compare utility over expected site conditions, $\mathbb{E}[U_{ijt}]$, to the expected utility of the outside option, $\mathbb{E}[U_{i0t}]$. Denote $R_{ijt} = 1$ if the individual chooses to reserve at campground j for arrival date t. When ε_{ijt} is distributed iid type I extreme value, the probability of observing $R_{ijt} = 1$ is given by:

$$\begin{aligned}
\mathbb{P}(R_{ijt} = 1) &= \mathbb{P}(\mathbb{E}[U_{ijt}] \geq \mathbb{E}[U_{i0t}]) \\
&= \mathbb{P}(\mathbb{E}[V_{ijt} + \varepsilon_{ijt}] \geq \mathbb{E}[V_{i0t} + \varepsilon_{i0t}]) \\
&= \mathbb{P}(\mathbb{E}[V_{ijt}] + \varepsilon_{ijt} \geq 0 + \varepsilon_{i0t}) \\
&= \mathbb{P}(\varepsilon_{i0t} - \varepsilon_{ijt} \leq \mathbb{E}[V_{ijt}]) \\
&= \frac{\exp(\mathbb{E}[V_{ijt}])}{1 + \exp(\mathbb{E}[V_{ijt}])}, \qquad (1.4)
\end{aligned}$$

noting that $V_{i0t} = 0$, and that ε_{ijt} is non-random from the perspective of the individual such that $\mathbb{E}[\varepsilon_{ijt}] = \varepsilon_{ijt}$.

The reservers are counted based on the reservations in the Recreation.gov dataset; for example, a reservation for four people is counted as four reservers. The non-reservers are determined based on zip code-level populations within each concentric ring, less the number of people from each zip code that held a reservation to a different campground on that day. The unit of observation for the zonal estimation is a campground by day by 50 km distance bin, where each row of data reports the number of people choosing outcome variable $R_{ijt} \in \{0, 1\}$.

For example, on August 1, 2015, Diamond Lake in Oregon saw 49 reservers ($R_{ijt} = 1$) from distance bin $(350, 400]$ and approximately 2.7 million non-reservers ($R_{ijt} = 0$) from distance bin $(350, 400]$, which includes non-reserving residents from Portland, Oregon and Redding, California. This implies a reservation rate of 1.8 per 100,000 individuals. All estimations use frequency weights for the number of individuals choosing either $R_{ijt} = 0$ or $R_{ijt} = 1$.

We use a zonal model for the reservation decision for several reasons. The primary purpose of the reservation estimation is to construct a control function that accounts for preferences in the cancellation estimation. As we will see, a person can only cancel a trip if they previously held a reservation. Therefore, preferences from the reservation decision likely play a role in the cancellation. The zonal reservation model accounts for these preferences while providing substantial flexibility over a multinomial logit approach. In this setting we have more than 1,200 arrival dates to define choice occasions, nearly 5 million reservations for the reserving individuals, nearly 5,400 zip codes to account for the non-reserving individuals, and 999 campgrounds to form the choice set. It would be infeasible to use all of the data in a multinomial logit model. One could reduce the size of the dataset by, for example, restricting the study to a single region or year. However, smoke is temporally and spatially correlated within regions, meaning we require multiple regions and years to provide necessary variation. The regional and temporal correlation of smoke also mean that site substitution is less likely to play a role in identifying the smoke parameter, a matter which we discuss further in Appendix A.3. Because we require regional and temporal variation, fixed effects are crucial to remove location- and time-specific unobservables across many heterogeneous sites. The zonal model accommodates a high number of fixed effects and is comptuationally less expensive than the contraction mapping method used in many multinomial logit studies (Berry 1994). This computational speed makes a difference when bootstrapping standard errors in the two stage model.

Denoting the set of parameters $\{\delta, \phi, \gamma, \psi_j, \lambda_t\}$ as ω, the likelihood and log likelihood function of a representative individual's reservation decision are written as:

$$\mathcal{L}(\omega|R_{ijt}) = \prod_{i=1}^{N}\prod_{j=0}^{J}\prod_{t=1}^{T} \mathbb{P}(R_{ijt}=1|\omega)^{R_{ijt}} \left(1-\mathbb{P}(R_{ijt}=1|\omega)\right)^{1-R_{ijt}}; \tag{1.5}$$

$$\ell(\omega|R_{ijt}) = \sum_{i=1}^{N}\sum_{j=0}^{J}\sum_{t=1}^{T} R_{ijt}\log\left(\mathbb{P}(R_{ijt}=1|\omega)\right) + (1-R_{ijt})\log\left(1-\mathbb{P}(R_{ijt}=1)\right), \tag{1.6}$$

for N agents, T choice occasions, and J sites. At the zonal level, we group each visitor i into travel cost zone $z \in \{1, 2, ..., Z\}$ to estimate the zonal travel cost model. Let N^0_{zjt} and N^1_{zjt} denote the number of non-reservers and reservers in each zone, respectively. For each zone the average travel costs for non-reservers and reservers are $\bar{c}^0_{zjt} = \frac{1}{N^0_{zjt}}\sum_{i\in z}(1-R_{ijt})c_{ijt}$ and $\bar{c}^1_{zjt} = \frac{1}{N^1_{zjt}}\sum_{i\in z} R_{ijt}c_{ijt}$. The likelihood function and log likelihood function are written as:

$$\mathcal{L}(\omega|R_{ijt}) = \prod_{z=1}^{Z}\prod_{j=0}^{J}\prod_{t=1}^{T} \mathbb{P}(R_{ijt}=1|\omega)^{N^1_{zjt}}\left(1-\mathbb{P}(R_{ijt}=1|\omega)\right)^{N^0_{zjt}}; \tag{1.7}$$

$$\ell(\omega|R_{ijt}) = \sum_{z=1}^{Z}\sum_{j=0}^{J}\sum_{t=1}^{T} N^1_{zjt}\log\left(\mathbb{P}(R_{ijt}=1|\omega)\right) + N^0_{zjt}\log\left(1-\mathbb{P}(R_{ijt}=1|\omega)\right). \tag{1.8}$$

Maximization of equation 1.8 yields utility parameters given a representative agent i from zone z.

1.3.2 Cancellations

For the second stage cancellation decision we model a binary choice at the level of the individual trip.[21] Assume that an agent chose to reserve at campground j. Close to the arrival date, within τ days, new preferences υ_{ijt} are realized. The agent chooses whether or not to

[21] In Appendix A.3 we show that very few users cancel their trip and rebook at another site for the same choice occasion. Close to the arrival date, many campgrounds are fully booked, which can prevent substitution. In addition, because smoke conditions are spatially and temporally correlated, substitution is unlikely an important factor in the identification of the smoke parameter. Therefore, a binary cancellation decision is a reasonable representation of the choice that visitors face.

cancel based on realized conditions. Let the utility from cancellation be:

$$U_{ijt} = V_{ijt} + \upsilon_{ijt}. \tag{1.9}$$

Because agents only face a cancellation decision if they previously made a reservation, we allow for correlation between their preferences close to the time of arrival υ_{ijt} and their preferences at the time of reservation ε_{ijt}. We assume a linear correlation structure:

$$\upsilon_{ijt} = \rho\varepsilon_{ijt} + \eta_{ijt}, \tag{1.10}$$

where η_{ijt} is distributed iid type I extreme value. The variable η_{ijt} reflects additional shocks to the agent's preferences close to the trip. For example, an unforeseen work obligation might raise the opportunity cost of the visit, or the agent could learn new information that increases their anticipation of the trip. A value of $\rho \neq 0$ implies that preferences at the time of reservation influence the cancellation decision, which we will see is an empirically testable hypothesis.

Let $C_{ijt} = 1$ if the agent cancels their reservation and 0 if they follow through. Within τ days of arrival, site conditions such as smoke s_{jt} are approximately known to the individual, so they maximize utility over realized conditions by comparing U_{ijt} to U_{i0t}. The probability that an individual does not cancel, i.e. that they follow through with their reservation, is:

$$\begin{aligned}
\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1) &= \mathbb{P}(U_{ijt} \geq U_{i0t}) \\
&= \mathbb{P}(V_{ijt} + \upsilon_{ijt} \geq V_{i0t} + \upsilon_{i0t}) \\
&= \mathbb{P}(V_{ijt} + \rho\varepsilon_{ijt} + \eta_{ijt} \geq 0 + \rho\varepsilon_{i0t} + \eta_{i0t}) \\
&= \mathbb{P}(\eta_{i0t} - \eta_{ijt} \leq V_{ijt} - \rho(\varepsilon_{i0t} - \varepsilon_{ijt})),
\end{aligned} \tag{1.11}$$

again substituting for $V_{i0t} = 0$.

Equation 1.11 presents challenges for the econometrician. The variables ε_{i0t} and ε_{ijt} are unobserved. However, omission of these variables will bias parameter estimates because they are correlated with travel cost among the selected sample. The selected sample is such that we only observe the cancellation decision for visitors that have already made a reservation. For those that did reserve, the correlation is $\mathbb{E}[c_{ijt}\varepsilon_{ijt}|R_{ijt} = 1] > 0$; among the selected sample of reservers, those with a high travel cost tend to have a high taste for the site. This relationship downward biases estimates of the travel cost parameter δ in the cancellation decision and thus inflates estimates of WTP $= \phi/\delta$. Appendix A.4 explores this relationship using a numerical example. We show that the bias arises only when preferences are correlated ($\rho \neq 0$ in equation 1.10) and when we can only observe the cancellation decision for the selected sample of reservers ($R_{ijt} = 1$).

1.3.3 Control function

To correct for this bias we develop a novel control function approach (Wooldridge 2015). We begin by noting the conditional distribution of $(\varepsilon_{i0t} - \varepsilon_{ijt})$ in the selected sample of reservers. Let $f(\cdot)$ be the logistic density, $F(\cdot)$ the logistic distribution, and define $\tilde{\varepsilon}_{ijt} \equiv (\varepsilon_{i0t} - \varepsilon_{ijt})$. The conditional density of $\tilde{\varepsilon}_{ijt}$ is:

$$\begin{aligned} f(\ \tilde{\varepsilon}_{ijt} \mid R_{ijt} = 1) &= f(\ \tilde{\varepsilon}_{ijt} \mid \tilde{\varepsilon}_{ijt} \leq \mathbb{E}[V_{ijt}] - \mathbb{E}[V_{i0t}]) \\ &= \frac{f(\tilde{\varepsilon}_{ijt}) \cdot \mathbb{1}\{\tilde{\varepsilon}_{ijt} \leq \mathbb{E}[V_{ijt}] - \mathbb{E}[V_{i0t}]\}}{F(\mathbb{E}[V_{ijt}] - \mathbb{E}[V_{i0t}])} \\ &= \frac{f(\tilde{\varepsilon}_{ijt}) \cdot \mathbb{1}\{\tilde{\varepsilon}_{ijt} \leq \mathbb{E}[V_{ijt}]\}}{\mathbb{P}(R_{ijt} = 1)}, \end{aligned} \tag{1.12}$$

where the first line follows from the reservation condition in equation 1.4, the second line from the definition of a truncated density, and the third line by noting that $V_{i0t} = 0$ and that

$F(\mathbb{E}[V_{ijt}]) = \mathbb{P}(R_{ijt} = 1)$. An estimand for $\tilde{\varepsilon}_{ijt}$ is given by:

$$\begin{aligned}
\mathbb{E}[\ \tilde{\varepsilon}_{ijt} \mid \tilde{\varepsilon}_{ijt} \leq \mathbb{E}[V_{ijt}]] &= \int_{-\infty}^{\infty} \tilde{\varepsilon}_{ijt}\ f(\tilde{\varepsilon}_{ijt} \mid \tilde{\varepsilon}_{ijt} \leq \mathbb{E}[V_{ijt}])\ d\tilde{\varepsilon}_{ijt} \\
&= \frac{\int_{-\infty}^{\mathbb{E}[V_{ijt}]} \tilde{\varepsilon}_{ijt}\ f(\tilde{\varepsilon}_{ijt})\ d\tilde{\varepsilon}_{ijt}}{\mathbb{P}(R_{ijt} = 1)} \\
&= \frac{\mathbb{E}[V_{ijt}] \cdot \frac{\exp(\mathbb{E}[V_{ijt}])}{1+\exp(\mathbb{E}[V_{ijt}])} - \log(1 + \exp(\mathbb{E}[V_{ijt}]))}{\mathbb{P}(R_{ijt} = 1)} \\
&= \frac{\mathbb{E}[V_{ijt}] \cdot \mathbb{P}(R_{ijt} = 1) - I_{ijt}}{\mathbb{P}(R_{ijt} = 1)} \\
&= \mathbb{E}[V_{ijt}] - \frac{I_{ijt}}{\mathbb{P}(R_{ijt} = 1)}. \qquad (1.13)
\end{aligned}$$

The first line follows from the definition of a conditional expectation, the second line by substituting in equation 1.12, the third line by evaluating the definite integral, the fourth line by substituting equation 1.4 and by defining $I_{ijt} \equiv \log(1 + \exp(\mathbb{E}[V_{ijt}])$, and the final line through simplification. Equation 1.13 contains familiar terms. The $\mathbb{E}[V_{ijt}]$ term gives the expected utility of the site choice from the reservation decision. The second term contains the value I_{ijt}, which is equivalent to the inclusive value in the nested logit literature (Train 2009). This term approximates the expected maximal utility a visitor could expect from holding the reservation, which includes either the trip or the cancellation. The I_{ijt} term is scaled by the inverse of the probability that they would reserve at the site.

The estimand $\tilde{\varepsilon}_{ijt}$ captures the preferences of individual i from their reservation decision, allowing for unbiased estimation of the travel cost parameter in the cancellation problem. Since travel cost is positively correlated with ε_{ijt}, we expect that it is negatively correlated with $\tilde{\varepsilon}_{ijt} \equiv (\varepsilon_{i0t} - \varepsilon_{ijt})$. We also expect a higher value of $\tilde{\varepsilon}_{ijt}$ to increase the likelihood of cancellation, as in equation 1.11. In Appendix A.4 we illustrate the bias correction of this estimand through a numerical example.

Estimation of the cancellation decision proceeds through the following two stage process.

First, we estimate the parameters of the reservation decision $\mathbb{P}(R_{ijt} = 1)$ by maximizing a zonal log likelihood function as in equation 1.8, for reservations made earlier than $t - \tau$ and using expected site conditions. Then, we use the parameters to create a fitted value $\hat{\hat{\varepsilon}}_{ijt}$ for every observed reservation. We substitute them into the trip-level equation for the cancellation decision, where each row of data is a trip with a dependent variable $C_{ijt} \in \{0, 1\}$ indicating whether the user cancelled the trip. In this second stage the independent variables in V_{ijt} use realized rather than expected site conditions since users approximately know the site conditions close to the arrival date. For individual i, the likelihood and log likelihood function for the cancellation decision are:

$$\mathcal{L}(\omega|C_{ijt}, R_{ijt} = 1) = \prod_{i=1}^{N}\prod_{j=0}^{J}\prod_{t=1}^{T} \mathbb{P}(C_{ijt} = 0|\omega, R_{ijt} = 1)^{1-C_{ijt}} \left(1 - \mathbb{P}(C_{ijt} = 0|\omega, R_{ijt} = 1)\right)^{C_{ijt}}; \tag{1.14}$$

$$\ell(\omega|C_{ijt}, R_{ijt} = 1) = \sum_{i=1}^{N}\sum_{j=0}^{J}\sum_{t=1}^{T} (1 - C_{ijt}) \log\left(\mathbb{P}(C_{ijt} = 0|\omega, R_{ijt} = 1)\right) + C_{ijt} \log\left(1 - \mathbb{P}(C_{ijt} = 0|\omega, R_{ijt} = 1)\right). \tag{1.15}$$

Because of the two stage estimation the researcher can use a bootstrapping process to obtain appropriate standard errors (Cameron and Miller 2015, Wooldridge 2015).

1.3.4 Numerical example

In Appendix A.4 we provide a numerical example of the bias correction of our control function. We simulate 10,000 draws with $N = 100,000$ users who reserve and cancel. We assign each user random travel costs, smoke conditions, and preferences ε_{ijt} and $\upsilon_{ijt} = \rho\varepsilon_{ijt} + \eta_{ijt}$. Arbitrarily, we assert a true WTP to avoid smoke of $\phi/\delta = 2$. We vary two dimensions in the simulation. First, we test the role of dependent preferences in the two stages by turning ρ on ($\rho \neq 0$) and off ($\rho = 0$). Second, we test the role of sample selection. Unlike with the real recreation data, in the simulation we observe the counterfactual cancellation decisions of users who never held a reservation. In the simulation we test the cancellation estimation on both the selected sample of reservers and among the full sample, which includes non-reservers.

Table 1.1 summarizes results from the simulation. Columns 2 and 3 show that either correlated preferences or sample selection alone do not bias WTP estimates. It is only in column 4, when both conditions are present, that WTP is biased. In Appendix A.4 we discuss how this bias operates through correlation between preferences and travel cost in the selected sample, which attenuates estimates of the travel cost parameter. In column 5, we maintain both sample selection and correlated preferences, but introduce our control function $\tilde{\varepsilon}_{ijt}$. Across Monte Carlo simulations the control function corrects the bias and includes the true WTP in the confidence interval. For a full treatment, refer to Appendix A.4.

Table 1.1: Numerical example for 10,000 simulations of cancellation estimation, bias, and bias correction from $\tilde{\varepsilon}_{ijt}$ control function.

	(1)	(2)	(3)	(4)	(5)
WTP	2.00**	2.00**	2.00**	3.77**	1.98**
	(0.08)	(0.10)	(0.11)	(0.46)	(0.17)
Users	All users	All users	Reservers	Reservers	Reservers
ρ		Yes		Yes	Yes
2-step estim.					$\tilde{\varepsilon}_{ijt}$

Notes: True WTP = 2. N = 100,000 users. * p < 0.05, ** p < 0.01.

1.4 Estimation

In this section we estimate the welfare damages of wildfire smoke for outdoor recreation. As discussed in the previous section, the estimation follows a two stage process that links reservations ahead of time to cancellations close to arrival. Figure 1.3 shows the timing of decisions. We restrict the data to the set of users who booked more than a week ahead of time, or $\tau = 7$ in Figure 1.3, and who subsequently decided whether to cancel within a week of the arrival date. We therefore exclude reservations which were cancelled more than a week in advance. We also focus on trips scheduled for the months of May to September and over the years 2010 to 2017. Lastly, we limit attention to trips coming from within 650 km (400 miles), as described in Section 1.2.6. These restrictions result in a sample of 2,723,940 reservations.[22]

Our analysis explores the sample selection issues characterized in the previous section, namely that a visitor can only cancel a trip if they previously demonstrated a taste for the site by reserving. Without accounting for this sample selection, the results would imply that wildfire smoke causes \$154 in welfare damages per person per trip. However, when accounting for sample selection using a control function, we find damages of \$107 per person per trip. We show that the control function operates by correcting for the correlation between a user's preferences and their travel cost in the selected sample.

We also discuss how damages vary based on the severity of smoke. Welfare damages monotonically increase in the duration of smoke events. The main results set the variable of interest s_{jt} equal to one if there was at least one hazardous smoke day in the week of arrival, $t - \tau$. However, when a campground was affected by smoke on two, three, or up to seven days in the week of arrival, we find damages of up to \$432 per person per trip. These damages increase at an increasing rate, implying convexity in the duration of smoke events.

Damages are attenuated, however, when wildfire smoke is far from an active fire. When we remove observations for which there is an active wildfire within 20 km, we find reduced damage estimates of \$85 per person per trip. The estimates are robust to a placebo which reassigns smoke events to the weeks following an arrival date.

1.4.1 Cancellations close to arrival

Figure 1.4 displays how the cancellation rate varies by travel cost and wildfire smoke conditions. The figure shows that users cancel their trips at higher rates during smoke conditions than during non-smoke conditions. This relationship does not appear to vary by travel cost, as the distance between the red and blue points is relatively constant across travel cost bins.

[22] A "reservation" or "trip" is composed of multiple "transactions," which could include, for instance, an initial booking, payment, check in, cancellation, or refund.

Visually, the slope between cancellation rate and travel cost appears shallow. As explored in Section 1.3 and Appendix A.4, this shallow slope is likely due to positive correlation between travel cost and the unobserved preference parameter ε_{ijt} among the selected sample of reservers. Intuitively, if we were to observe someone reserve at site j despite a high travel cost, on average they should have a higher preference ε_{ijt} for the site than for someone with a similar travel cost that did not reserve, such that $\mathbb{E}[\varepsilon_{ijt}c_{ijt}|R_{ijt} = 1] > 0$. If ignored, we expect this correlation to depress the magnitude of the travel cost coefficient in the estimation of cancellations $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$, which translates to a shallow slope in Figure 1.4.

Figure 1.4: Cancellation rate close to arrival.

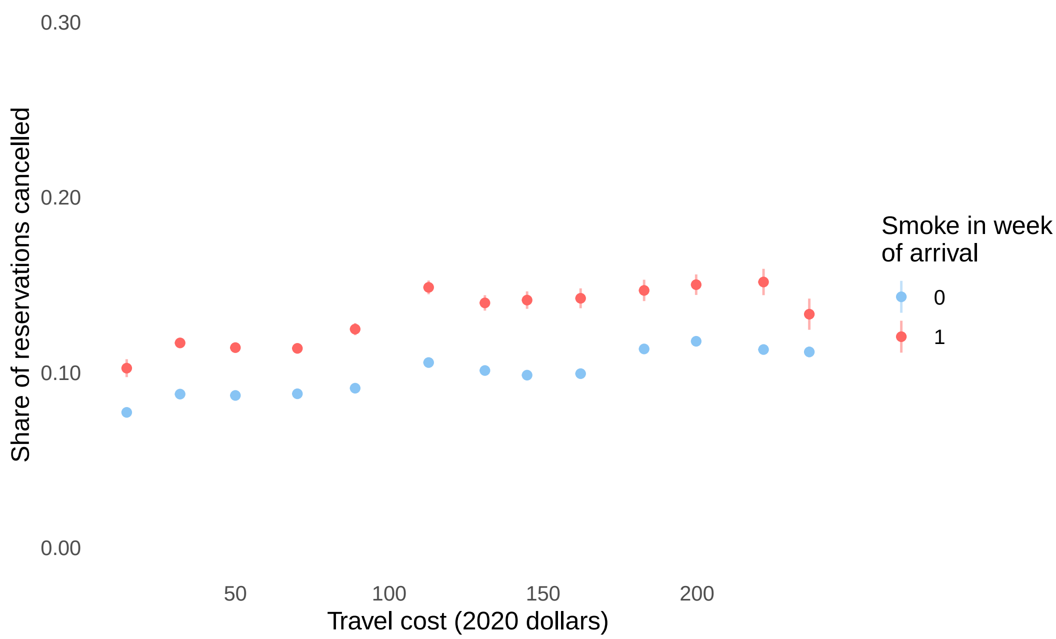


Table 1.2 reports results for biased estimation of cancellations $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ using the trip-level maximum likelihood function of equation 1.15. These estimates ignore the correlation between ε_{ijt} and travel cost among the set of users that chose to reserve. WTP is computed by taking the ratio of marginal disutility in smoke to marginal disutility in expenditure, i.e. the smoke coefficient divided by the travel cost coefficient. Standard errors for WTP are computed

using the delta method.[23] In all estimations the observations are weighted using frequency weights since a single reservation might represent, for example, two visitors or eight visitors.

In column 1 we display results without controlling for campground or seasonal fixed effects. Columns 2 through 4 add fixed effects. We include a campground fixed effect to account for location-specific, time-invariant unobservables related to site quality. We also account for differences in reservation rates based on the day of the week, since weekends see higher reservation activity than weekdays. A campground by week fixed effect controls for unobserved location-specific seasonality, such as seasonal campground-specific natural phenomena. Lastly, we include various year fixed effects to account for time-related unobservables. Column 4 would imply that wildfire smoke causes $154 in lost welfare per person per trip. This result is likely upward biased since WTP $= \phi/\delta$ and we expect the travel cost parameter δ to be attenuated.

[23] For an example of the delta method for the ratio of two coefficients, such as the ratio in our WTP estimate, an interested reader may refer to Casella and Berger (2002), example 5.5.27.

Table 1.2: $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ within one week, uncorrected for sample selection.

	(1)	(2)	(3)	(4)
Smoke in week of arrival	-0.2195**	-0.2615**	-0.2346**	-0.2615**
	(0.0238)	(0.0283)	(0.0273)	(0.0215)
Travel cost (dollars)	-0.0024**	-0.0017**	-0.0017**	-0.0017**
	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Inv. distance to wildfire (km^{-1})	-11.1276**	-12.0389**	-11.9174**	-7.8003**
	(0.9266)	(2.4288)	(2.4432)	(0.8291)
High temp. (degrees C)	0.0198**	0.0287**	0.0292**	0.0307**
	(0.0045)	(0.0023)	(0.0023)	(0.0022)
Low temp. (degrees C)	-0.0033	-0.0205**	-0.0214**	-0.0253**
	(0.0058)	(0.0025)	(0.0025)	(0.0025)
Precip. in week of arrival (mm)	-0.0041**	-0.0058**	-0.0060**	-0.0057**
	(0.0011)	(0.0009)	(0.0009)	(0.0009)
N	2,723,830	2,692,468	2,692,468	2,689,216
WTP	91.1**	153.4**	137.35**	154.04**
	(12.36)	(21.06)	(19.85)	(15.43)
Campground FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Campground x week-of-year FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

To correct for the biased WTP in Table 1.2 we use the control function described in equation 1.13, $\tilde{\varepsilon}_{ijt} = \mathbb{E}[V_{ijt}] - \frac{I_{ijt}}{\mathbb{P}(R_{ijt}=1)}$. The first step is to estimate the probability of reservation earlier than one week based on expected site conditions and using a zonal travel cost model. Then, we fit the parameters from the reservation estimation to form an estimate for $\tilde{\varepsilon}_{ijt}$. This estimate is used as a covariate in the trip-level estimation of cancellations $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$, after site conditions become approximately known to visitors.

We construct expected site conditions in the following way. For temperature and precipitation, we use climate normals from our PRISM data source, which represent average weather conditions from the period 1980 to 2010. Because travel cost is likely known to the individual ahead of time, we use the visitor's actual travel cost. For expected smoke and expected distance to fire, we use the average conditions over the past four years. For example, if a site was affected by smoke for one out of the past four years, we code expected smoke as 0.25.

Table 1.3 shows results from the first stage reservation decision $\mathbb{P}(R_{ijt} = 1)$ implied by equation 1.8. Users appear unexpectedly more likely to reserve at a campground with a higher expectation of wildfire smoke. Including more fixed effects generally decreases the magnitude and significance of the estimate, including moving the WTP closer to zero. Still, even with a high number of seasonal fixed effects we may be unable to remove the correlation of seasonal variation in camping with wildfire smoke. Nevertheless, the primary purpose to estimate the likelihood of reservation $\mathbb{P}(R_{ijt} = 1)$ is as an input for the control function $\tilde{\varepsilon}_{ijt}$ in the estimation of $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$, so we should be unconcerned by the direction of the smoke expectations parameter.

Table 1.3: $\mathbb{P}(R_{ijt} = 1)$ for reservations made earlier than one week based on expected site conditions.

	(1)	(2)	(3)	(4)
Smoke exp.	0.9260**	0.2513**	0.1032**	0.0822*
	(0.0036)	(0.0423)	(0.0363)	(0.0324)
Travel cost (dollars)	-0.0202**	-0.0244**	-0.0244**	-0.0244**
	(0.0000)	(0.0013)	(0.0013)	(0.0013)
Inv. distance to wildfire exp. (km^{-1})	39.6901**	6.0569**	6.1590**	6.7856**
	(0.0742)	(1.7451)	(1.5707)	(1.4654)
High temp. exp. (degrees C)	0.0191**	0.0597**	0.0611**	0.0588**
	(0.0001)	(0.0130)	(0.0131)	(0.0126)
Low temp. exp. (degrees C)	-0.0191**	-0.0818**	-0.0835**	-0.0812**
	(0.0001)	(0.0153)	(0.0153)	(0.0148)
Precip. exp. in week of arrival (mm)	-0.0126**	0.0071**	0.0066*	0.0067*
	(0.0001)	(0.0027)	(0.0027)	(0.0027)
N	15,209,187	12,668,366	12,668,366	12,298,572
WTP	-45.93**	-10.31**	-4.23**	-3.37*
	(0.18)	(1.72)	(1.45)	(1.31)
Campground FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Campground x week-of-year FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

After zonal estimation of $\mathbb{P}(R_{ijt} = 1)$ for early reservers, we use the parameter estimates to create fitted probabilities of reservation at the trip level. Figures A.7 and A.8 in Appendix A.1 show the variation in fitted probability $\mathbb{P}(R_{ijt} = 1)$ and in the control function $\tilde{\varepsilon}_{ijt}$. Since we expect that preferences and travel costs are correlated in the selected sample, $\mathbb{E}[c_{ijt}\varepsilon_{ijt}|R_{ijt} = 1] > 0$, then it should be true that our control function is inversely correlated with travel cost, $\mathbb{E}[c_{ijt}(\varepsilon_{i0t} - \varepsilon_{ijt})|R_{ijt} = 1] < 0$. Figure 1.5 illustrates this relationship using the fitted values of $\tilde{\varepsilon}_{ijt}$ for the sample of reservers. The slope of the fitted line follows the expected direction. Using 400 bootstrapped estimations and the fixed effects from model (4) we find that

$c_{ijt} = -(239.738 + 24.70\ \tilde{\varepsilon}_{ijt})$, where the intercept and slope coefficients are both significant at the 0.01 level. This empirical result is consistent with the prediction of our theory and numerical exercise in Section 1.3 and Appendix A.4.

Figure 1.5: Relationship between control function $\tilde{\varepsilon}_{ijt}$ and travel cost using model (4) demonstrates correlation between preferences and travel cost in the selected sample of reservers.

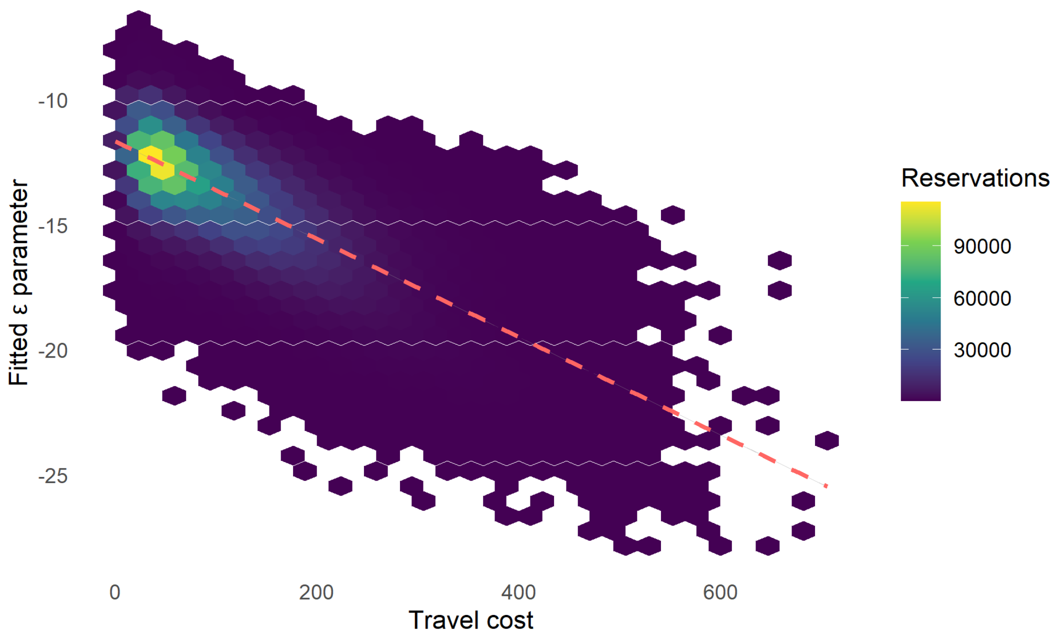


Table 1.4 reports the main trip-level results for the cancellation estimation $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ using the bias correcting control function $\tilde{\varepsilon}_{ijt}$. The coefficient for $\tilde{\varepsilon}_{ijt}$ is significant, suggesting that preferences at the time of reservation are an important determinant of the cancellation decision. In addition, comparing to Table 1.2, the travel cost coefficient was the only parameter to change when including $\tilde{\varepsilon}_{ijt}$, which is consistent with the notion that sample selection bias operates through correlation with travel cost. Overall, the WTP estimates are reduced to \$107 per person per trip of lost utility due to cancellations. By comparison, the biased results in Table 1.2 were \$154 per person per trip, which is 44% higher.

Table 1.4: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ within one week, corrected for sample selection.

	(1)	(2)	(3)	(4)
Smoke in week of arrival	-0.2175**	-0.2708**	-0.2438**	-0.2603**
	(0.0247)	(0.0238)	(0.0221)	(0.0218)
Travel cost (dollars)	-0.0026**	-0.0024**	-0.0024**	-0.0025**
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-11.1017**	-10.8883**	-10.7067**	-7.8141**
	(0.8580)	(1.4280)	(1.4288)	(0.7920)
High temp. (degrees C)	0.0202**	0.0284**	0.0289**	0.0306**
	(0.0043)	(0.0024)	(0.0024)	(0.0023)
Low temp. (degrees C)	-0.0037	-0.0204**	-0.0214**	-0.0252**
	(0.0052)	(0.0026)	(0.0025)	(0.0025)
Precip. in week of arrival (mm)	-0.0041**	-0.0058**	-0.0060**	-0.0057**
	(0.0010)	(0.0009)	(0.0009)	(0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0112	-0.0356**	-0.0366**	-0.0385**
	(0.0284)	(0.0106)	(0.0105)	(0.0106)
N	2,723,034	2,691,655	2,691,655	2,688,739
WTP	85.23**	113.91**	101.50**	107.14**
	(17.82)	(18.48)	(16.50)	(16.33)
Campground FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Campground x week-of-year FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Bootstrapped std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

Wooldridge (2015) recommends bootstrapping standard errors for control functions because of the two stage estimation process. We follow the clustered bootstrapping process of Cameron and Miller (2015), drawing with replacement at the campground level for 400 bootstraps. In Appendix A.5 we report results from Shapiro-Wilk tests for normality, failing to reject the null hypothesis that the bootstrapped smoke coefficients and travel cost coefficients are normally distributed. These tests suggest that 400 bootstraps are adequate for the analysis.

1.4.2 Relationship of damages to smoke duration

In this section we investigate how welfare losses vary by the severity of smoke events. Severity could refer either to the intensity or duration of a smoke event. We explore the relationship of damages to the duration of an event. In our main specification the variable of interest is an indicator equal to one if the campground was affected by at least one day of wildfire smoke in the week of arrival. We respecify the equation of interest, $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$, and allow for differential effects based on the number of smoke-affected days in the week of arrival.

Figure 1.6 plots the welfare damages visually as a function of the number of smoke days in the week of arrival. For full results an interested reader may refer to Table A.2 in Appendix A.1. Damages monotonically increase in the number of smoke days. When a campground was affected by smoke on all seven days in the week of arrival, we find welfare damages of \$432 per person per trip. Further, these damages appear to increase at an increasing rate. That is, welfare damages are approximately convex in the number of smoke days in the arrival week. Figure 1.7 demonstrates this relationship by showing that the marginal willingness to pay (MWTP) generally increases in the number of smoke-affected days in the week of arrival. On average, WTP rises about \$62 with each additional day of smoke.

Two potential mechanisms could explain these results. First, additional smoke days correspond to the severity of an event, as measured by duration. Visitors may be more likely to cancel during severe events. Second, additional smoke days in the week of arrival communicate the likelihood of smoke on the actual arrival date. Multiple days of smoke in the week leading up may increase a visitor's expectation of smoke during their own visit. This expectation might raise the probability of cancellation. For example, in a regression of an indicator variable $\mathbb{1}\{\text{campground is smoke-affected}\}$ on indicator variables for one, two, ..., seven days of smoke in the week before arrival, each additional smoke day increases the probability of smoke on the actual day of arrival. In such a regression, two days of smoke in the week raises the probability of smoke on the arrival date by 0.301; six days of smoke in the week raises the probability of smoke on the arrival date by 0.739.

Figure 1.6: Welfare damages are greater for weeks that were more smoke-affected, consistent with either more severe events or increased certainty of smoke conditions.

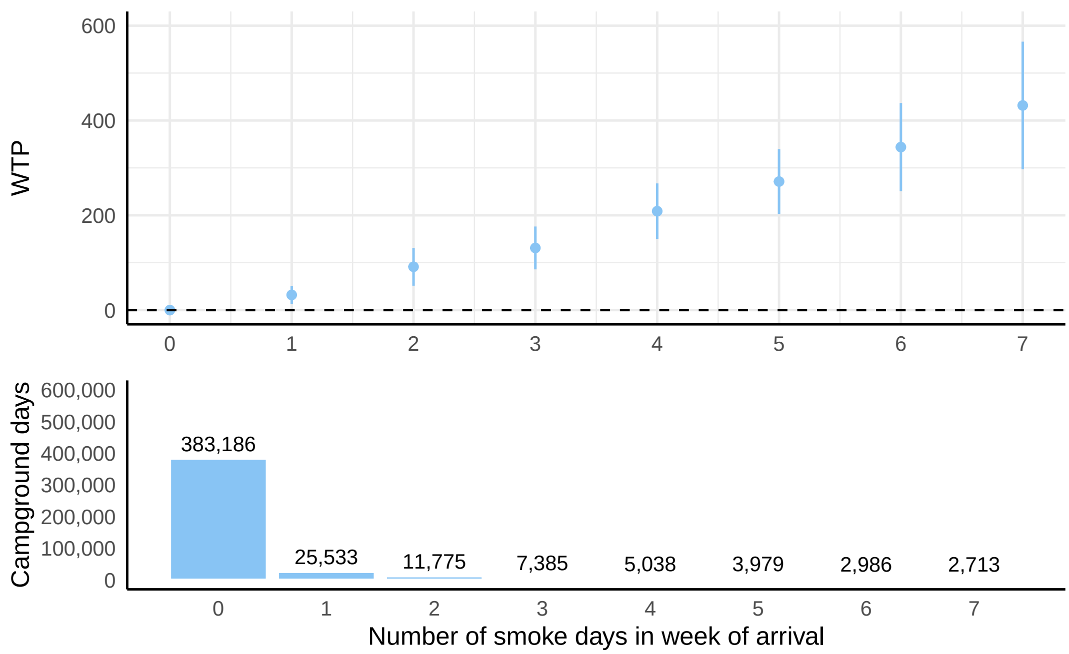
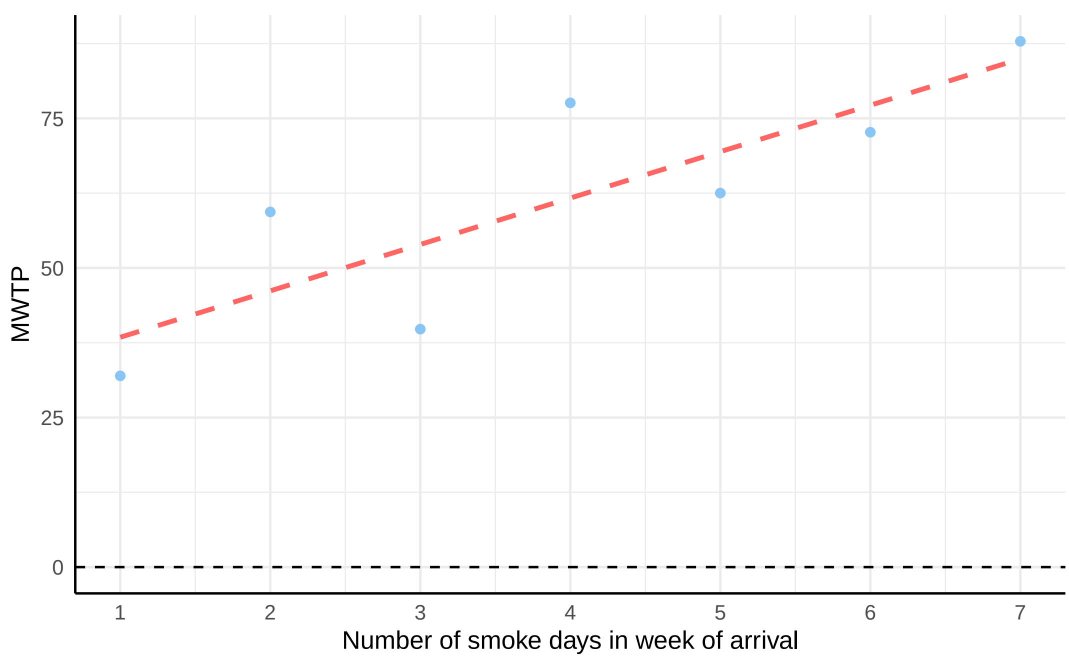


Figure 1.7: Marginal willingness to pay (MWTP) increases with additional smoke days.



1.4.3 The role of active wildfires

The existing literature has found that visitors to National Parks are less avoidant of wildfire smoke that originates from distant sources (Cai 2021). In this section we investigate how nearby active wildfires affect the main estimates. Although the main estimation controls for proximity to active wildfire, one might still be concerned that individuals avoid recreation primarily due to fire rather than smoke. If smoke days are highly correlated with nearness to fire it could increase the estimated smoke coefficient and inflate WTP. To address this possibility, we reestimate the main specifications but remove observations for which there was a nearby active fire.

We consider a campground as near to fire on day t if there is an active burning wildfire within 20 km (12 miles), a threshold we have used in previous work (Gellman et al. 2022). Table 1.5 reports the number of reservations affected by either smoke or fire conditions. When there is fire nearby, there is nearly an equal number of smoke- and non-smoke-affected reservations. However, due to the large distances that smoke travels, most smoke-affected reservations are not for campgrounds near an actively burning wildfire.

Table 1.5: Reservations with smoke or fire conditions in the estimating dataset.

Smoke in week of arrival	Fire within 20 km	Number of reservations	Percent of sample (%)
0	0	2,356,407	86.5
1	0	322,114	11.8
0	1	24,199	0.9
1	1	21,220	0.8

Table 1.6 reports results for the cancellation estimation $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ when removing observations with nearby active wildfire. We find welfare damages of \$85 per person per trip due to smoke. By comparison, in the main specification we estimated lost welfare of \$107 per person per trip. The omission of fire days thus reduced estimated welfare damages by approximately 20%. These results are consistent with the findings of Cai (2021), who found that outdoor

recreationists are less responsive to smoke originating from distant sources of fire.

Table 1.6: $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$, removing days with wildfire within 20 km.

	(1)	(2)	(3)	(4)
Smoke in week of arrival	-0.1678**	-0.2323**	-0.2119**	-0.2116**
	(0.0224)	(0.0195)	(0.0173)	(0.0177)
Travel cost (dollars)	-0.0028**	-0.0024**	-0.0025**	-0.0025**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-9.4566**	-7.7163**	-7.2826**	-6.5691**
	(1.1591)	(1.0196)	(1.0794)	(0.8965)
High temp. (degrees C)	0.0195**	0.0275**	0.0277**	0.0298**
	(0.0043)	(0.0021)	(0.0021)	(0.0021)
Low temp. (degrees C)	-0.0029	-0.0202**	-0.0208**	-0.0249**
	(0.0056)	(0.0025)	(0.0025)	(0.0025)
Precip. in week of arrival (mm)	-0.0043**	-0.0060**	-0.0062**	-0.0059**
	(0.0011)	(0.0009)	(0.0009)	(0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0129	-0.0348**	-0.0357**	-0.0377**
	(0.0261)	(0.0121)	(0.0121)	(0.0123)
N	2,677,628	2,645,592	2,645,592	2,642,695
WTP	60.97**	95.08**	85.96**	84.66**
	(12.4)	(13.13)	(12.03)	(12)
Campground FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Campground x week-of-year FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

1.4.4 Placebo test for smoke

As a robustness check, we devise a placebo test to check whether the smoke coefficient actually measures responses to wildfire smoke. The placebo considers the responses of visitors whose campground was not affected by smoke until one or two weeks after their arrival. If visitors are truly averting recreation due to smoke then we should see no response to these placebos. Of the 2.38 million reservations without smoke in the week of arrival, there are more than 375,000 placebo reservations for campgrounds that saw smoke in the week or second week after arrival.

Table 1.7 displays results from the placebo test. Across the main specifications we find null responses to the two smoke placebos. Comparing to Table 1.4, most coefficients remain the same for this placebo test. This exercise should add confidence that individuals are actually responding to smoke in the main estimation.

Table 1.7: Placebo test for $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ using smoke long after arrival.

	(1)	(2)	(3)	(4)
Smoke in week after arrival	0.0874**	0.0248	0.0226	0.0066
	(0.0190)	(0.0163)	(0.0155)	(0.0159)
Smoke two weeks after arrival	0.0783**	0.0041	0.0034	-0.0042
	(0.0231)	(0.0147)	(0.0146)	(0.0156)
Travel cost (dollars)	-0.0027**	-0.0025**	-0.0025**	-0.0025**
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-8.5921**	-7.3229**	-7.2413**	-5.2047**
	(0.8373)	(0.8998)	(0.8823)	(0.7795)
High temp. (degrees C)	0.0201**	0.0294**	0.0285**	0.0303**
	(0.0043)	(0.0022)	(0.0022)	(0.0022)
Low temp. (degrees C)	-0.0010	-0.0184**	-0.0184**	-0.0221**
	(0.0057)	(0.0026)	(0.0026)	(0.0025)
Precip. in week of arrival (mm)	-0.0039**	-0.0062**	-0.0062**	-0.0058**
	(0.0011)	(0.0009)	(0.0009)	(0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.0089	-0.0332**	-0.0337**	-0.0352**
	(0.0262)	(0.0123)	(0.0122)	(0.0124)
N	2,379,842	2,344,620	2,344,620	2,340,894
Campground FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Campground x week-of-year FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

1.4.5 Additional results and robustness checks

We report several additional results and robustness checks in the appendices. These checks include an exploration of the role of no shows in the estimation of cancellation probability. In addition, we vary the distance threshold that defines the sample restriction. Lastly, we show how results vary by the popularity of the recreation destination.

One concern when studying cancellations is the question of whether an individual will formally cancel their reservation, or whether they will simply not show up. For most campgrounds we do not observe whether an individual checks in to their campground or not. However, campers have an incentive to cancel their reservation. For cancellations made more than 24 hours before the arrival date, visitors are reimbursed for the full cost of the reservation less a $10 cancellation fee; and, when cancelling within 24 hours of arrival, they are still reimbursed for the full trip less the $10 fee and the price of the first night's stay. Still, we further explore this question in Appendix A.6. For a small subset of campgrounds we are able to observe no shows. Among the sample of campgrounds reporting no shows we demonstrate that the inclusion or exclusion of no show observations in the estimation of cancellations $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ does not change the estimates for the smoke or travel cost coefficients. For a discussion of this issue the interested reader may refer to Appendix A.6.

We also explore alternative distance thresholds for the sample restriction. In the main results we limit attention to reservations made within 650 km of one-way driving distance, or approximately 400 miles. Figure 1.1 shows that this distance restriction results in the inclusion of more than 85% of all reservations. Appendix A.7 reports how estimates vary with this threshold. Increasing the distance threshold attenuates the parameter estimate for travel cost, which is an input to welfare calculation. This relationship is possibly due to the inclusion of some visitors at greater distances who chose not to cancel their reservations. As a result, the estimated welfare damages increase as the distance threshold is relaxed. For more information, see Appendix A.7.

Lastly, we assess which types of campgrounds drive the parameter estimates. Even with a high number of fixed effects, visitors could respond differentially to disamenities at highly valued destinations such as Glacier National Park as opposed to small, primarily local US Forest Service campgrounds. Appendix A.8 reports heterogeneous results by campground popularity, where popularity is defined by annual visitation. We find that visitors are less responsive to both smoke and to travel cost at the most popular destinations. Visitors may be more tolerant of environmental disamenities at highly valued destinations. Across most specifications, welfare damages are highest for destinations in the middle quartiles of popularity.

1.5 Total welfare losses

In the preceding sections we have estimated per trip damages of wildfire smoke. We now turn to an appraisal of the total annual welfare damages for recreation. We combine the camping data from Recreation.gov with overall visitation data from federal and state agencies to determine the total number of outdoor visits in the west that are affected by smoke each year. As a back of the envelope calculation we multiply total smoke-affected visitation by the empirical per trip welfare estimate to approximate the total annual welfare loss due to smoke in the west. One limitation of this analysis is that the welfare estimates are derived from camping activity, which may not be representative of losses to other forms of recreation such as angling, swimming, or daytime visits. Still, this figure approximates the relative magnitude of total annual smoke damages for recreation in the western United States.

We find that across federal and state lands, an average of 21.5 million outdoor recreation visits per year are affected by wildfire smoke. Multiplying by a per trip damage of \$107 per person, this result implies more than \$2.3 billion of welfare losses each year due to smoke. This back of the envelope estimate represents the lost welfare to inframarginal visitors and does not include the value of lost trips.

To arrive at this number we use total visitation numbers from the National Park Service,[24]

[24] National Park Service. Annual Summary Report. `https://irma.nps.gov/STATS`.

US Forest Service,[25] Bureau of Land Management,[26] US Army Corps of Engineers,[27] and the National Association of State Park Directors (Smith et al. 2019) for the years 2008 to 2017. These data sources have varying levels of spatial and temporal granularity. For each data source we use the Recreation.gov data to determine, at the relevant spatial and temporal scale, the proportion of total visits at each agency that were affected by smoke. For more information on the estimation of smoke-affected visitation, an interested reader may refer to Appendix A.9.

Table 1.8 displays estimates of total visitation, smoke-affected visitation, and total welfare losses by agency. One key point is the high overall level of outdoor recreation, with more than 511 million annual visits to state and federal lands in the western United States. In addition, a high proportion of these visits are affected by smoke. We estimate that approximately 21.5 million visits per year are affected by wildfire smoke, or 4.2%. When multiplied by the per trip estimate of \$107, we find total annual welfare losses of approximately \$2.3 billion due to smoke. Nearly half of these damages occur at state parks, which see larger visitation compared to federal agencies. Of any agency, the US Army Corps of Engineers saw the highest proportion of its visitors affected by smoke. This is likely due to the fact that much of that agency's visitation (nearly 40%) occurs at lakes and reservoirs in the Pacific Northwest, a region which has seen particularly high wildfire smoke impacts relative to other regions (Burke et al. 2021a, Gellman et al. 2022, Miller et al. 2021).

[25] US Forest Service. National Visitor Use Monitoring Program. `https://www.fs.usda.gov/about-agency/nvum`.

[26] Bureau of Land Management. Public Land Statistics. `https://www.blm.gov/about/data/public-land-statistics`.

[27] US Army Corps of Engineers. Value to the Nation. `https://www.iwr.usace.army.mil/Missions/Value-to-the-Nation`.

Table 1.8: Smoke-affected recreation visits and welfare losses for the western US, by agency, 2008 to 2017.

	Total visits/year (millions)	Smoke-affected visits/year (millions)	Welfare loss/year (millions)
National Park Service	102.6	2.3	\$248.1
US Forest Service	108.0	4.8	\$511.4
Bureau of Land Management	59.8	2.5	\$267.3
US Army Corps of Engineers	46.4	2.4	\$251.7
State Parks	194.5	9.6	\$1,022.1
Total	511.4	21.5	\$2,300.6

Notes: Welfare loss computed by multiplying \$107 per trip by smoke-affected visits.

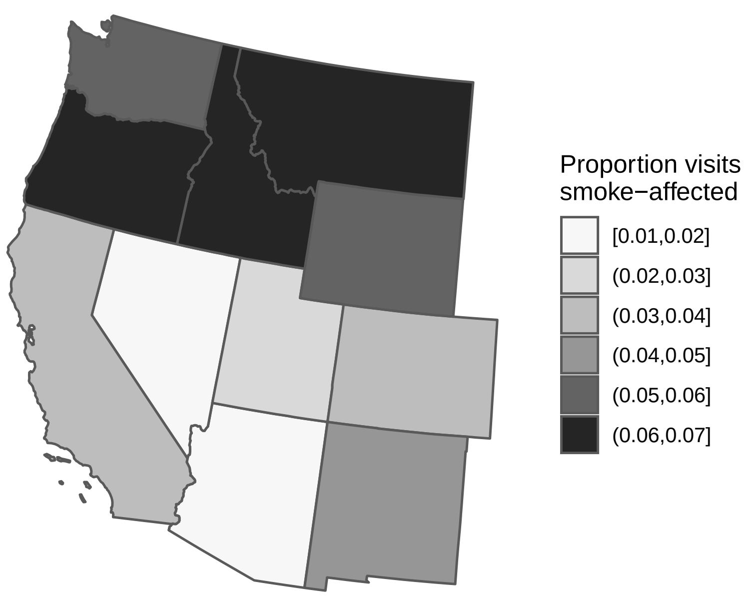
Welfare losses vary by region. Some states saw high smoke damages due to high baseline levels of visitation, while damages in other regions were driven by a high proportion of smoke-affected visits. Table 1.9 reports losses by state, while Figure 1.8 maps the proportion of visits that were affected by smoke in each state. For states such as California and Colorado, damages are large due to high visitation. States such as Oregon and Washington saw both relatively high visitation and a high share of smoke-impacted visits. At the other end of the spectrum, states in the Southwest such as Arizona, Nevada, and Utah saw high visitation but a low proportion of smoke-affected visits. In Northern Rocky Mountain states like Idaho, Montana, and Wyoming, damages are driven by a high share of smoke-affected days. As a whole, these findings show the high cost of wildfire smoke for outdoor recreation in the western United States.

Table 1.9: Smoke-affected recreation visits and welfare losses for the western US, by state, 2008 to 2017.

	Total visits/year (millions)	Smoke-affected visits/year (millions)	Welfare loss/year (millions)
California	162.7	6.1	$649.6
Oregon	69.9	4.4	$466.2
Washington	64.8	3.3	$351.9
Colorado	55.3	2.1	$220.9
Idaho	19.6	1.3	$136.8
Wyoming	21.9	1.2	$131.6
Montana	18.3	1.1	$121.8
Utah	32.1	0.8	$84.8
New Mexico	13.7	0.6	$60.9
Arizona	33.0	0.4	$46.3
Nevada	20.2	0.3	$29.8
Total	511.4	21.5	$2,300.6

Notes: Welfare losses computed by multiplying $107 per trip by smoke-affected visits.

Figure 1.8: Estimated proportion of visits affected by smoke per year.



1.6 Conclusion

This study provides the first revealed preference welfare estimates of the damage of wildfire smoke for outdoor recreation. Using high frequency data on campground reservations, wildfire, smoke, and air pollution, we study avoidance behavior at federally managed lands in the western United States. We estimate that wildfire smoke causes welfare losses of $107 per person per trip. These damages increase at an increasing rate when campgrounds are affected by consecutive days of smoke, and are attenuated when smoke-affected campgrounds are far from active wildfires. Combining these results with federal and state data on total visitation, we estimate that 21.5 million outdoor recreation visits per year are affected by smoke, with associated welfare losses of $2.3 billion.

The paper provides several contributions to the literature. First, we contibute by using novel methods and data. We value a temporary environmental bad, wildfire smoke, in a context where visitors face changing sets of information. To do so, we develop a two stage decision structure that links preferences with a control function. This model draws on work from economists concerned with sample selection in non-linear models (Greene 2012, Terza 2009), as well as researchers confronting sample selection in recreation settings (Cameron and DeShazo 2013, Cameron and Kolstoe 2022, Kolstoe and Cameron 2017, Lewis et al. 2019). The framework we develop could be used in other studies facing sample selection or sequential choices. Further, our use of administrative data complements recent literature using large or innovative datasets to study recreation across multi-state regions (Cameron and Kolstoe 2022, Dundas and von Haefen 2020, English et al. 2018).

We also add to the existing literature on the costs of wildfire smoke. To contextualize the results of this study, we compare to several other studies on the costs of wildfire smoke. Most of these studies have used survey methods, healthcare costs, or have valued changes in mortality using the value of a statistical life (VSL). Richardson et al. (2012) report results from a survey following a large wildfire in Los Angeles County. They asked respondents about avoidance behavior during this fire, namely expenditures on air purifiers, as well as health outcomes and risk perceptions. They derive a WTP to avert one wildfire induced symptom day of $84 in 2009 dollars, or $102 when adjusted to 2020 dollars. We estimate the WTP to avoid an exposure day, rather than a symptom day. Taking the empirical estimate of $107 per trip, this translates to approximately $38 per day, based on an average trip length of 2.84 days.

We can also compare total welfare results to the literature. We estimate welfare losses of approximately $2.3 billion per year for recreation in the western United States. Miller et al. (2021) combined a VSL with estimates of mortality among elderly Medicare recipients due to wildfire smoke. They found between $6 billion and $170 billion in annual damages, in 2021 dollars. These results mainly vary due to assumptions on remaining years of life, since their sample is comprised largely of elderly individuals. When assuming that those who die from wildfire smoke would have lived an additional 3.5 years, they arrive at a lower bound of $6 billion. Borgschulte et al. (2022) found annual lost labor earnings of $125 billion per year, in 2018 dollars, due to wildfire smoke. Several other studies have found costs of wildfire smoke for test scores, crime, and hospital visits (Burkhardt et al. 2019, Cullen 2020, Wen and Burke 2021).

Estimating these costs can inform public policy. The federal government spends an average of $2.8 billion per year on fire suppression, and the State of California spends $900 million per year on suppression.[28,29] Wildfires destroy thousands of structures per year, which has cost tens of billions of dollars in recent years (Baylis and Boomhower 2021, Buechi et al. 2021). Both states and the federal government have pledged to increase fuels treatment projects to mitigate the risk of fire ignition and spread. California has jointly declared a goal with the US Forest Service to treat more than 1 million acres of hazardous vegetation per year.[30] Consistent with this goal, California has proposed to spend $1.2 billion across Fiscal Years 2022-23 and

[28] National Interagency Fire Center. Suppression Costs. `https://www.nifc.gov/fire-information/statistics/suppression-costs`.

[29] California Department of Forestry and Fire Protection. Suppression Costs. `https://www.fire.ca.gov/stats-events`.

[30] Agreement for shared stewardship of California's forest and rangelands between the State of California and the USDA Forest Service, Pacific Southwest Region. `https://www.gov.ca.gov/wp-content/uploads/2020/08/8.12.20-CA-Shared-Stewardship-MOU.pdf`.

2023-24 for fire mitigation activities such as vegetation management and home hardening.[31] Understanding the cost of wildfires is crucial to assess the benefit of these public policies. Our study contributes to a growing understanding of the costs of wildfire smoke.

[31] California Legislative Analyst's Office. The 2022-23 Budget Wildfire and Forest Resilience Package. https://lao.ca.gov/Publications/Report/4495.

Chapter 2

Wildfire, smoke, and outdoor recreation in the western United States

2.1 Introduction

Outdoor recreation on public lands in the United States has never been more popular. National parks saw 327.5 million visitors in 2019, and the six highest-visitation years on record were 2014–2019 (NPS 2019a). Visits to Bureau of Land Management (BLM) sites, such as national monuments and national conservation areas, rose by 20% over the past ten years (BLM 2019). In the western United States, where more than half the land is owned by the federal government and many of the most famous national parks are located (including the Grand Canyon, Glacier, Yellowstone, and Yosemite), outdoor recreation is a significant economic driver. In Montana, for example, outdoor recreation accounts for 5% of state GDP, compared to 2.2% nationally (BEA 2019).

As outdoor recreation has increased in popularity, wildfires in the American West have become more frequent and more severe (Abatzoglou and Williams 2016, Westerling 2016, Crockett and Westerling 2016). Wildfires pose a problem for outdoor recreation for three reasons. First, they frequently burn on public lands used for recreation, in some cases impacting visitor experiences for years into the future (Englin et al. 2001, Hesseln et al. 2003, Hilger and Englin 2009). In 2018, 63% of the acreage burned in wildfires in the western United States was on federal lands (Hoover and Hanson 2019). Second, fire season coincides with outdoor recreation season. Approximately 48.5% of visits to national parks in 2018 occurred between June and September, which overlaps with peak wildfire season in many parts of the western US (NPS 2019b). Third, outdoor recreationists spend large amounts of time outside. Recent estimates indicate that up to half of $PM_{2.5}$ exposure in some parts of the western United States is attributable to wildfire smoke (Burke et al. 2021). Exposure to unhealthy air quality from wildfire smoke can reduce enjoyment of the recreation activity, lead to respiratory health problems, and offset the health benefits of physical activity (Korrick et al. 1998).

Much of the literature on wildfire and outdoor recreation has focused on the impacts that a fire-damaged landscape has on recreation in the years after a fire. Using a combination of recreation site visit data and responses to survey questions about visitation under hypothetical fire conditions, studies have examined how various fire characteristics, such as size, severity, and age, affect the frequency of trips and the value of outdoor recreation (Englin et al. 2001, Hesseln et al. 2003, Loomis et al. 2001, Hesseln et al. 2004, Starbuck et al. 2006, Boxall and Englin 2008, Sánchez et al. 2016). These studies typically focus on relatively small geographic areas and a limited number of fires, or sometimes a single fire event. Two studies have used multiple years of national park visitation data to analyze how fire affected visitation in Yellowstone National Park (Duffield et al. 2013) and five national parks in Utah (Kim and Jakus 2019). Some studies have used the effects of fire as a way to assess the value of forest characteristics, including forest age (Englin et al. 2006).

The effect of wildfire smoke on recreation has received decidedly less attention. Two studies collected survey data to analyze how outdoor activity, including exercise and recreation, changed in response to a wildfire event (Richardson et al. 2012, Fowler et al. 2019), but these studies were focused in urban areas. We are aware of only one study focused on evaluating the impact of wildfire smoke on outdoor recreation away from home, a recent paper that used a case study and survey approach to evaluate changes to public lands users' recreation experiences and trip planning (White et al. 2020). A few studies have examined effects of air quality on recreation. For example, a 2018 study using monthly visitation data found that air pollution is about as severe in some national parks as in US urban areas, and that it negatively affects visitation (Keiser et al. 2018).In a study of the effect of smog alerts on outdoor recreation in southern California, Graff-Zivin and Neidell (2011) found that residents make short-run adjustments to shift outdoor activities from days with smog alerts to days with better air quality. However, the specific effects of wildfire smoke on outdoor recreation are largely unexplored, and several studies show that exposure to particulate matter (PM) from smoke has different effects on health outcomes and behavior than exposure to PM from typical urban sources (Kochi et al. 2010).

We combine daily observational data on outdoor recreation over a ten-year period across the western continental United States, daily satellite data on wildfire burn areas and smoke plumes, and ground-level air quality monitoring data. We assess the impact of wildfire and smoke on outdoor recreation across a large region and multiple fire events. Our recreation data are drawn from the Recreation.gov website, which is used to make reservations for a variety of activities at more than 3,700 federally managed facilities across the United States. We focus on camping, one of the most popular nature-based recreation activities and the source of most reservations in the Recreation.gov system. Camping has relatively high smoke exposure, given the many hours campers spend outdoors. Our data include camping reservations and walk-in registrations at more than 1,000 individual campgrounds in the western United States on each day of the year from 2008 through 2017 and information on reservation cancellations and early check-outs.

We address two main research questions. First, we ask how many people are directly affected by wildfires and wildfire smoke each year while camping on public lands in the western United

States. Using these estimates, we calculate the share of total camper-days affected by wildfires and smoke and the spatial variation of the impacts across the region. The daily data from the Recreation.gov system allows us to calculate the first comprehensive estimates of fire and smoke impacts on outdoor recreationists. Compared to other data sources, which are often either survey-based and limited geographically or aggregate monthly or annual data, Recreation.gov provides daily counts of visitors at specific latitude-longitude locations (the locations of their reserved campgrounds). Not only does this give us a better understanding of the number of individuals in a recreation area at a given time, but once merged with daily data on fire and smoke, it allows us to estimate smoke and fire impacts at a much finer spatial resolution than in previous research. In addition to quantifying the number of campers affected, we combine our data with broader monthly visitation data for the national parks in our sample to estimate the total number of all visitors (not just overnight campers) at national parks affected by fire and smoke.

Second, we ask how fire and smoke alters campground use. Specifically, using panel fixed effects regression models, we analyze the following outcomes at the individual campground level: (i) campground occupancy rates, (ii) trip cancellation rates prior to arrival, and (iii) trip cancellation rates after arrival. The estimates from these models provide evidence on the extent to which people alter their recreation plans to avoid fire and smoke, and the first causal estimates thus far on the effects of wildfire smoke on outdoor recreation behavior. Our daily campground use data are particularly valuable for estimating impacts of wildfire smoke on visitation since wildfire smoke may be transient and short-lived.

Our analysis reveals that 124,000 campground visitor-days per year, on average, were within 20 kilometers (km) of an active wildfire over our ten-year sample period and nearly 400,000 campground visitor-days per year were affected by air pollution from wildfire smoke. Seventy percent of the campground visitor-days affected by fire and 42% affected by adverse smoke conditions were in California, highlighting both the prevalence of wildfire and popularity of outdoor recreation on public lands in the state. The northern states of Montana, Idaho, Washington, and Oregon accounted for only 16% of the campground visitor-days affected by fire but 38 % of the visitor-days affected by smoke, underscoring the tendency of smoke to travel long distances with prevailing winds from south to northeast. Moreover, because of the shorter outdoor recreation season in the north, these four states had the greatest share of campground visitor-days affected by smoke, 7% over the ten-year period. A total of 392,000 national park visitor-days per year were near a wildfire, and 1 million park visitor-days per year were affected by air pollution from wildfire smoke.

Finally, our regression results show statistically significant impacts on campground occupancy rates and cancellation rates from fire and smoke. When a fire is within 20 km of a campground, the occupancy rate drops 6.4 percentage points, on average, and cancellation rates before arrival more than double. The magnitudes of the smoke impacts are comparatively small, however. The occupancy rate falls by only 1.3 percentage points under adverse smoke conditions. We attribute this small effect, in part, to the challenge of finding an open campsite at many national parks in the peak summer months (Walls et al. 2018). Cancelling a trip because of smoky conditions may mean foregoing a visit for the entire season, which many travelers may be unwilling to do. Indeed, we estimate separate regressions by campground popularity quartiles and find that smoke has the smallest effect on occupancy rates in the most popular campgrounds. In a back-of-the envelope welfare calculation, combining our results with valuation estimates in the literature, we find that wildfire smoke causes welfare losses from smoke-related illnesses and avoided camping trips of approximately \$4.8 million per year. These losses are an underestimate of the full welfare loss, as they do not include the disutility of camping during smoky conditions. Nonetheless, they provide some sense of the welfare losses to outdoor recreationists from wildfire smoke—losses that are likely to rise as wildfire activity continues to escalate in the western United States.

2.2 Data and methods

2.2.1 Recreation data

We assembled a panel dataset comprising daily campsite reservations, proximity to active wildfires, and air-pollution-related smoke conditions at federally managed campgrounds. We source the data from Recreation.gov. Though not all federally managed campgrounds are reservable, and some sites are managed through alternative systems, Recreation.gov is the primary online system through which visitors can make and cancel reservations at federal campgrounds. We obtained historical data for 2008–2017 from the website managers. The complete database includes 90 million transactions by 7 million unique users of federal outdoor recreation facilities for each day of the year between 2008 and 2017. We focus on campground facilities in the 11 western continental US states, reducing the dataset to approximately 25 million transactions by 3.1 million unique users at 1,069 campgrounds managed by the US Forest Service, BLM, the US Army Corps of Engineers, National Park Service (NPS), and Bureau of Reclamation. Campgrounds in our dataset belong to 269 distinct "recreation areas," which include national parks, lakes, or reservoirs managed by the Army Corps of Engineers, ranger districts in national forests, and resource areas or districts managed by BLM.

Our dataset includes all transactions online, by phone, and on-site (such as walk-in reservations or early check-outs). For the western campgrounds in our analysis, 81% of transactions were made online, 10% over the phone, and 9% on-site. The dataset includes the date of each transaction, the scheduled arrival and departure dates, payments, dates of cancellation, group size, zip code of origin, and campground information. For most campgrounds, we do not observe whether the individual checked in to the campground on the scheduled date, so we cannot identify "no-shows" at all locations. However, campers have a financial incentive to cancel when plans change, mitigating this concern. They usually receive a full refund less a \$10 service fee if they cancel more than one day prior to the scheduled arrival date and a full refund less a \$10 service fee plus the cost of one night's stay when they cancel within one day of the scheduled arrival date. We aggregate reservation records from the individual campsites to the campground level to construct a daily panel of use measures for each campground in our dataset. Our measures of interest are the number of occupants, occupancy rate (i.e., the share of sites in use), and pre- and post-arrival cancellation rates (the number of reservations cancelled prior to arrival and during the stay, respectively, as a share of all reservations). Appendix B.1 provides more information about the construction of the dataset from the raw Recreation.gov database.

For every campground we determine the number of daily occupants based on the number of uncancelled reservations. We measure the occupancy rate on date t as the proportion of campground sites that are reserved (and for which reservations have not been cancelled) on date t. Formally, the occupancy rate variable is (occupied campsites$_{it}$)/(total number of campsites$_{it}$). The occupancy rate provides a measure of overall site use, which we expect will decline during nearby wildfire activity or periods of heavy smoke, due to both decreases in new reservations and increases in cancelled reservations. Appendix B.1 describes how we calculate the total number of campsites (the denominator in the occupancy rate variable) for each campground on each day.

We also consider two measures of cancellations. The pre-arrival cancellation rate is the number of cancelled reservations as a share of total reservations for arrival date t. We consider only the cancellations that occurred within one week of arrival, because these trips are most likely to be influenced by current and anticipated fire and smoke conditions.

Visitors may also decide to end their visit early in response to fire or smoke. Therefore, for each campground, we also measure the post-arrival cancellation rate as the number of cancellations made on date t for visits that began prior to date t and had a scheduled departure date after day t, calculated as a share of the number of occupants at the campground on day t.

In a supplementary analysis, we estimate the total number of national park visitors (campers and noncampers) exposed to fire and smoke. For this analysis, we use data from NPS Visitor Use Statistics, which provide monthly visitation data for individual national parks (NPS 2019a).

We combine these data with our estimates of calculated exposure of campground users to obtain an estimate of total numbers of national park visitors affected by fire and smoke.

2.2.2 Active fire and smoke data

Locations of active wildfires come from MODIS fire detection data (Giglio et al. 2016). MODIS is an instrument aboard NASA's Terra and Aqua satellites capable of detecting fire activity. MODIS fire detection data provide centroids of 1 km observations with a temporal resolution of 1–2 days for all observed fire activity, including agricultural burning and prescribed fires. We restrict fire detections to those associated with wildfires by selecting those near in space (within 1 km) to and occurring during the same time as wildfires in the USGS Monitoring Trends in Burn Severity (MTBS) dataset, which maps perimeters of wildfires larger than 1,000 acres in the western United States (Eidenshink et al. 2007). An advantage to using this modified MODIS dataset, rather than simply the final fire perimeters from MTBS, is that MODIS data more reliably identify the period during which fires are actively burning. We measured the distance between each campground and the nearest active wildfire for each date in the study period and used that distance to identify campgrounds that were within 20 km of an actively burning fire on each date. In Appendix B.2, we show results for alternative distances.

Days with adverse smoke conditions are based on data from the NOAA HMS and the US Environmental Protection Agency (EPA). Since 2005, NOAA analysts have used imagery from GOES satellites to map smoke plume boundaries. Usually twice a day—once in the morning and once in the evening—analysts use 2–4 hour satellite imagery animations to trace polygons delineating the boundary of each smoke plume they observe. They identify each plume as low, medium, or heavy smoke. The NOAA HMS smoke product has been used recently in studies of smoke's contribution to air pollution and air pollution's effect on crime (Preisler et al. 2015, Burkhardt et al. 2019). A disadvantage of the NOAA HMS smoke data is that because plumes are identified based on aerial imagery, and smoke may be high in the air column, they do not necessarily identify locations with poor on-the-ground air quality. We combine the smoke data with data provided by Burkhardt et al. (2019), who interpolate EPA daily surface-level $PM_{2.5}$ monitoring data to a 15 km grid using kriging, a geostatistical spatial interpolation method that has been shown to be effective for air quality data over large areas (e.g., Jerrett et al. 2005). The data and interpolation method are described in detail in Burkhardt et al. (2019). Following their approach, we calculate seasonal means and standard deviations of air quality on days that each cell is not covered by a smoke plume. We then identify air-quality-impacted smoke days as days on which a campground is covered by a smoke plume and $PM_{2.5}$ is at least 1.64 standard deviations above the within-cell seasonal mean for nonsmoky days, which represents the 95th percentile of a normal distribution. This method eliminates many of the areas covered by smoke plumes because they fall below the 95th percentile for $PM_{2.5}$. In Appendix B.2, we show results for an alternative, less conservative, assumption using only the smoke plume data without the adjustment from the ground-level monitors.

2.2.3 Quantification of total wildfire and smoke impacts on outdoor recreation

The first part of our analysis involves a spatial merge of the campgrounds in our dataset with the wildfire data and combined smoke plume-$PM_{2.5}$ monitor data to calculate the total number of campground-days near wildfires and affected by adverse smoke conditions over the 2008–2017 sample period. Using the total number of days the campground is open (as described in Appendix B.1), we then calculate the share of campground-days affected by fire and smoke in each year.

Using the reservation data from Recreation.gov, we tally the sum of campers at each campground on each day in our sample. An individual camper that visits a park for one day is tallied as a single camper-day. We merge the daily camper-days panel with the wildfire, smoke, and $PM_{2.5}$ data at the campground level and estimate the total number, and share, of camper-days affected by fire and smoke over the ten-year sample period.

Finally, we estimate the total number of national park visitor-days affected by fire and smoke by multiplying monthly visitor-days from the NPS Visitor Use Statistics database for each of the 30 national parks in our sample by the ratio of monthly camper-days affected to total monthly camper-days at each park.

2.2.4 Analysis of behavioral responses to fire and smoke

We estimate the effects of wildfire and wildfire smoke on camping behavior at campground i on date t using the following regression specification:

$$y_{it} = \beta^f fire_{it} + \beta^s smoke_{it} + \gamma precip_{it} + \phi temp_{it} + \psi_i + \delta_t + \lambda_{k(i),t} + \varepsilon_{it} \tag{2.1}$$

where y_{it} = {occupancy rate, pre-arrival cancellation rate, post-arrival cancellation rate} at campground i on date t; $fire_{it}$ is an indicator equal to 1 if a fire is within 20 km of campground i on date t; $smoke_{it}$ is an indicator equal to 1 if campground i is affected by adverse smoke conditions on date t; $precip_{it}$ is the amount of rainfall, in millimeters, at the campground on date t; $temp_{it}$ is the normalized difference between the campground's temperature on date t and its ten-year average on that week of year, where the normalization is based on the standard deviation of temperatures for that week; ψ_i is a set of campground fixed effects; δ_t includes week-of-year and day-of-week fixed effects and indicators for federal holidays; and $\lambda_{k(i),t}$ includes recreation area by month-of-year and recreation area by year fixed effects. The fixed effects control for seasonal factors and unobserved campground and recreation area characteristics that drive occupancy rates and cancellations. The precipitation and temperature variables control for weather effects that might affect camping decisions and outcomes. Thus, our model isolates the impacts of fire and smoke by controlling for a variety of unobserved factors that could be correlated with both fire and smoke and campground use. Regressions are weighted by the number of campsites at campground i on date t to account for heteroskedasticity. Standard errors are clustered at the recreation area level to allow for errors to be correlated across campgrounds in the same area.

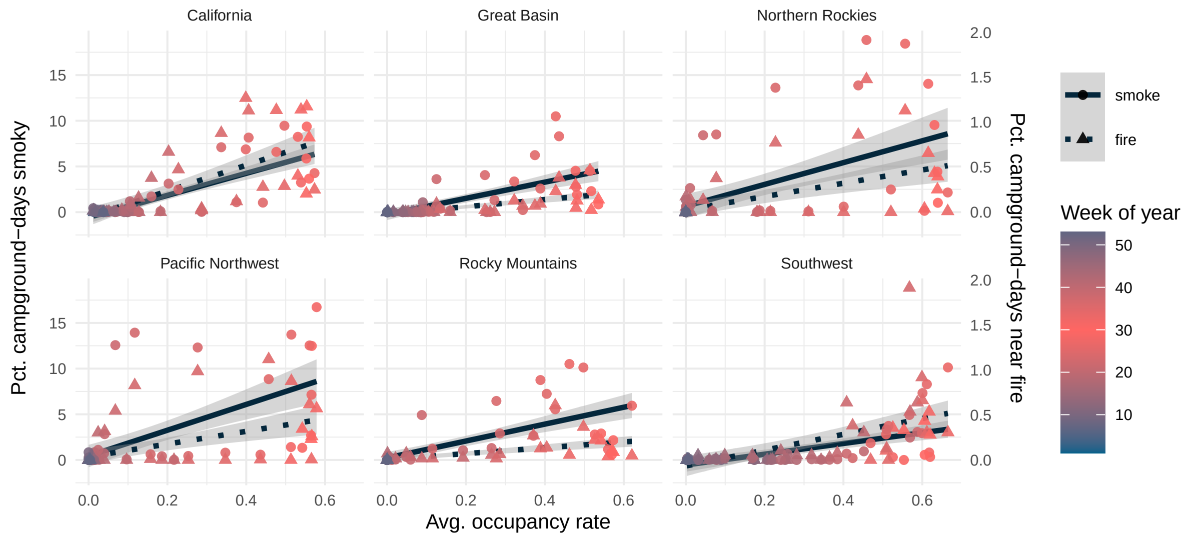
In Appendix B.2, we test distance bandwidths of 10 km and 30 km for the fire variable and relax our measure of adverse smoke conditions by using the smoke plumes data without the ground-level $PM_{2.5}$ readings adjustment.

2.3 Results

2.3.1 Campgrounds and campground visitor-days affected by wildfire and smoke

Consistent with our initial expectations, and the findings of previous literature, we find that increased recreational activity coincides with wildfire and smoke events. Participation in camping and other outdoor recreation activities on public lands is highly seasonal. Good weather, long hours of daylight, school holidays, and other factors lead most people to national parks and other recreation areas during summer months, when wildfires are most common. Figure 2.1 plots average campground occupancy rates within each week of the year against the frequency of campground-days with smoke (left y-axis) or a wildfire nearby (right y-axis) for six subregions of the western United States. Each triangle (fire) and circle (smoke) is colored by week—redder colors are closer to the middle of the summer, and bluer colors correspond to winter. In each region, higher occupancy rates are positively correlated with the fraction of campground-days that are smoky or near a fire; further, campground occupancy, fire, and smoke all coincide in the summer months.

Figure 2.1: Average overall campground occupancy and percentage of days with fire (triangles) and smoke (circles) within each region and week-of-year, 2008–2017. Solid and dotted lines show fitted values for fire and smoke, respectively, with shaded 95% confidence intervals. The six regions are defined in the text.



Campgrounds in our sample were near active burning fires (within 20 km) an average of 1.5 days per year, corresponding to 1.7% of the days those campgrounds were open (Table 2.1, panel I, columns 1 and 2). The frequency with which campgrounds experienced nearby fires varied across western subregions. In Southwest states (Arizona and New Mexico) and California, campgrounds experienced nearby fires more than two days per year on average, and the Rocky Mountains (Colorado and Wyoming) and Great Basin (Nevada and Utah) campgrounds had fires nearby an average of only 0.5 days per year. The result for California is relatively high because wildfires were common in the state. Fires were less frequent in the Southwest, but those that did occur were often close to federally managed campgrounds, especially the Grand Canyon. Within a larger distance of 30 km to the nearest fire, more campgrounds were affected: an average of 2.8 days per year, or 3.0% of the days campgrounds were open during the period (Appendix B.2).

Table 2.1: Annual campground- and camper-days near wildfires and with adverse smoke conditions, by region. Campground-days are the number of days campgrounds in each region were within 20 km of an active fire (Panel I) or had adverse smoke conditions (panel II). Camper-days multiply the number of days campgrounds in each region were affected by the number of campers at each campground on affected days. Each campground's total available campground-days are calculated as the number of days each year the campground had at least one occupant.

	Campground-days		Camper-days	
	Avg. annual days per campground	Percent total available campground-days	Avg. annual camper-days (thousands)	Percent total camper-days
I. Fire				
California	2.5	2.0	86	2.1
Great Basin	0.5	0.6	3	0.3
Northern Rockies	1.5	1.9	7	1.0
Pacific Northwest	1.5	2.2	13	0.9
Rocky Mountains	0.5	0.6	2	0.2
Southwest	2.1	2.0	14	1.8
Total	1.5	1.7	124	1.4
II. Smoke				
California	6	5	160	4
Great Basin	4	5	23	3
Northern Rockies	9	11	49	7
Pacific Northwest	9	12	95	7
Rocky Mountains	6	7	41	4
Southwest	4	4	15	2
Total	7	7	383	4

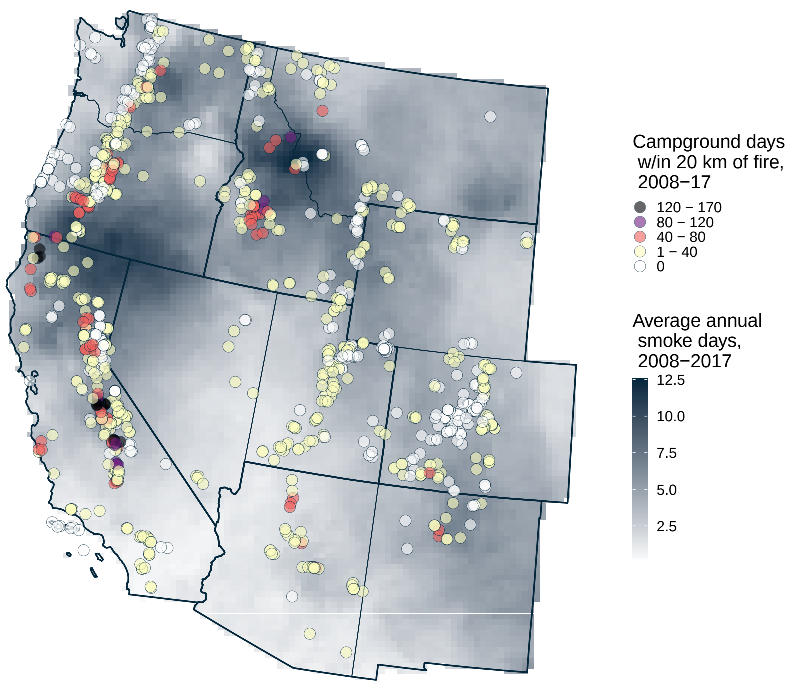
On average, 124,000 camper-days per year were within 20 km of an active wildfire, and 86,000 of these—nearly 70%—were in California (Table 2.1, panel I, columns 3 and 4). As a share of total camper-days, the number near an active fire ranged from an average of 0.2% in the Rocky Mountains to 2.1% in California; the overall average was 1.4%. If we relax the distance bandwidth to 30 km within an active wildfire, the number of affected camper-days rises to 218,000, and the percent of affected days rises to 2.5 (Appendix B.2).

In contrast to fire, smoke affects campgrounds and campers more often. On average, across the western states, campgrounds experienced adverse smoke conditions seven days per year, representing 7% of the days that campgrounds were open (Table 2.1, panel II, columns 1 and 2). Campgrounds in the Northern Rockies (Idaho and Montana) and Pacific Northwest states (Oregon and Washington) were especially affected, with 10 and 12% of campground-days, respectively, experiencing adverse smoke conditions. These subregions have actively burning wildfires less frequently than other regions, but prevailing wind patterns bringing smoke from fires in the south mean that they are disproportionately affected by smoke. Not only was the average number of smoky days higher than in other subregions, but the percent of available campground-days affected by smoke was much higher due to the shorter camping season in those subregions, particularly in the Northern Rockies.

Nearly 400,000 camper-days per year, on average, were under adverse smoke conditions during our sample period, with 160,000 in California (Table 2.1, panel II, columns 3 and 4). However, that number accounts for only 4% of all camper-days in California, much lower than the Pacific Northwest and Northern Rockies subregions. This difference likely owes to the comparatively longer camping season in California. By contrast, in the Northern Rockies, 7% of camper-days were under adverse smoke conditions. On average, across the western continental United States, 4% of camper-days had air quality impaired by wildfire smoke. These findings suggest that a nontrivial portion of the camping season is impacted by poor air quality due to smoke in many parts of the western United States.

Impacts show substantial regional heterogeneity. Figure 2.2 combines the fire and smoke information in a map of the western United States. The gray base map shows the average number of annual days with adverse smoke conditions on a 15 km by 15 km grid. Smoke is most frequent in northern California and southern Oregon and along the Idaho-Montana border. Markers represent the location of campgrounds, with colors denoting the total number of campground-days with a nearby wildfire (within 20 km) over the study period. The map shows that California has a higher number of fire-affected campground-days than most other states. Colorado, for example, has many campgrounds but few campground-days near a fire, and Eastern Oregon has many days with smoky conditions but few campgrounds.

Figure 2.2: Geographic distribution of smoke and fire impacts on campgrounds.



Although wildfire activity has increased in the western United States over the past several decades (Westerling 2016), we observed no clear trend in the number of campground-days near wildfires over 2008–2017 (see Figure B.2 in Appendix B.2). The 10-year study period is likely too short to observe longer term trends in campground impacts, especially given the substantial year-to-year variation in fire events.

2.3.2 National park visitor-days affected by wildfire and smoke

Campers are only a subset of all visitors at many federal recreation sites, particularly at national parks. Although we do not have daily data on all visitors, we can approximate the full impact of fire and smoke at national parks by combining our estimated fire- and smoke-affected camper-days with monthly total visitation data collected by the NPS. We find that, on average, 392,000 visitor-days per year at the national parks in our sample were close to active wildfires; Yosemite accounts for over half of this number (Table 2.2). Approximately 1 million visitor-days per year occurred during adverse smoke conditions, and these impacts were spread out across a larger number of parks. Once again, this highlights the wide-ranging effects of smoke across the region. Total visitor-days affected by fire and smoke exceed the numbers of camper-days at national parks by factors of 6 and 12, respectively.

Table 2.2: Annual camper-days and annual estimated total visitor-days near fire and with adverse smoke conditions at selected national parks. Camper-days are the number of days campgrounds in each region were within 20 km of an active fire or with adverse smoke conditions, multiplied by the number of campers at each campground on affected days. Estimated total visitor-days with fire and smoke are calculated by multiplying total smoke and fire camper-days per month at each NPS site by the ratio of total visitors to campers at each site in that month.

	Fire		Smoke	
	Camper-days per year (thousands)	Estimated total visitor-days per year (thousands)	Camper-days per year (thousands)	Estimated total visitor-days per year (thousands)
Yosemite National Park	47	206	40	175
Glacier National Park	2	51	7	159
Rocky Mountain National Park	0.009	0.8	7	110
Mount Rainier National Park	0	0	6	61
Grand Canyon National Park	9	91	4	43
Total (all parks in sample)	61	392	83	1000

2.3.3 Changes in recreation site use due to wildfire and smoke

Our results suggest a substantial number of people are affected every year by fire and smoke while recreating on public lands. In this section, we analyze the extent to which fire and smoke lead to averting behavior that affects campground use outcomes.

Table 2.3 displays summary statistics for the dependent variables of interest for estimation of equation 2.1 – campground occupancy rates and pre- and post-arrival cancellation rates (as defined above). Before controlling for other factors, Table 2.3 shows evidence of changes in recreation site use in response to fire and smoke. Column 1 reports means for a baseline scenario with no smoke or fire. Column 2 shows how mean occupancy and cancellation rates change when a fire is burning within 20 km. Column 4 reports mean values for dates with adverse air quality due to wildfire smoke. As expected, cancellation rates increase with fire or smoke. In contrast, occupancy rates are higher, on average, on dates with fire or smoke. This result may be because fire and smoke tend to occur during times of year that are popular for camping (Figure 2.1). This highlights the need for a regression analysis that controls for these temporal effects.

Table 2.3: Summary statistics for campground recreational activity. The t-stat reported is from a test of the difference in means relative to the baseline (no smoke or fire), clustering at the recreation area level. The smoke variable indicates whether a campground had adverse smoke conditions; the fire variable is for active fires within 20 km of a campground. The observations are restricted to May through September.

	Baseline Mean	Fire		Smoke	
		Mean	t-stat	Mean	t-stat
Occupancy rate	0.306	0.348	1.380	0.365	8.470
Pre-arrival cancellation rate	0.073	0.211	12.740	0.106	8.420
Post-arrival cancellation rate	0.002	0.021	7.400	0.004	4.110
No. of obs.	1,281,992	12,839		59,264	

Table 2.4 shows the results of estimating the model in equation 2.1. We find statistically significant evidence that campground use decreases and campground cancellations increase on smoky days and days when wildfires burn within 20 km. On days with nearby wildfires, the campground occupancy rate declines, on average, by 6.4 percentage points. With an average of 30.6% of campsites occupied in the baseline (Table 2.3), this indicates a drop to 24.6% when a fire is nearby. The pre-arrival cancellation rate increases by 8.7 percentage points with a

fire nearby, more than double the baseline average cancellation rate of 7.3%. The post-arrival cancellation (or early departure) rate increases by 1.3 percentage points, an order of magnitude greater than the baseline average post-arrival cancellation rate, which is only 0.2%. Using a relaxed bandwidth of 30 km for the nearest fire, we still observe statistically significant effects: a campground occupancy rate that is 4.2 percentage points lower and increases in pre-arrival and mid-stay cancellation rates of 6.1 and 0.8 percentage points, respectively (Appendix B.2).

Table 2.4: Estimated effects of wildfire and smoke on campground use. All columns include campground, recreation area by month-of-year, recreation area by year, week-of-year, and day-of-week fixed effects, as well as indicators for holidays and days before holidays. In addition, regressions control for the upcoming week's total precipitation. Campground observations are weighted by the number of campsites, and standard errors, shown in brackets, are clustered by recreation area. The observations are restricted to May through September. ** $p < 0.01$.

	Occupancy rate	Pre-arrival cancellation rate	Post-arrival cancellation rate
Fire	-0.064**	0.087**	0.013**
	[0.011]	[0.012]	[0.0019]
Smoke	-0.013**	0.023**	0.0014**
	[0.0022]	[0.0023]	[0.00037]
Mean of dep. var.	0.31	0.076	0.0024
No. of obs.	1,349,460	688,653	842,240
R^2	0.72	0.047	0.13

Our estimates for the effect of fire on recreation do not distinguish among several channels through which fires affect campground use. During fire events, campgrounds may close, causing reservations to be cancelled by the managing agency. Fires can also result in road closures, and even if roads remain open, campers may cancel if they are worried that further fire spread might disrupt their plans. We interpret our estimates of the effect of fire on campground use as inclusive of each of these channels.

The estimated effects of smoke on camping decisions are more modest (Table 2.4). On days with adverse smoke conditions, occupancy rates decline by only 1.3 percentage point (from

30.6% of campsites occupied to 29.3% for the average campground). Pre-arrival cancellation rates rise by approximately 2.3 percentage points (a 32% increase from the baseline average cancellation rate of 7.3), and post-arrival cancellation rates rise by one-tenth of a percentage point (nearly a 50% increase from the baseline rate). When using only smoke plumes to identify smoky days, estimated effects of smoke on occupancy and cancellation are more modest but remain statistically significant in most cases (Appendix B.2).

Campgrounds and roads do not typically close due to smoke; therefore, we interpret changes in campground use as indicative of avoidance behavior on the part of campers. This behavior may be driven by concern over health impacts of exposure to smoke or by decreased amenity values due to diminished views. Regardless of motivation, we find that the magnitude of the resulting changes in total campground use is, on average, relatively small.

The detail provided in our daily damping data allowed us to further investigate differential avoidance behavior responses based on specific recreation areas. We posit that visitors could be more willing to camp during adverse conditions at a popular location like Glacier National Park relative to a smaller local campground. Limited visitation seasons at northern parks like Glacier, as well as competitive reservations at popular parks like Yosemite, could lead campers to brave the smoky conditions rather than forego a trip altogether. To test for heterogeneous responses, we ran a version of the regression that allows responses to fire and smoke to vary according to campground popularity. To determine popularity, we measured campgrounds' historical average occupancy rates and segmented the results into quartiles (Table 2.5). In line with our hypothesis, the occupancy rate was less responsive to smoke at the most popular campgrounds (the top occupancy quartile) than at less popular ones. We found no statistically significant differences in cancellation rates in response to smoke by site popularity, however.

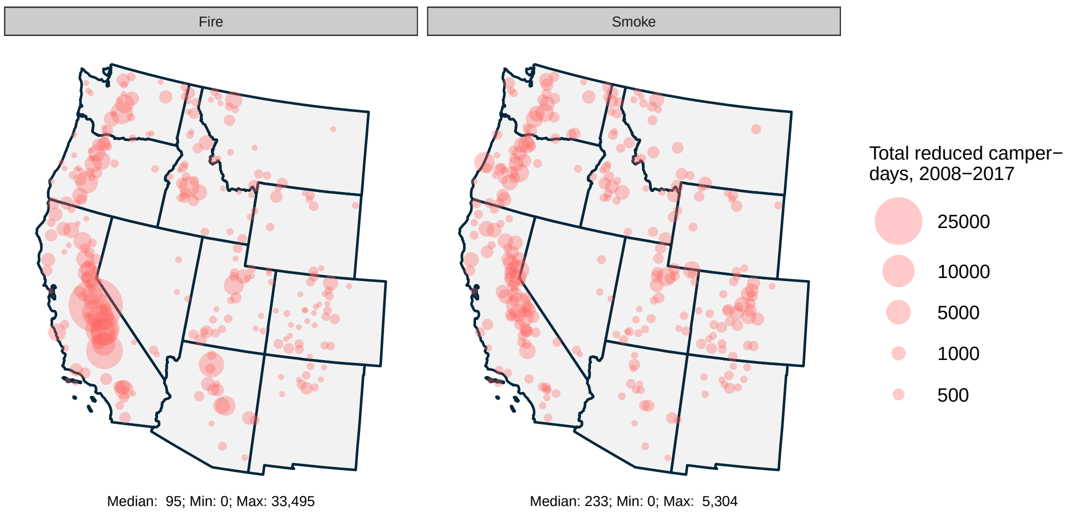
Table 2.5: Heterogeneity in responses to wildfire and smoke by popularity of campground. All columns include campground, recreation area by month-of-year, recreation area by year, week-of-year, and day-of-week fixed effects, as well as indicators for holidays and days before holidays. In addition, regressions control for the upcoming week's total precipitation. Campground observations are weighted by the number of campsites, and standard errors, shown in brackets, are clustered by recreation area. The observations are restricted to May through September. Quartiles based on campground popularity as measured by mean occupancy rates over the sample period on days when campground is open. ** $p < 0.01$; * $p < 0.05$.

	Occupancy rate	Pre-arrival cancellation rate	Post-arrival cancellation rate
Fire	-0.029*	0.112**	0.014**
	[0.011]	[0.024]	[0.004]
Smoke	-0.030**	0.022**	0.0005
	[0.004]	[0.004]	[0.001]
Fire x first quartile (most popular)	-0.044*	-0.048	-0.005
	[0.022]	[0.026]	[0.005]
Smoke x first quartile	0.027**	0.002	0.002*
	[0.007]	[0.005]	[0.002]
Fire x second quartile	-0.047*	0.01	0.01
	[0.021]	[0.031]	[0.007]
Smoke x second quartile	0.031**	-0.001	0.001
	[0.007]	[0.005]	[0.001]
Fire x third quartile	-0.047	0.016	0.007
	[0.025]	[0.031]	[0.005]
Smoke x third quartile	0.014*	-0.001	0.0003
	[0.006]	[0.004]	[0.001]
Mean of dep. var.	0.31	0.076	0.0024
No. of obs.	1,349,460	688,653	842,240
R^2	0.72	0.048	0.13

Responsiveness to fire was greater at more popular sites. Figure 2.3 uses our estimated regression results from Table 2.4 to map total declines in the number of camper-days due to fire and smoke over the course of the study period. We calculate declines in the number of campground-days due to fire (smoke) by multiplying the estimated fire (smoke) coefficient in the occupancy rate regression by the product of the average number of occupied sites at each campground on days without fire (smoke), the average number of campers per campsite at each campground, and the average number of days per year with fire (smoke) at each campground.

We aggregate these campground figures to the recreation area level, which are the numbers shown on the map. Because fires tend to occur during times of year with greater occupancy (Figure 2.1), we expect that these estimates understate total reductions in campground use due to fire and smoke.

Figure 2.3: Geographic distribution of recreational responses to smoke and fire.



The figure highlights several key findings. First, although fires occur infrequently at many locations, our regression results suggest that the marginal effects of fire on recreation behavior are relatively large. As a result, fires have large effects compared to smoke. This shows up as large circles on the fire maps, which are mainly in California—Yosemite in particular.

Second, although fire has much larger effects in some locations than others, the magnitude of the smoke effects is more consistent across locations. Fire caused much greater decreases in visitation than smoke at the most impacted campgrounds, but the median campground experienced 259 fewer camper-days per year on average due to smoke and only 95 fewer camper-days per year on average due to nearby fires. In subregions with comparatively few fires—namely, the Pacific Northwest and the Northern Rockies—smoke is still prevalent and has a similar impact on recreation behavior as in other locations.

Third, the consequences of fire and smoke for changes in recreation site use over the 10-year period are low to moderate in most places, but we see large impacts in some regions and years. In Yosemite, the recreation area most impacted by fire, nearly 3,400 camper-days each year were lost due to fires. These impacts were not spread evenly across years. In 2012, the year of the Cascade fire, which struck Yosemite and surrounding areas in June and July, we estimate more than 8,500 fewer camper-days due to nearby fire. Smoke also had its greatest effects in Yosemite: campers spent 590 fewer days per year there, on average, as a result of adverse smoke conditions.

We can combine our estimates of the reductions in camper-days from fire and smoke with consumer surplus values for outdoor recreation estimated in the literature to obtain a back-of-the-envelope estimate of the total annual consumer surplus loss to campers who forego their trips because of fire or smoke. Rosenberger et al. (2017) provide a review and summary of estimates of the value of fourteen outdoor recreation activities, including camping, on US Forest Service lands by region. Kaval and Loomis (2003) provide similar estimates for national parks, also by region. We combine the mean values from these two studies, which are per activity day per person, with our predicted declines in camper-days, and inflate to 2020 dollars. The consumer surplus loss from fire and smoke across the 11 western states in our study averages $1.3 million and $662,000 per year, respectively. Seventy-five percent of the consumer surplus loss from fire and 41% of the loss from smoke occurs in California.

In addition to losses from recreationists who forfeit their trips, there are also losses experienced by recreationists who continue with their plans but experience health effects or visual disamenities from smoke. Richardson et al. (2012), using survey data from households in the Los Angeles area after a major fire, estimate an average cost of smoke-related illness (costs of medications, doctor visits, and missed workdays) per exposed person per day of $9.50. Inflating to 2020 dollars and multiplying by the average number of camper-days affected by adverse smoke conditions per year (383,000, from Table 2.1), we estimate illness costs of $4.1 million per year. This may be an underestimate since our adverse smoke conditions measure is conservative and omits some days with low density smoke, which nevertheless may impact health.

Using the average number of camper-days per year that intersect a smoke plume (1,588,000, from Table B.1) in place of the average number of camper-days with adverse smoke conditions, we estimate illness costs of approximately \$15.1 million per year. Adding these costs to the losses from avoided trips gives a total losses of \$4.8-\$15.8 million per year from wildfire smoke. This calculation is back-of-the-envelope and underestimates the full welfare losses to exposed campers as it only includes cost of illness and not the diminished value of the trip. Nonetheless, it provides some sense of the magnitude of the welfare impacts from wildfire smoke experienced by campers on public lands.

2.4 Discussion

Increases in the popularity of outdoor recreation and increases in visitation to western public lands in the United States are coinciding with another trend: the rising number and size of wildfires. Our study, which merged detailed daily camping data at 1,069 western campgrounds with spatial wildfire, smoke plume, and air quality data over a 10-year period, documents the extent of the impacts nearby actively burning wildfires and wildfire smoke have on outdoor recreation in the region, and provides causal estimates for how outdoor recreationists respond to fires and smoke. Importantly, we provide the first estimates of wildfire smoke impacts on recreation on public lands across the continental western United States. Smoke, which disperses over great distances, affects many more people than fire itself. We calculated that 383,000 camper-days per year, on average, took place under adverse smoke conditions, or 4% of all camper-days. Using monthly visitation data for the 27 national parks in our sample, we scaled the camping results and estimated that approximately one million national park visitor-days per year, on average, were potentially affected by smoke over the 10-year sample period. As our data exclude a few national parks in the region, this is likely to be an underestimate of the full effects of smoke on national park visitors.

We found that campground use declines in response to fire and smoke. The magnitudes of the estimated adjustments were relatively small, however. Average occupancy rates, for example, decline by 6.4 percentage points for a fire within 20 km and only 1.3 percentage points for adverse smoke conditions. Effects on recreation site use on particularly threatening days (when a fire is very close by or air quality is especially poor) are likely to be greater. Moreover, measurement error may bias these estimated effects downward to some extent. Campers may change their plans without cancelling their reservations, so that we are counting some visits that do not occur. We feel that the magnitude of this error is likely to be small, however, as we observe cancellations in the data and the refund policy provides a financial incentive to cancel.

The minimal effects of fire and smoke on campground usage may be a consequence of constraints on either vacation times or campground availability. As shown in Walls et al. (2018), it is challenging to find an open campsite at many national parks in the peak summer months, so cancelling a trip because of smoky conditions may mean foregoing the entire season. Indeed, we find that the effect of smoke on the average occupancy rate is attenuated in the most popular campgrounds (Table 2.5).

Unfortunately, this lack of behavioral response by campers may mean significant exposure to poor air quality. The contribution of wildfire smoke to $PM_{2.5}$ concentrations in the United States has increased substantially since about the mid-2000s, now accounting for approximately half of overall $PM_{2.5}$ exposure in the western United States (Burke et al. 2021). The literature finds consistent evidence of an association between wildfire smoke and general respiratory health effects, especially exacerbation of asthma and chronic obstructive pulmonary disease, as well as an association between smoke and increased risk of respiratory infections and all-cause mortality (Reid et al. 2016; Cascio 2018). Because camping involves extended time outdoors and is often accompanied by strenuous activities, such as hiking, recreational campers are likely to be particularly at risk of health impacts in smoky conditions. Some studies have found that the negative health effects of elevated levels of air pollution can offset the benefits of exercise (Korrick et al. 1998, Guo 2020).

In addition to health impacts, smoke can cause haze and reduced visibility. For visitors to scenic public lands in the western United States, especially signature national parks, such as Grand Teton, Glacier, and the Grand Canyon, reduced visibility can significantly lower the value of the visit. Stated preference survey studies of visibility in national parks have found that improved visibility is highly valued (Rowe et al. 1980, Schulze et al. 1983). One study found that survey respondents would pay about \$120 per year in the southeastern United States and about \$80 per year in the Southwest for visibility improvement programs that would remove the 20 percent worst visibility days (Boyle et al. 2016). A separate study in southwestern British Columbia found that survey respondents were willing to pay \$92–\$112 per year per household (in 2002 Canadian dollars) for a 5–20% improvement in visual range (Haider et al. 2019). The authors apply these estimates to the number of poor visibility days due to wildfire in July and August of each year from 2002 through 2018 and calculate that the value of improving those days from "poor" to "excellent" would total \$120 million over the 17-year period.

US federal land management agencies could consider several policies to reduce the impacts that wildfires and associated smoke have on outdoor recreation. These policies can focus on lowering the threat of fire or increasing the ability of outdoor recreationists to adapt. Lowering the threat can be achieved through mechanical thinning of forests, prescribed burns, and managed wildfires (Kalies and Kent 2016). These activities work in areas where heavy fuel loads have contributed to increasing wildfire activity. Although prescribed burns and managed wildfires produce smoke, they can be used opportunistically during times of the year with minimal impacts on human activities, including outdoor recreation. Prescribed burns also reduce future wildfire activity (Cochrane et al. 2012). While these land management strategies are routinely used by agencies to reduce wildfire hazard, their pace and scale needs to increase dramatically to result in substantial reductions in wildfire hazards and impacts to recreationists and the regions outdoor recreation economy (Clavet et al. 2021).

Adaptation can take the form of shifts in the location and timing of visits to public lands to reduce exposure. To encourage these behavioral adjustments, recreationists may need a "nudge." As one example, land managers could employ flexible pricing strategies across peak and nonpeak camping seasons by region that could be coupled with other incentives to visit less fire- and smoke-prone locations during peak fire season. In addition, increasing the supply of campsites in less risky locations could help. With wildfires predicted to increase with climate change and outdoor recreation on public lands more popular than ever, policymakers will need to devise creative strategies to both reduce the likelihood and severity of fires and mitigate their impacts on outdoor recreationists.

Chapter 3

Wildfire smoke in the United States

3.1 Introduction

Wildfire activity is increasing in the western United States, and associated smoke emissions have led to increased particulate pollution across the country. Smoke travels thousands of miles, creating dangerous air quality both in the western United States and in other regions. As the climate warms over the 21st century, these impacts are expected to increase.

Research has documented significant impacts of wildfire smoke to human health, well-being, and the economy. Smoke emissions produce numerous pollutants, including carbon monoxide (CO), nitrogen dioxide (NO_2), nitrogen oxides (NOx), ozone (O_3), volatile organic compounds (VOCs), and particulate matter with diameter less than 2.5 μg ($PM_{2.5}$) and 10 μg (PM_{10}) (Cascio 2018, Reid et al. 2016). Many of these pollutants are criteria pollutants in the Clean Air Act (CAA), but are regulated only for urban and industrial sources.

In this feature we discuss economic and social science research on wildfire smoke in the United States. In Section 3.2 we first summarize national and regional smoke trends, while highlighting how smoke affects communities differently than ambient pollution from urban and industrial sources. Section 3.3 surveys the growing literature on the impacts of wildfire smoke to human health, the economy, well-being, and behavior. In Section 3.4 we argue that current federal policy creates barriers to management activities that could mitigate wildfire smoke, and argue for solutions.

3.2 Wildfire smoke trends

Wildfire smoke pollution is increasing in the United States. This trend has been documented by a combination of on-the-ground air quality monitoring, satellite-derived wildfire smoke images, and machine learning approaches. Smoke pollution is currently undermining federal air quality goals, and impacts are expected to increase with climate change. Pollution from these smoke events is consequential for both indoor and outdoor air quality, and it has affected subpopulations differently than $PM_{2.5}$ from industrial air pollution sources.

Wildfire smoke has accounted for up to 25% of $PM_{2.5}$ in recent years across the United States, and up to half in some areas of the western United States (Burke et al. 2021, O'Dell et al. 2019). Although overall levels of ambient $PM_{2.5}$ pollution had previously been declining for several decades, wildfire smoke pollution has reversed those trends for 31 states (Burke et al. 2023). The presence of smoke increases daily county-level $PM_{2.5}$ concentrations by an average of 1.0 to 4.0 μg/m3 (Borgschulte et al. 2022, Burke et al. 2022, Childs et al. 2022, Miller et al. 2021). However, this increase can exceed 10 μg/m3 (1.5% of smoke days), 20 μg/m3 (0.3% of smoke days), or even 100 μg/m3 (0.01% of smoke days) (Childs et al. 2022). From 2011 to 2022, wildfire smoke caused at least 25% of daily exceedances over 35 μg/m3 in seven states, where 35 μg/m3 is the daily concentration threshold used as part of the CAA (Burke et al. 2023). Figures 3.1 and 3.2 illustrate the increasing trend of wildfire smoke in the United States. Smoke emissions from wildfires are expected to increase over the 21st century due to continuing climate-driven increases in fire activity (Burke et al. 2023, Hurteau et al. 2014, Liu et al. 2022).

Figure 3.1: Number of smoke days per year by county using Childs et al. (2022) data.

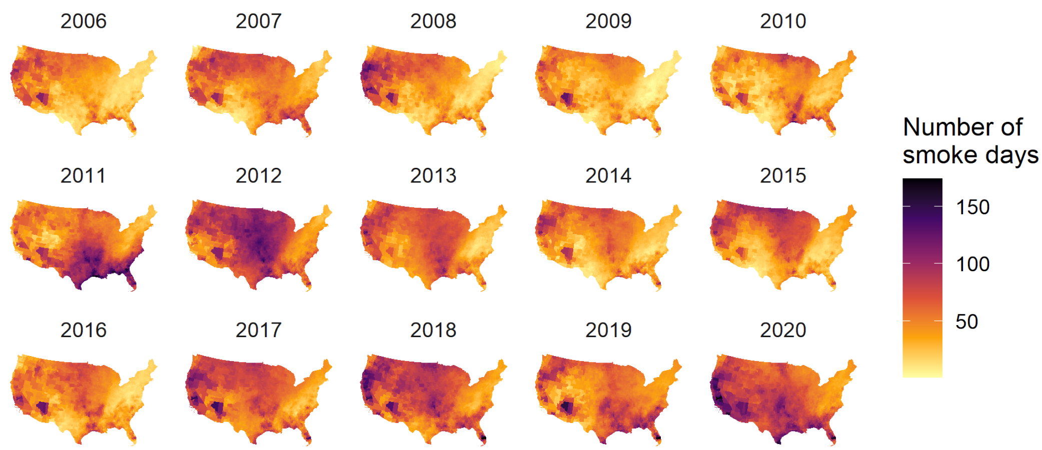
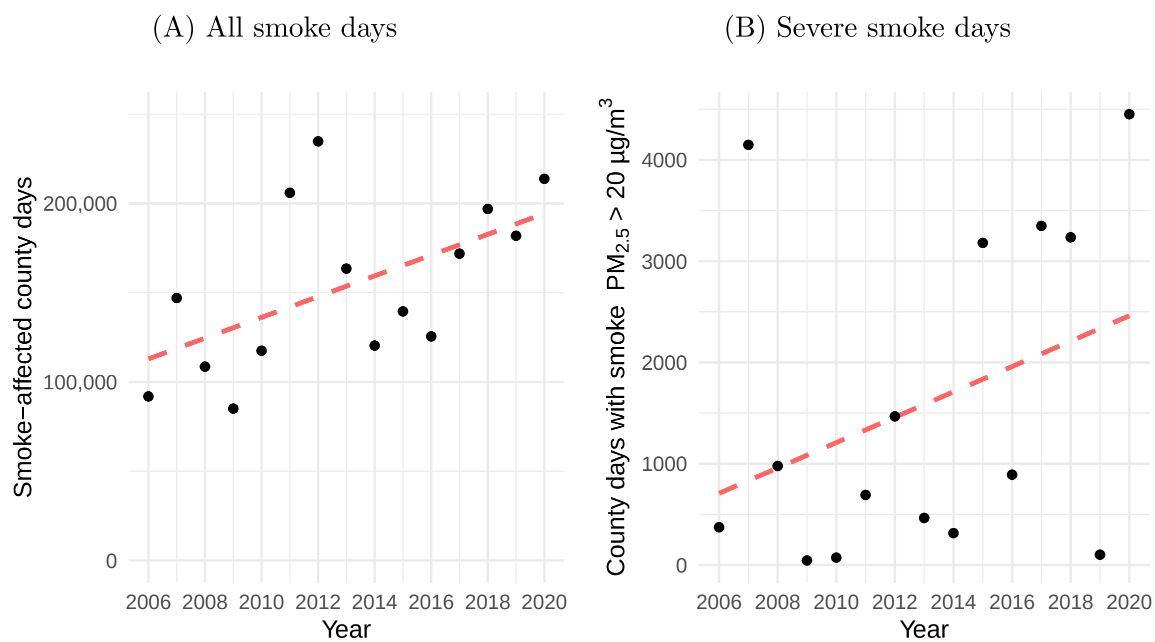


Figure 3.2: Trend in (A) smoke days and (B) severe smoke days using Childs et al. (2022) data.



This smoke pollution affects populations differently than $PM_{2.5}$ from ambient urban sources. A majority of experienced smoke $PM_{2.5}$ comes from sources outside the local jurisdiction, with 87% coming from fires in other counties and 60% from fires in other states (Wen et al. 2023). Most exposure has been concentrated in the western United States, especially the Pacific Northwest (Burke et al. 2021, Burke et al. 2023). Counties with greater shares of white residents are less exposed to overall $PM_{2.5}$, but are more exposed to $PM_{2.5}$ from smoke; however, exposure is uncorrelated with income (Burke et al. 2021, Burke et al. 2022).

The degree of vulnerability to this exposure does vary across populations, in part due to differences in time spent outdoors and due to differences in impacts on indoor air quality (Liang et al. 2021, Marlier et al. 2022, O'Dell et al. 2022, Wen and Burke 2022). In general, a 1 µg/m3 increase in outdoor $PM_{2.5}$ is associated with an increase in indoor $PM_{2.5}$ by 0.15 to 0.4 µg/m3 (Burke et al. 2022, Liang et al. 2021, O'Dell et al. 2022). Indoor air pollution can triple during smoke events and can exceed the 35 µg/m3 standard set by the Environmental Protection Agency (EPA), though infiltration varies by building type (Burke et al. 2022, Liang et al. 2021, O'Dell et al. 2022). These results suggest limited benefit to policies that focus on indoor sheltering as a response to smoke.

3.3 Impacts of wildfire smoke

The economics and natural science literatures have documented numerous impacts of wildfire smoke. These impacts include health effects, economic effects, and well-being effects. Smoke is salient; individuals engage in costly defensive behavior to avoid it.

3.3.1 Health effects

Most studies of health effects have focused primarily on the $PM_{2.5}$ from wildfire smoke, which has been found to be more toxic than $PM_{2.5}$ from general urban ambient $PM_{2.5}$ (Kochi et al. 2010, Aguilera et al. 2021). Smoke has numerous consequences for human health, including mortality, morbidity, and impacts on pregnancy, infants, and children. The majority of research, particularly in the economics literature, has limited attention to the short-term impacts of acute exposure to smoke.

Wildfire smoke has been found to increase mortality both globally and in North America (Cascio 2018, Johnston et al. 2012, Miller et al. 2021, Reid et al. 2016). While there is strong evidence for smoke's effect on all-cause mortality, more work is needed to clarify whether respiratory or cardiovascular disease is the main channel (Cascio 2018, Reid et al. 2016). Miller et al. (2021) estimated the increased mortality due to wildfire smoke among elderly Medicare recipients in the United States. Their average treatment effect suggests that a 1 μg/m3 increase in daily $PM_{2.5}$ increases elderly mortality by 0.62 deaths per million people over the following three-day period. They find a concave relationship of mortality to $PM_{2.5}$, which contrasts with prior literature that has assumed a convex damage function. Applying value of statistical life (VSL) estimates, they find welfare damages of between \$6 and \$170 billion per year due to smoke-related mortality, depending on the assumptions on remaining years of life.

Morbidity effects of wildfire smoke include respiratory and cardiovascular impacts. Both Reid et al. (2016) and Cascio (2018) find that, across a large number of studies, wildfire smoke exposure is strongly linked to respiratory health problems, particularly asthma, chronic obstructive pulmonary disease, and infections. Evidence is mixed for the effect of wildfire smoke pollution on cardiovascular diseases. Heft-Neal et al. (2023) estimated the effects of wildfire smoke $PM_{2.5}$ concentrations on emergency room visits in California. Low and moderate levels of wildfire smoke increase total emergency room visits by 1 to 1.5% in the week following exposure, while extreme levels of smoke increase respiratory emergency visits by 30 to 110% in the week following exposure. The authors find that wildfire smoke increased emergency room visits by 3,000 per year in California from 2006 to 2017. Other studies to document increased respiratory and/or cardiovascular emergency room visits due to wildfire smoke include Cullen (2020) and Parthum et al. (2017).

Smoke is also known to affect pregnancy, infants, and children. For example, Heft-Neal et al. (2022) estimated associations between wildfire smoke exposure during pregnancy and preterm birth in Cailfornia, finding that each additional day of exposure to any wildfire smoke during pregnancy was associated with a 0.49% increase in the risk of preterm birth. Similarly, McCoy and Zhao (2021) estimated the effects of wildfire smoke exposure on infant health. Using a difference-in-differences approach, they showed that exposure to wildfire smoke causes a 0.034 increase in the probability of low birthweight. Lastly, Wen and Burke (2022) showed that wildfire smoke decreases cognitive performance of children, finding reductions in exam performance due to smoke, especially for younger primary school children.

3.3.2 Economic effects

There is emerging literature on the impacts of wildfire smoke on productivity, labor supply, education, and agricultural output. Much of the early evidence is consistent with a large related literature on the effects of $PM_{2.5}$ on various forms of economic activity. Studies of general air pollution impacts are suggestive of the likely impacts of wildfire smoke, which contains large concentrations of $PM_{2.5}$.

Particulate pollution, in general, leads to declines in economic productivity. Several studies have documented this phenomenon in both the service and the manufacturing sector, as well as at an aggregate economic level (Chang et al. 2016, Chang et al. 2019, Dechezlepretre et al. 2019, Fu et al. 2021, He et al. 2019). The relevant time frames for measurement vary from short-run daily levels using pollution shocks (Chang et al. 2016, Chang et al. 2019) to medium- to long-run measurements (Fu et al. 2017, He et al. 2019). For example, He et al. (2019) examined productivity based on exposure over 25 days, while Fu et al. (2017) examined the effect of air pollution on annual productivity. Similarly, Dechezlepretre et al. (2019) studied effects of air pollution on gross domestic product at an annual level.

One potential mechanism to explain declines in productivity is that particulate pollution negatively affects cognitive function (Archsmith et al. 2021, Bedi et al. 2021, La Nauze and Severnini 2021, Lai et al. 2021, Schmidt 2022, Graff Zivin and Neidell 2012). Wildfire smoke contains high concentrations of $PM_{2.5}$ and therefore likely affects productivity similarly through cognitive decline. This effect, for example, was documented in the Wen and Burke (2022) study on school performance in the United States.

Reduced air quality can also decrease labor supply in the medium to long term. Reductions in labor supply have been measured both for general air pollution (Aragon et al. 2017) as well as for wildfire smoke (Borgschulte et al. 2022). Borgschulte et al. (2022) used county-level data to estimate that an additional day of wildfire smoke exposure reduces quarterly earnings by 0.1%, where 13% of the earnings losses were explained by extensive margin responses such as employment reductions and labor exits. The primary estimating equation in Borgschulte et al. (2022) regresses changes in labor market outcomes on the number of smoke days at a quarterly level. This approach contrasts with distributed lag measures of smoke such as that by Miller et al. (2021) or Heft-Neal et al. (2023), who studied short-term effects of smoke. Labor supply may also contract at these shorter time scales through a health channel. Both Borgschulte et al. (2022) and Dechezlepretre et al. (2019) found that welfare losses from wildfire smoke and from general particulate pollution, respectively, were on par with welfare losses from mortality; for example, Borgschulte estimated that the welfare value of lost earnings due to wildfire smoke is $125 billion per year.

In the long run, smoke and particulate pollution may decrease productivity and earnings by affecting educational outcomes (Chen et al. 2018, Pham and Roach 2023). Wen and Burke (2022) calculated that smoke exposure to primary school students in 2016, a severe smoke year, likely reduced discounted future earnings by $1.7 billion, or $111 per student. Severe smoke years are projected to grow more frequent with climate change (Liu et al. 2022, Hurteau et al. 2014).

Smoke also has effects on agriculture. There has been concern about the negative effects of “smoke taint” on winegrowing, but evidence indicates that, overall, smoke may benefit agriculture in the near term. Behrer and Wang (2022) measured the impacts of wildfire smoke on agriculture in the American Midwest over the period 2006 to 2020. Smoke plumes alter direct, diffuse, and total sunlight, all of which affect crop yields. They find that low-density smoke plumes increase yields, possibly by increasing the proportion of diffuse light, whereas medium- and high-density plumes decrease yields. Because there is currently a greater proportion of low-density plumes, the net effect is to increase crop yields, but these benefits are expected to dissipate by 2050.

3.3.3 Well-being effects

Beyond health and economic output, wildfire smoke has numerous effects on human well-being. These effects include reduced happiness or sentiment, increased violent crime, and lost or impaired outdoor recreation.

Several studies have measured the effect of wildfire smoke on sentiment and well-being. Both Burke et al. (2022) and Loureiro et al. (2022) performed text analysis on high frequency social media data, finding that large wildfire smoke events significantly reduced sentiment; Burke et al. (2022) found that effects were driven by wealthy locations, with a more muted response in lower-income neighborhoods. Studies of general air pollution have documented similar phenomena using social media and text analysis (Du et al. 2022, Shan et al. 2022). Results from these studies of social media are consistent with evidence from survey-based approaches, which have found that wildfire smoke exposure is associated with reduced subjective well-being or place-based satisfaction (Jones 2017, Rubin and Wong-Parodi 2022).

Wildfire smoke has also been used to study the effect of air pollution on crime. Burkhardt et al. (2019) used daily variation in a subset of United States counties to estimate that $PM_{2.5}$ and ozone increase violent crime. They find no differential effect of pollution when wildfire smoke is present, suggesting that smoke likely affects crime only through the channel of pollution. Burkhardt et al. (2020) repeated this analysis at a monthly level, but for the entire coverage of United States counties. Instead of treating smoke as an interaction variable, they used it as an instrument for $PM_{2.5}$, similar to the instrumental variable strategy of Borgschulte et al. (2022) and Miller et al. (2021). The use of smoke as an instrumental variable implies an exclusion restriction whereby smoke can only affect an outcome variable through the channel of pollution;

however, in other contexts, smoke may affect well-being through amenity effects.

Smoke has consequences for outdoor recreation, which is a welfare-enhancing activity. Visitation to public lands continues to increase in popularity, but these areas are also highly exposed to wildfire smoke. Gellman et al. (2022b) found that, in some regions of the western United States, more than 10% of available federal campground days were affected by high pollution smoke over the period 2008 to 2017. This smoke reduces visitation, but the effects vary by distance to the origin of the fire (Cai 2021, Gellman et al. 2022a, Gellman et al. 2022b). Gellman et al. (2022a) estimated that high pollution smoke affected 21.5 million outdoor visits per year on state and federal lands in the western United States over the period 2008 to 2017, with welfare losses of $2.3 billion per year.

3.3.4 Behavioral adjustments

Individuals are aware of high severity smoke events and, in response, seek information on air quality and health impacts. Behavioral adjustments to smoke include staying at home, engaging in health-protective behavior, or leaving an area entirely. These behavioral adjustments can be costly. Over time, increased wildfire smoke could potentially lead to outmigration from heavily-affected areas.

Evidence from both large data analysis and from survey methods shows that large wildfire smoke events are highly salient for individuals. Burke et al. (2022) found that, during large smoke events, individuals search the internet more for information about air quality and health protection. These results are consistent with studies using survey and interview methods, which have found that individuals are aware of smoke, search for health information on the internet, and link smoke to their own health effects (Fowler et al. 2019, Masri et al. 2023, Richardson et al. 2012, Santana et al. 2021).

Individuals take various actions to avoid smoke or mitigate its damages. Burke et al. (2022) used cell phone data to find that residents of smoke-affected counties are more likely to stay at home at higher levels of smoke pollution; similarly, Holloway and Rubin (2022) used cell phone data to find that high income and whiter populations leave their home counties at higher rates than other socioeconomic groups during smoke events, presumably as avoidance. Heft-Neal et al. (2023) reported that emergency room visits for accidental injuries decrease during smoke events, suggesting people avoid normal activities due to smoke. Studies using survey or interview methods have found that smoke-affected respondents avoid work, run the air conditioner more, use home air cleaners, stay indoors, and avoid normal outdoor recreation or exercise (Fowler et al. 2019, Richardson et al. 2012, Santana et al. 2021). Individuals may also take steps to reduce $PM_{2.5}$ infiltration levels, such as by sealing doors or windows (Liang et al. 2021).

The ability to engage in protective behavior may vary across socioeconomic populations (Burke et al. 2022, Holloway and Rubin 2022, O'Dell et al. 2022). Defensive actions can be costly, including for health-protecting defensive investments like air purifiers (Ito and Zhang 2020, Richardson et al. 2012). Staying home during smoke events is also costly, for example, by reducing short run labor force participation (Aragon et al. 2017, Borgschulte et al. 2022). Smoke-related pollution may induce individuals to avoid welfare enhancing activities such as outdoor recreation (Cai 2021, Gellman et al. 2022a, Gellman et al. 2022b).

Over time, there is potential that increases in wildfire smoke could cause outmigration from heavily-affected areas. Because wildfire smoke impacts are episodic and highly spatially correlated, no quantitative estimates exist regarding the effects of wildfire smoke on migration or home values in the United States. The issue has been studied in India, where Tiwari (2023) estimated the effect of smoke pollution from agricultural fires on migration. In the United States and in international contexts, studies have estimated the effect of general air pollution on home values (Chay and Greenstone 2005, Freeman et al. 2018, Nam et al. 2022), as well as on migration (Chen et al. 2022). It is possible that the effects of smoke may only be capitalized into home values through an air quality channel, rather than a climate risk channel; for example, a large literature finds imperfect capitalization of climate risk into real estate and insurance due to information failures, market failures, or beliefs (Bakkensen and Barrage 2022, Gibson and

Mullins 2020, Hadziomerspahic 2022, Hino and Burke 2021, Keys and Mulder 2020, Mulder 2021, Wagner 2022). Rubin and Wong-Parodi (2022) found in a survey of California residents that, among those who intended to move in the next five years, nearly a quarter reported that wildfire and smoke affected their decision to migrate at least a moderate amount.

3.4 Policy responses

The CAA has been successful in reducing $PM_{2.5}$ concentrations across the country; however, the CAA is not currently positioned to drive down wildfire smoke. The CAA centers on regulating controllable human-caused emissions. Currently, wildfire smoke is treated as an uncontrollable "exceptional event" which is exempt from determinations of attainment status. Therefore, the EPA has not played a role in regulating wildfire smoke or encouraging mitigation of smoke. Perversely, it is actually more difficult for prescribed burns, which are a management strategy to reduce the risk of high severity fires by clearing understory vegetation, to obtain the exemption status of "exceptional event" than for wildland fires (Williams 2021).

Responsibility for mitigating wildfire smoke has primarily been the province of land management agencies and private landowners. Due to concern over the increasing impacts from wildfires, the federal government has recently invested large sums of money in wildfire hazard mitigation, much of it to be distributed by land management agencies such as the US Forest Service. For example, the Infrastructure Investment and Jobs Act (IIJA) of 2021 included $3.4 billion in funding for wildfire risk reduction, including $500 million for prescribed burning, as well as $2.6 billion for ecosystem restoration projects. Though there is increasing recognition of the importance of wildfire smoke impacts relative to other impacts from wildfires, the US Forest Service has generally not made wildfire smoke impacts a primary criterion in determining priority wildfire treatment locations. For example, priority "firesheds" for initial IIJA landscape investments were identified based on potential to reduce exposure of communities and natural resources to catastrophic fire risk, to allow for investment in underserved communities, and to leverage community partnerships (US Forest Service 2022); potential to reduce smoke impacts was not a primary consideration.

As the prevalence of wildfire smoke continues to increase and reverse the air quality gains of the CAA (Burke et al. 2023), there is need for concentrated and coordinated policymaking efforts to encourage wildfire smoke mitigation (US Government Accountability Office 2023). First, prescribed fires, a primary tool for reducing the likelihood of large and severe wildfires, themselves emit smoke, albeit typically at lower and less sustained levels. Regulations should acknowledge this "smoke paradox" and allow increased use of prescribed fires by land managers (Williams 2021, Jones et al. 2022).

Moreover, policy should do more to encourage such activities. Simply removing the exceptional event exemption for all wildfire smoke would be overly punitive to states and their local authorities, which are responsible for attainment of national ambient air quality standards (NAAQS), since increases in wildfire smoke are unrelated to urban or industrial pollution. Rather, smoke has been driven by climate change, as well as decades of federal fire management that has largely prioritized fire suppression and allowed dry fuels to accumulate in forests. Instead, Williams (2021) suggests a way to use the framework of the CAA to incentivize smoke mitigation. In her framework, states would be allowed to treat wildfires as exceptional events only if they are able to show they are taking all reasonable steps to encourage appropriate forest management to reduce wildfire risk. Such steps could include fuels management projects such as thinning and controlled burns, home hardening, or the encouragement of community preparedness organizations like Firewise Communities and Fire Safe Councils.

In the shorter run, more should be done to encourage adaptation and reduce the burden of impacts from smoke. Because indoor air pollution increases significantly during smoke events, current policy reliance on self-protection may have limited benefit (Burke et al. 2022). At a local level, communities can provide better information on clean air centers, which are shelters in public buildings with improved air filtration (Treves et al. 2022). At a federal level, the EPA can continue to provide information about air quality conditions, as well as potential consequences of exposure to high levels of smoke.

3.5 Conclusion

As large wildfires grow more frequent, the United States has seen increasing impacts of smoke. In some years, counties might spend nearly a third of the year under wildfire smoke (Childs et al. 2022). During extreme events, smoke increases pollution above federal attainment standards for particulate matter pollution. Trends are most severe in the western states, especially the Pacific Northwest, but have affected the entire continental United States. These impacts are projected to grow over the 21st century as the climate warms.

The economics and social sciences literature has documented numerous impacts from wildfire smoke for health, the economy, well-being, and behavior. Most of these impacts are through the channel of pollution. Although smoke contains many pollutants, most studies focus on the $PM_{2.5}$ produced from smoke. While there has been a great deal of attention paid to short run responses, identifying longer term impacts, such as the effect of repeated seasonal exposure to smoke, is more difficult to empirically identify with observational data.

Although air quality is federally regulated by the EPA, these regulations were designed for urban and industrial air pollution. Currently, the lack of air quality exemptions for smoke from prescribed fires creates barriers to mitigation activities that could ultimately reduce the severity of future smoke. We propose ways that the EPA could modify existing regulations.

Appendix A

Appendix to Chapter 1

A.1 Additional figures

Figure A.1: Recreation.gov web interface.

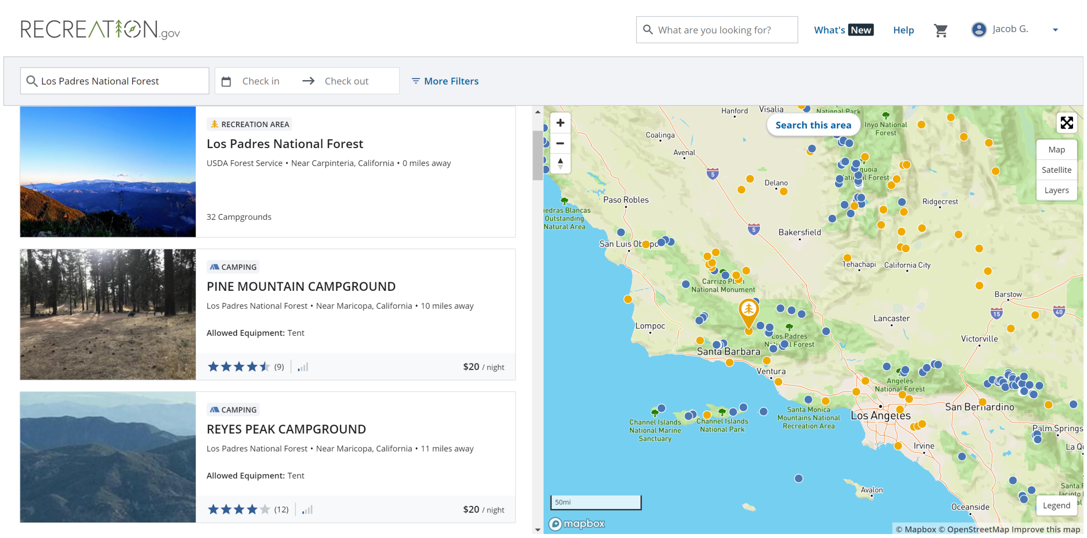


Figure A.2: Automobile route from Santa Barbara, California to Yosemite National Park.

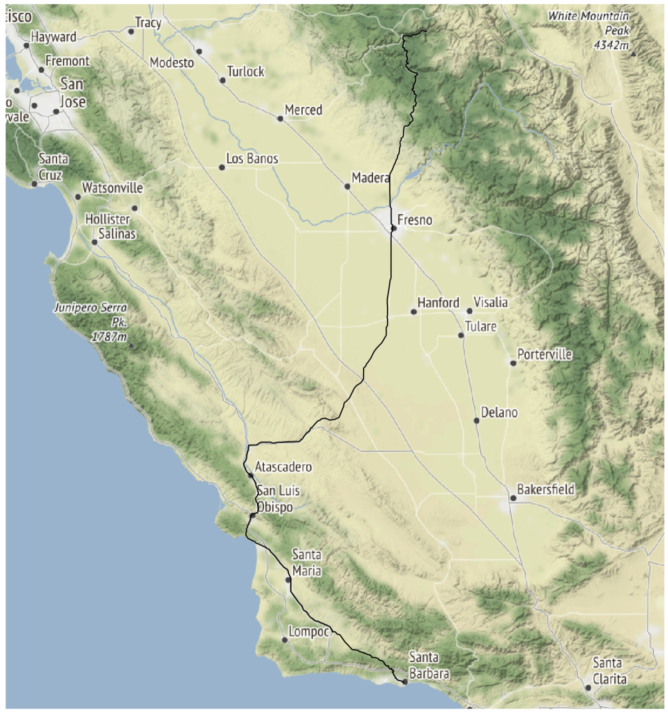


Figure A.3: NOAA smoke plumes and $PM_{2.5}$. Red areas are affected by smoke and poor air quality.

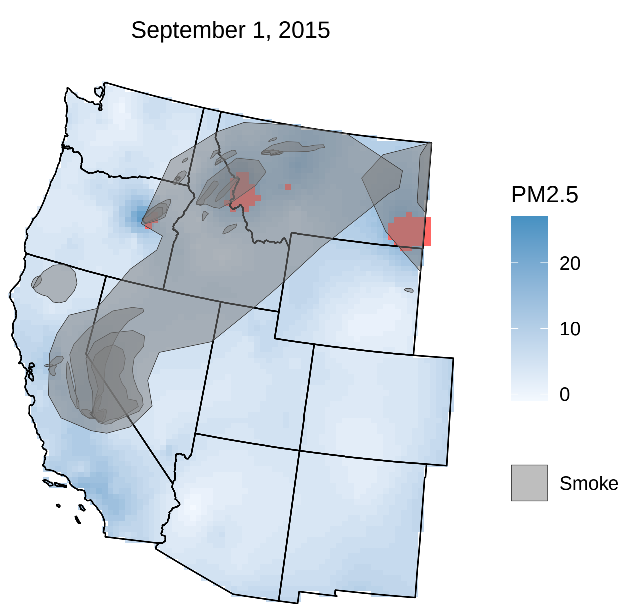


Figure A.4: Fire detection points and fire perimeters.

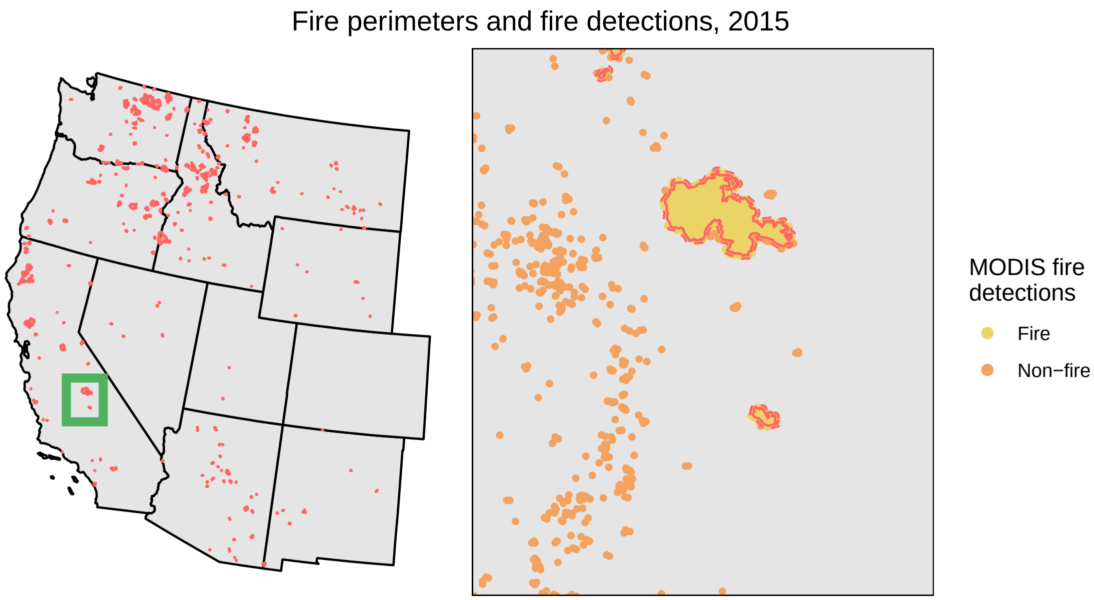


Figure A.5: Map of campgrounds in dataset.

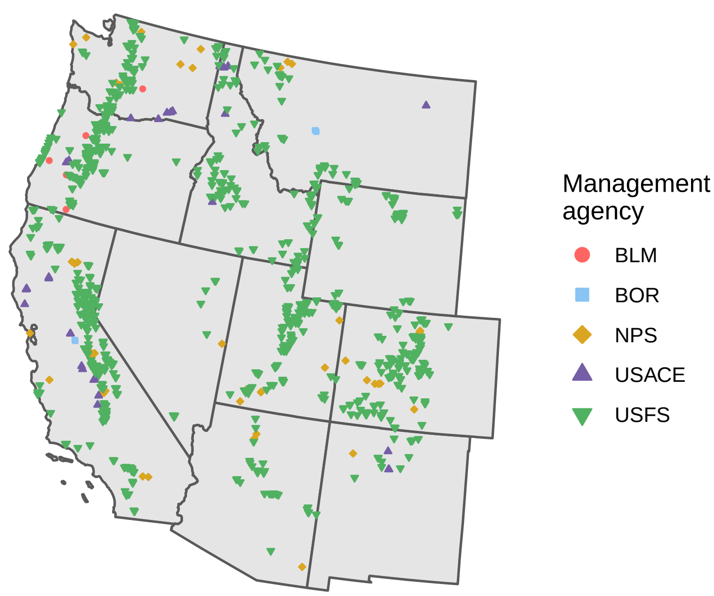


Table A.1: Most visited federally-managed campgrounds.

Campground	Recreation area	State	Agency	Annual average campers
Upper Pines	Yosemite NP	CA	NPS	99,820
Mather	Grand Canyon NP	AZ	NPS	59,196
Watchman	Zion NP	UT	NPS	49,389
Serrano	Big Bear, San Bernardino NF	CA	USFS	46,610
Pinecrest	Summit RD, Stanislaus NF	CA	USFS	36,576
Fallen Leaf	Lake Tahoe Basin	CA	USFS	32,966
Lodgepole	Sequoia And Kings Canyon NP	CA	NPS	30,634
North Pines	Yosemite NP	CA	NPS	26,883
Moraine Park	Rocky Mountain NP	CO	NPS	25,884
Lower Pines	Yosemite NP	CA	NPS	25,644
Wawona	Yosemite NP	CA	NPS	25,407
Hodgdon Meadow	Yosemite NP	CA	NPS	24,746
Pinnacles	Pinnacles NP	CA	NPS	24,210
Crane Flat	Yosemite NP	CA	NPS	23,844
Indian Cove	Joshua Tree NP	CA	NPS	23,376
Dogwood	Arrow Head, San Bernardino NF	CA	USFS	21,540
Acorn	New Hogan Lake	CA	USACE	21,164
Black Rock	Joshua Tree NP	CA	NPS	19,888
Kalaloch	Olympic NP	WA	NPS	18,105
Dinkey Creek	High Sierra RD, Sierra NF	CA	USFS	16,294
Logger	Truckee RD, Tahoe NF	CA	USFS	16,253
Diamond Lake	Diamond Lake RD, Umpqua NF	OR	USFS	15,683
Kyen	Lake Mendocino	CA	USACE	15,015
Dorst Creek	Sequoia And Kings Canyon NP	CA	NPS	14,435
North Rim	Grand Canyon NP	AZ	NPS	13,898
Ohanapecosh	Mount Rainier NP	WA	NPS	13,889
Devils Garden	Arches NP	UT	NPS	13,138
Oh Ridge	Mono Lake RD, Inyo NF	CA	USFS	13,063
Fish Creek	Glacier NP	MT	NPS	12,434
Manzanita Lake	Lassen Volcanic NP	CA	NPS	12,379

Figure A.6: Campground occupancy rates follow a bimodal distribution both on the date of arrival and one week in advance.

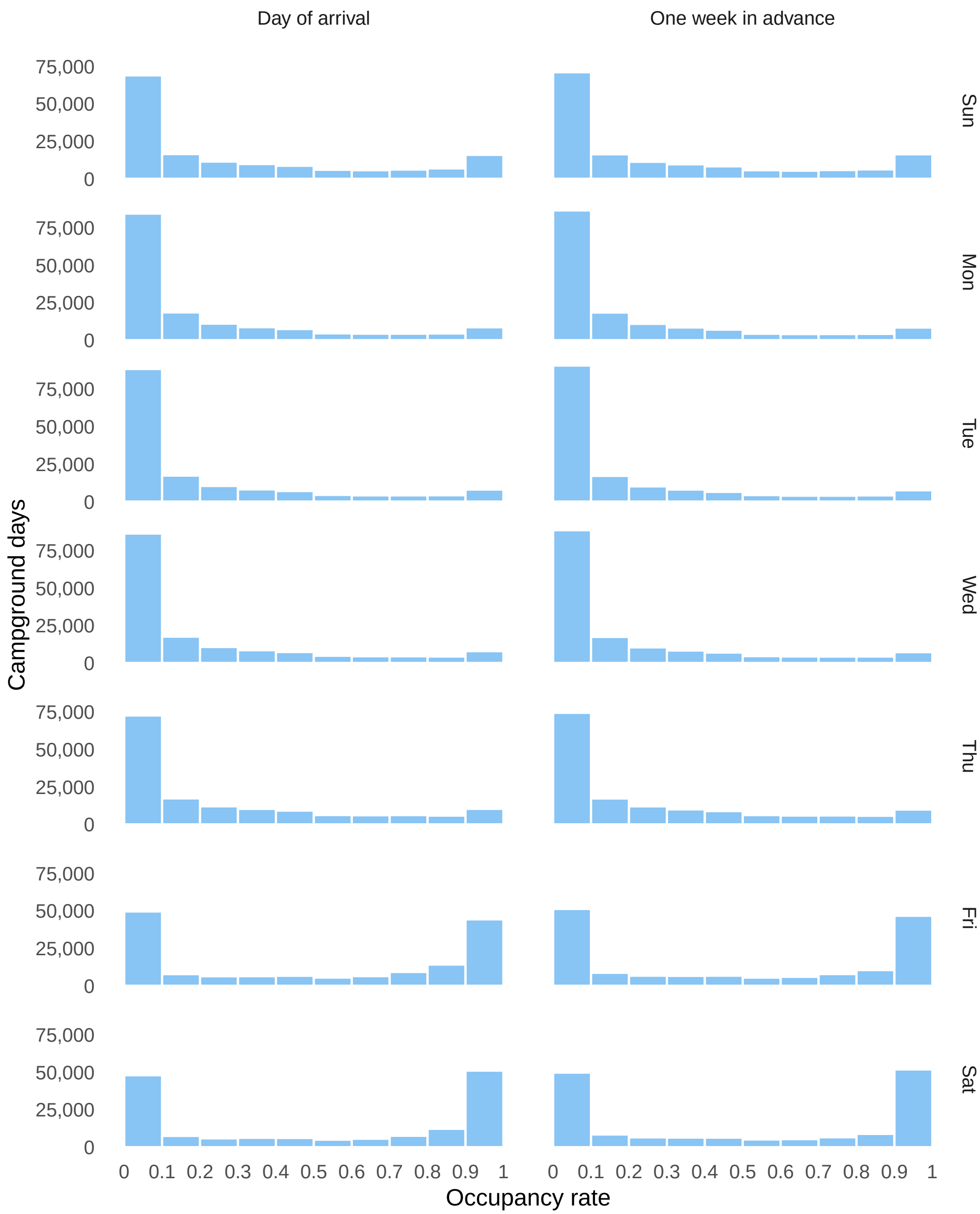


Figure A.7: Fitted $\mathbb{P}(R_{ijt} = 1)$ for reservations made earlier than one week from model (4).

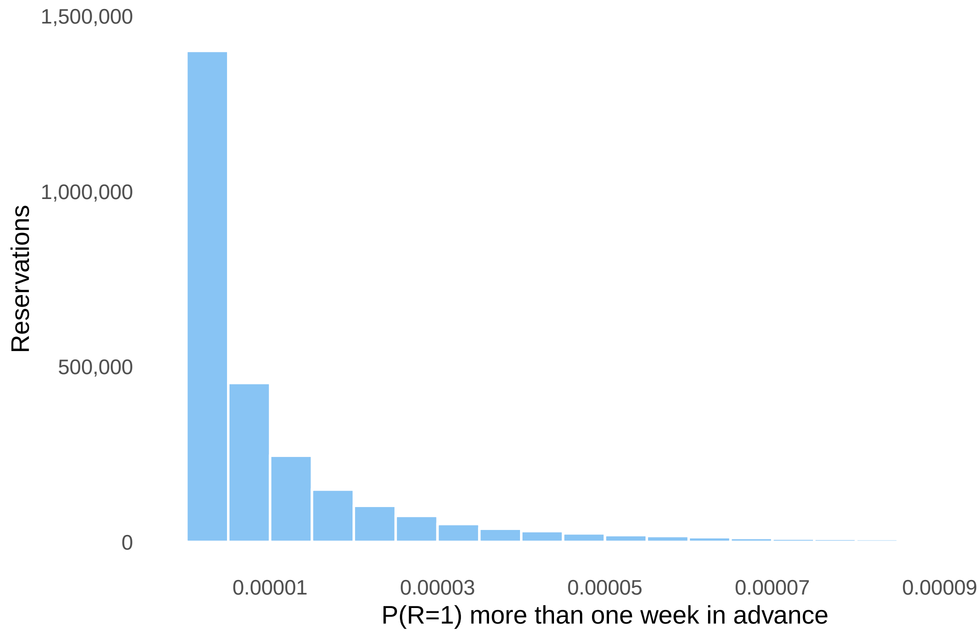


Figure A.8: Fitted $\tilde{\varepsilon}_{ijt}$ for reservations made earlier than one week from model (4).

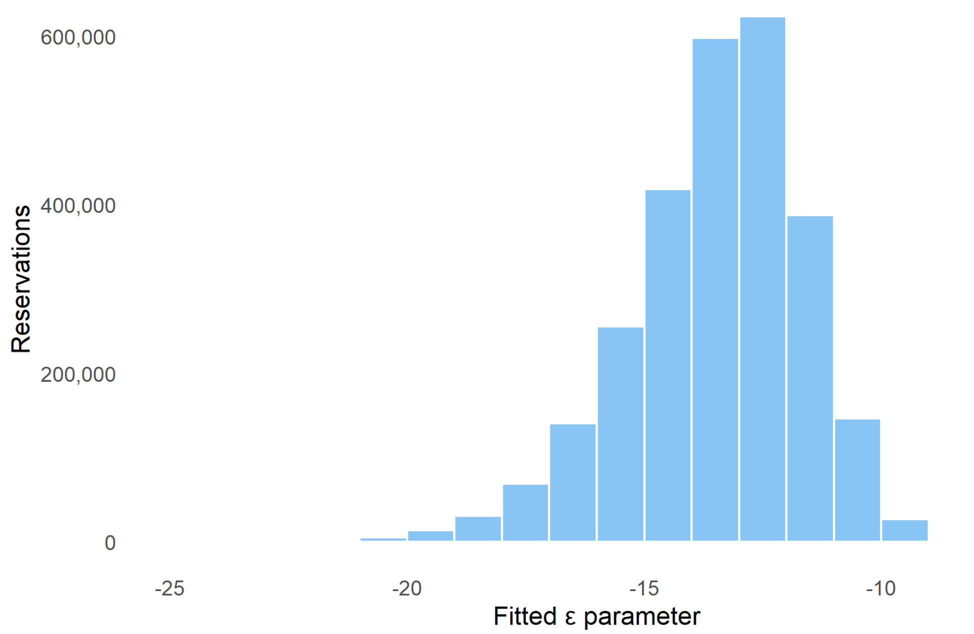


Table A.2: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, heterogeneity by smoke days in week before arrival.

	(1)	(2)	(3)	(4)
Travel cost (dollars)	-0.0025**	-0.0024**	-0.0024**	-0.0024**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-10.5524**	-11.6117**	-11.5449**	-7.4215**
	(0.9020)	(2.3964)	(2.4152)	(0.7843)
High temp. (degrees C)	0.0202**	0.0289**	0.0289**	0.0302**
	(0.0044)	(0.0023)	(0.0023)	(0.0021)
Low temp. (degrees C)	-0.0031	-0.0183**	-0.0189**	-0.0226**
	(0.0057)	(0.0025)	(0.0025)	(0.0025)
Precip. in week of arrival (mm)	-0.0043**	-0.0060**	-0.0061**	-0.0057**
	(0.0011)	(0.0009)	(0.0009)	(0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0027	-0.0342**	-0.0352**	-0.0368**
	(0.0255)	(0.0124)	(0.0124)	(0.0126)
Smoke days = 1	0.0158	-0.0718**	-0.0575*	-0.0776**
	(0.0268)	(0.0247)	(0.0246)	(0.0201)
Smoke days = 2	-0.1521**	-0.2164**	-0.1975**	-0.2217**
	(0.0436)	(0.0427)	(0.0416)	(0.0339)
Smoke days = 3	-0.2257**	-0.3050**	-0.2862**	-0.3182**
	(0.0410)	(0.0441)	(0.0437)	(0.0357)
Smoke days = 4	-0.4418**	-0.4792**	-0.4506**	-0.5066**
	(0.0472)	(0.0511)	(0.0502)	(0.0447)
Smoke days = 5	-0.5737**	-0.6032**	-0.5779**	-0.6583**
	(0.0448)	(0.0560)	(0.0551)	(0.0488)
Smoke days = 6	-0.7121**	-0.7612**	-0.7444**	-0.8348**
	(0.0603)	(0.0669)	(0.0669)	(0.0637)
Smoke days = 7	-1.0022**	-1.0065**	-0.9868**	-1.0481**
	(0.0660)	(0.0939)	(0.0922)	(0.0908)
WTP: 1 smoke day	-6.31	30.11*	23.87*	31.96**
	(10.45)	(11.92)	(11.38)	(9.66)
WTP: 2 smoke days	60.79**	90.8**	82.03**	91.32**
	(21.15)	(24.32)	(22.91)	(20.36)
WTP: 3 smoke days	90.26**	127.98**	118.9**	131.09**
	(22.07)	(27.66)	(26.04)	(23.07)
WTP: 4 smoke days	176.63**	201.07**	187.15**	208.68**
	(31.73)	(33.26)	(31.01)	(29.87)
WTP: 5 smoke days	229.38**	253.09**	240.06**	271.19**
	(38.74)	(39.86)	(36.75)	(34.92)
WTP: 6 smoke days	284.7**	319.4**	309.19**	343.87**
	(46.09)	(50.3)	(47.28)	(47.41)
WTP: 7 smoke days	400.7**	422.33**	409.86**	431.74**
	(59.86)	(73.41)	(68.21)	(68.64)
N	2,723,034	2,691,655	2,691,655	2,688,739
Campground FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Campground x week-of-year FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Std. err. clustered at campground level. * p < 0.05, ** p < 0.01.

A.2 Reservations close to arrival

This paper focuses on the cancellation decisions of visitors who reserve ahead of time, before smoke conditions are known, and who subsequently decide whether to cancel close to the arrival date, after site conditions are realized. Figure 1.3 illustrates the timing of decisions in the main analysis. We focus on this structure for several reasons. First, most reservations are made ahead of time. Figure 1.2 shows that, although a plurality of reservations are made within a week of arrival, the majority are made in advance. Second, by the time smoke conditions are known, many campgrounds are either fully booked or completely empty, which limits the variation needed to identify changes in campground activity due to wildfire smoke. Figure A.6 depicts this bimodal distribution. Congested campgrounds and empty campgrounds both prevent proper measurement of changes in recreation activity due to smoke. When campgrounds are completely booked, logistic regression would underestimate the latent demand for recreation on non-smoke days because campground occupancy meets a binding constraint; this analysis would lead to an underestimate of the coefficient on smoke. When campgrounds are empty on non-smoke days, there is similarly not identifying variation. We focus on cancellations because, once a visitor holds a reservation, they may always cancel it and do not face constraints.[1]

Still, we could have measured decisions for visitors who make new reservations close to the arrival date, when they are likely aware of smoke conditions. In this section we report results for a zonal travel cost model of new reservations close to the arrival date. We restrict the data to reservations made within a week of arrival during the months of May to September and over the years 2010 to 2017. We also limit attention to trips coming from within 650 km (400 miles), as described in Section 1.2.6. Lastly, we exclude new reservations which were also cancelled in the same week. These restrictions result in 693,501 same-week reservations. We aggregate these

[1]For a discussion of site substitution, refer to Appendix A.3. Users tend not to cancel and rebook for the same choice occasion. In addition, smoke conditions are spatially and temporally correlated among choice sets, meaning there is low variation of differences in smoke-related disutility among choice alternatives.

reservations for a zonal estimation as described in Section 1.3.1, but for same-week reservations rather than early reservations.

Figure A.9 shows how reservation rates vary by travel cost and wildfire smoke conditions. Reservation rates are much higher at lower levels of travel cost. Before controlling for other observable and unobservable factors, Figure A.9 shows that raw reservation rates are actually higher on days with smoke than on days without smoke. This difference is likely due to the fact that wildfire season overlaps with popular camping times, such as the American holidays of Independence Day and Labor Day. Therefore, fixed effects for location and seasonality are likely to be important.

Figure A.9: Reservation rate within one week of arrival.

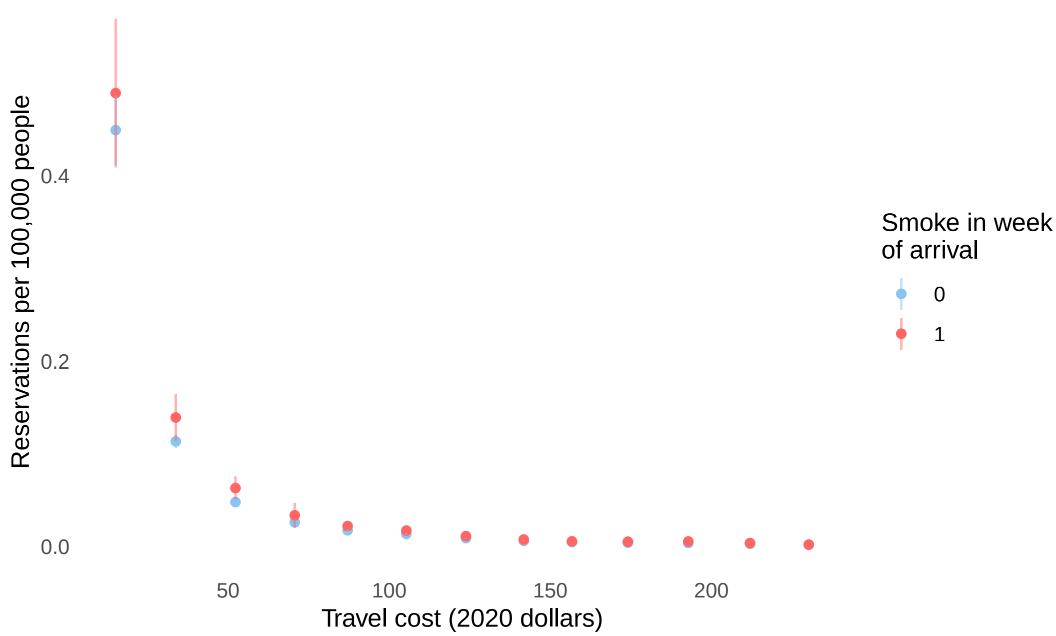


Table A.3 reports results for estimation of the reservation likelihood within one week, $\mathbb{P}(R_{ijt} = 1)$, using the zonal maximum likelihood function of equation 1.8. In all estimations the observations are weighted using frequency weights since a single row of data might represent, for example, 20 reservers or 2.3 million non-reservers. In column 1 we display results without controlling for campground or seasonal fixed effects. As suggested by Figure A.9, users are unconditionally more likely to reserve for dates that happened to be smoke-affected, yielding an unexpectedly positive coefficient on smoke. Columns 2 through 4 add fixed effects, which yield the expected sign for the smoke coefficient. The results in columns 2 through 4 indicate a WTP to avoid smoke of between \$1.45 and \$1.65 per person per trip. Given previous discussion of congested and empty campgrounds, we believe these estimates are less plausible than the paper's main set of results.

Table A.3: $\mathbb{P}(R_{ijt} = 1)$ for reservations within one week.

	(1)	(2)	(3)	(4)
Smoke in week of arrival	0.1382**	-0.0434**	-0.0406**	-0.0460**
	(0.0021)	(0.0125)	(0.0104)	(0.0091)
Travel cost (dollars)	-0.0241**	-0.0279**	-0.0279**	-0.0279**
	(0.0000)	(0.0017)	(0.0017)	(0.0017)
Inv. distance to wildfire (km^{-1})	-0.6732**	-2.0485**	-2.0798**	-1.9822**
	(0.0310)	(0.3046)	(0.3029)	(0.2809)
High temp. (degrees C)	0.0602**	0.0074**	0.0075**	0.0079**
	(0.0002)	(0.0012)	(0.0011)	(0.0010)
Low temp. (degrees C)	-0.0205**	-0.0044**	-0.0039**	-0.0047**
	(0.0002)	(0.0016)	(0.0015)	(0.0014)
Precip. in week of arrival (mm)	-0.0035**	-0.0028**	-0.0027**	-0.0028**
	(0.0001)	(0.0004)	(0.0004)	(0.0003)
N	13,792,677	10,913,738	10,913,738	10,542,160
WTP	-5.73**	1.55**	1.45**	1.65**
	(0.09)	(0.45)	(0.37)	(0.32)
Campground FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Campground x week-of-year FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

A.3 Site substitution

In the main analysis, both the trip-level cancellation decision and the zonal travel cost model imply a binary choice for the representative visitor. While one could have used a multinomial logit to model site substitution, we discuss in Section 1.3.1 the practical limitations of that approach and the advantages afforded by a zonal travel cost model. Moreover, the zonal reservation estimation and the binary cancellation decision should properly identify the parameters of interest, namely the marginal disutility of smoke and the marginal disutility of expenditure. In this section we first show that a binary cancellation decision is a realistic representation of the choice that users face. We also discuss the choice to model early reservations in a zonal setting.

We begin by discussing the binary cancellation decision. Substitution following a cancellation is uncommon. Of the 2,723,940 trips in the estimating dataset, there are 268,750 cancellations, implying a 9.87% raw cancellation rate. Among the cancelled reservations, approximately 10.3% of users "rebooked," meaning they made a new reservation for a date within a year of their original scheduled arrival date. However, rebookers rarely substitute for the same choice occasion. Only 11% of rebookings substituted to a different campground on the same week of arrival; multiplying by 10.3%, this implies that only 1.1% of all cancellations substituted to a different site for the same week. Intertemporal substitution is more common: 57% of all rebookings were for either the same campground or a different campground but at a later arrival week. Multiplying by 10.3%, this means that 5.8% of all cancellations intertemporally substituted.

Because this analysis is concerned with wildfire smoke, we note the smoke status of rebooked visits. Of all rebooked visits, 0.9% were smoke-affected and rebooked for a different week; 1% were smoke-affected and rebooked for the same week. Multiplying by 10.3%, this means that 0.09% and 0.1% of all cancellations could have ostensibly substituted due to wildfire smoke. We view these substitutions as uncommon. Therefore, modeling cancellations as a binary decision is a reasonable representation of the choice that visitors face.

One additional reason not to model site substitution is that smoke conditions are spatially and temporally correlated. This correlation could wash out differences in smoke-related utility between choice alternatives, variation which is needed to properly identify the smoke parameter. Figures A.10, A.11, and A.12 plot a visualization of this spatial and temporal correlation for Colorado, Oregon, and California. These figures sort campgrounds north to south on the vertical axis, while on the horizontal axis they plot days of the year during the summer months. Each tile represents a campground day and is colored according to the smoke conditions on those days. These figures reveal that, when one campground is smoke-affected, it tends to be the case that nearby campgrounds are also smoke-affected. Figure A.13 also shows this relationship as a histogram for all campground days in the estimating dataset.

Figure A.10: Spatial and temporal correlation of smoke in Colorado.

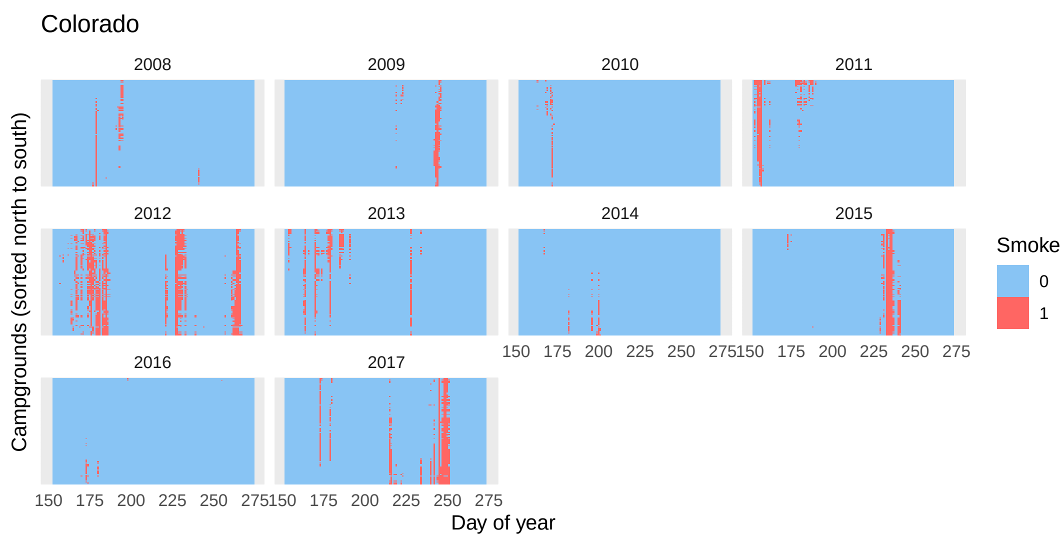


Figure A.11: Spatial and temporal correlation of smoke in Oregon.

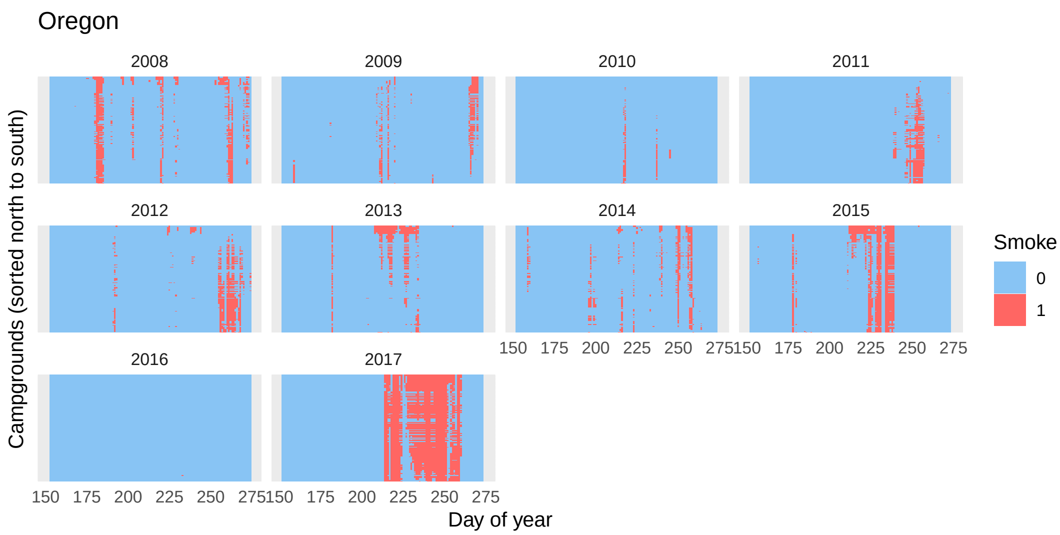


Figure A.12: Spatial and temporal correlation of smoke in California.

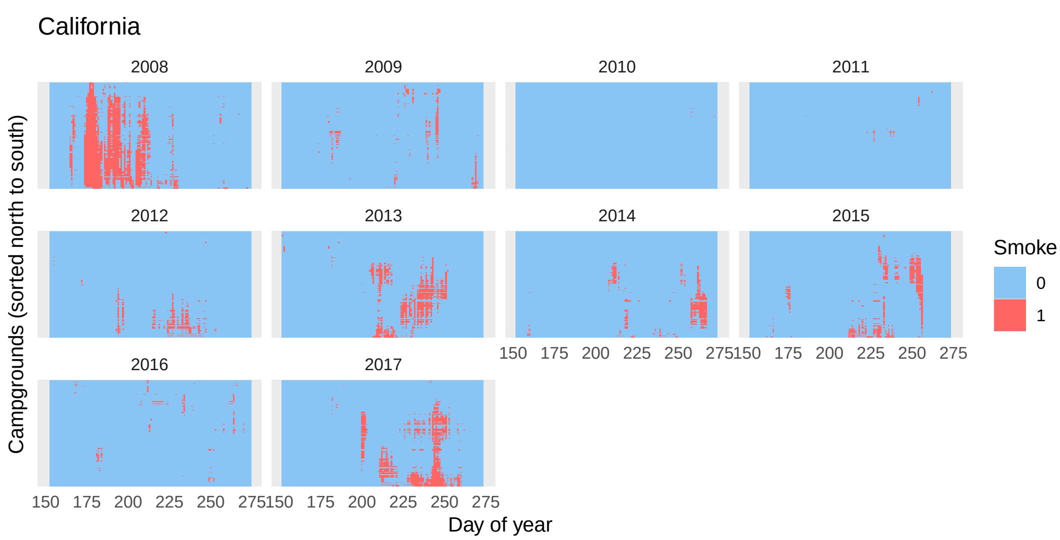
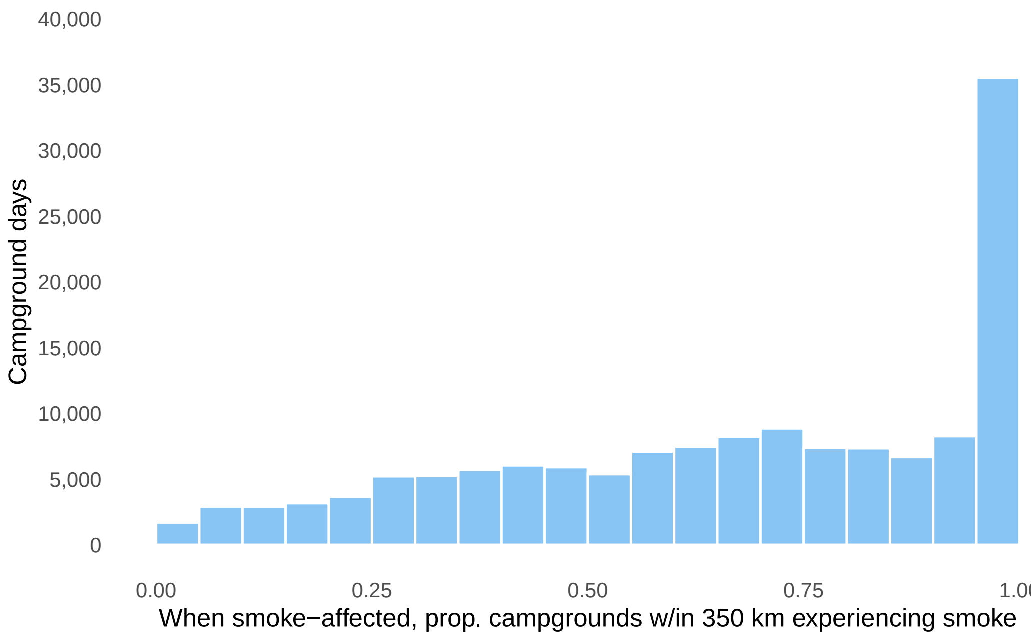


Figure A.13: When a campground is smoke-affected, proportion of campgrounds within 350 km experiencing smoke in the same week.



The goal of this study is to value the non-market damages of wildfire smoke. The parameters of interest to estimate welfare damages are the marginal disutility of wildfire smoke and the marginal disutility in expenditure. Both of these parameters arise from the cancellation model, when site conditions become known to individuals. As we discuss in Section 1.3.1, the main purpose for the reservation estimation is to build the control function that accounts for preferences in the cancellation estimation. These preferences are likely correlated with travel cost in the selected sample, which we explore theoretically in Appendix A.4 and show empirically in Figure 1.5. We are less concerned with the estimation of smoke in the reservation decision since the reservation occurs ahead of time, before smoke conditions are known. In addition, the binned travel cost zones provide variation to estimate how travel cost affects the likelihood of reservation. Overall, because we are less interested in site substitution for the reservation decision, we argue that the flexible computational advantages afforded by the zonal estimation justify this tradeoff. For more discussion, refer to Section 1.3.1.

A.4 Numerical example of sample selection correction

In Section 1.3.3 we proposed a control function approach to account for unobserved preferences $\tilde{\varepsilon}_{ijt}$ which could bias estimation of $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ if omitted. In this appendix we provide a numerical example to illustrate the source of this bias, its effect on estimation of WTP, and correction using a control function. We show that WTP is only biased when preferences for the reservation and cancellation decisions are correlated, and when the counterfactual cancellation decision of non-reservers is unobserved. Further, the bias operates through correlation between preferences and travel cost: among the selected sample of reservers, those with a high travel cost tend to have had a high taste for the site. This relationship downward biases estimates of the travel cost parameter in the cancellation decision. Finally, we demonstrate bias correction using the control function for $\tilde{\varepsilon}_{ijt}$ given in equation 1.13.

In this numerical example we simulate the two stage reservation and cancellation decision using a Monte Carlo of 10,000 random draws. For every iteration we generate $N = 100,000$ users i, each with a spatial coordinate $(x, y) \in [0, 1] \times [0, 1]$, where x and y are distributed uniform. In addition, we generate a single site j at a random coordinate $(x, y) \in [0, 1] \times [0, 1]$, where x and y are again distributed uniform. User i's travel cost c_{ij} is given by the Euclidean distance from i to j.

Users who reserve far in advance maximize utility based on expected smoke conditions. Define the utility from the reservation as $U^R_{ij} = \alpha_j + \delta c_{ij} + \phi\mathbb{E}[s_j] + \varepsilon_{ij}$. We will assert arbitrarily that $\alpha_j = 1$, $\delta = -0.8$, and $\phi = -1.6$. Therefore, the true WTP is $\phi/\delta = 2$. Each user's site-specific preference value of ε_{i0} and ε_{ij} are drawn from a type I extreme value distribution. Based on the "time of visitation" expected smoke conditions $\mathbb{E}[s_j]$ are drawn for each user from $\{0.1, 0.2, 0.4\}$ with equal probability. Users will choose to reserve $R_{ij} = 1 \iff U^R_{ij} \geq U^R_{i0}$.

For the cancellation decision the user decides based on realized smoke conditions. Let the utility from cancellation be $U^C_{ij} = \alpha_j + \delta c_{ij} + \phi s_j + \upsilon_{ij}$. Realized smoke s_j is drawn from $\{0, 1\}$ with $\mathbb{P}(s_j = 1) = 0.25$ for each user to create variation based on the "time of visitation."

We consider two types of errors υ_{ij} in the cancellation decision. The first is an independent error, $\upsilon_{ij}^{ind} \sim$ type I extreme value, which assumes the user's preferences in the cancellation decision are completely uncorrelated with their choice to have reserved. The second is a dependent error, $\upsilon_{ij}^{dep} = \rho\varepsilon_{ij} + \eta_{ij}$, which allows correlation of preferences between the reservation and the cancellation decision. We assume $\eta_{ij} \sim$ type I extreme value and arbitrarily set $\rho = 0.7$. Users will cancel $C_{ij} = 1 \iff U_{ij}^C \leq U_{i0}^C$. Because of the differing error structures we consider two cancellation decisions under both υ_{ij}^{ind} and υ_{ij}^{dep}, which we will denote C_{ij}^{ind} and C_{ij}^{dep}, respectively.

The selection issue in the real recreation data arises because we can only observe the cancellation decision for users that chose to make a reservation. However, under the Monte Carlo simulation, we can also examine the counterfactual cancellation decision of the non-reservers to see if they "would have" cancelled. We will show that, even with a dependent error υ_{ij}^{dep}, estimation of $\mathbb{P}(C_{ij} = 1)$ on the full sample (reservers and non-reservers) without observing ε_{ij} will still recover the true WTP since there is no selection effect. That is, the biased estimation of $\mathbb{P}(C_{ij} = 1 | R_{ij} = 1)$ comes from the fact that ε_{ij} and c_{ij} are correlated in the selected sample, not the full sample.

Table A.4: Example of users' reservation and cancellation decisions.

R_{ij}	C_{ij}^{ind}	C_{ij}^{dep}	N
0	0	0	9,004
0	0	1	15,135
0	1	0	5,453
0	1	1	12,849
1	0	0	24,759
1	0	1	8,215
1	1	0	16,141
1	1	1	8,444

Table A.4 shows an example of users' reservation and cancellation decisions from one iteration of the Monte Carlo. In this case non-reservers were more likely to cancel with correlated errors and reservers were less likely to cancel with correlated errors. This result is driven by their initial preferences about the site since reservers have a higher ε_{ij}. Figure A.14 illustrates this point by comparing the ε_{ij} of reservers to the total population.

Figure A.14: Example distribution of ε_{ij} for reservers and for all users.

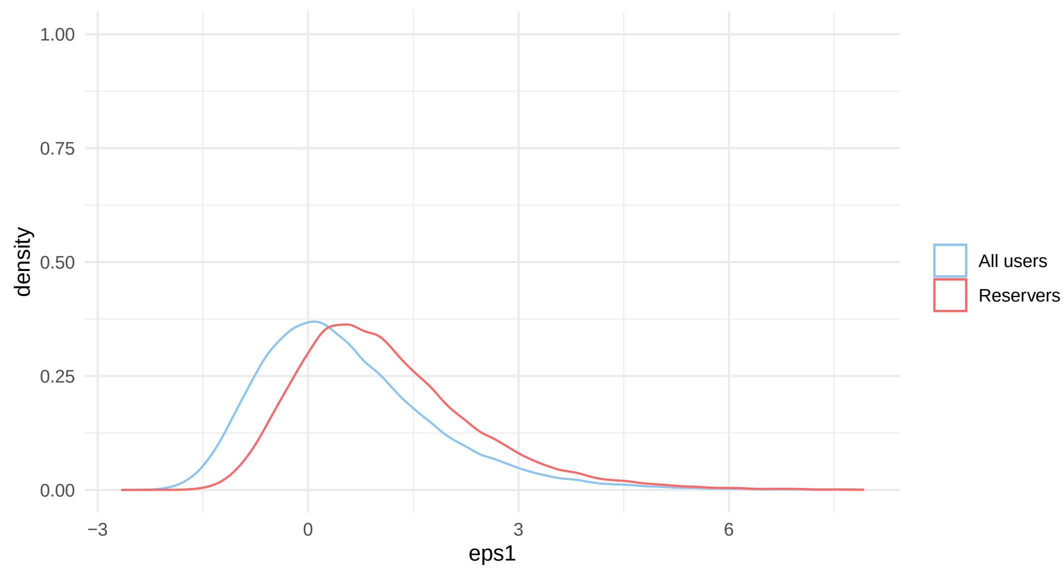


Figure A.15 plots the cancellation rate for reservers at various distances for smoke and non-smoke conditions. Results are shown under both independent and dependent errors. The figure illustrates several key points. First, the overall cancellation rate is lower with dependent errors, as indicated by the intercept of the fitted golden line. Users that made a reservation had a high initial preference for the site, so they are less likely overall to cancel. Second, the average effect of smoke, which is the distance between the red and blue points, is similar with independent and dependent errors. Third, the effect of travel cost, which is the slope of the golden fitted line, is attenuated when errors are dependent. This attenuation illustrates that the selection effect likely operates through positive correlation between ε_{ij} and travel cost.

We can further demonstrate this relationship by regressing distance on ε_{ij} in the full sample and the selected sample. Table A.5 shows an example of such a regression using one draw from the Monte Carlo simulation. Travel cost and distance are correlated among the selected sample, but not among all users.

Figure A.15: Example cancellation rate for reservers by distance and smoke.

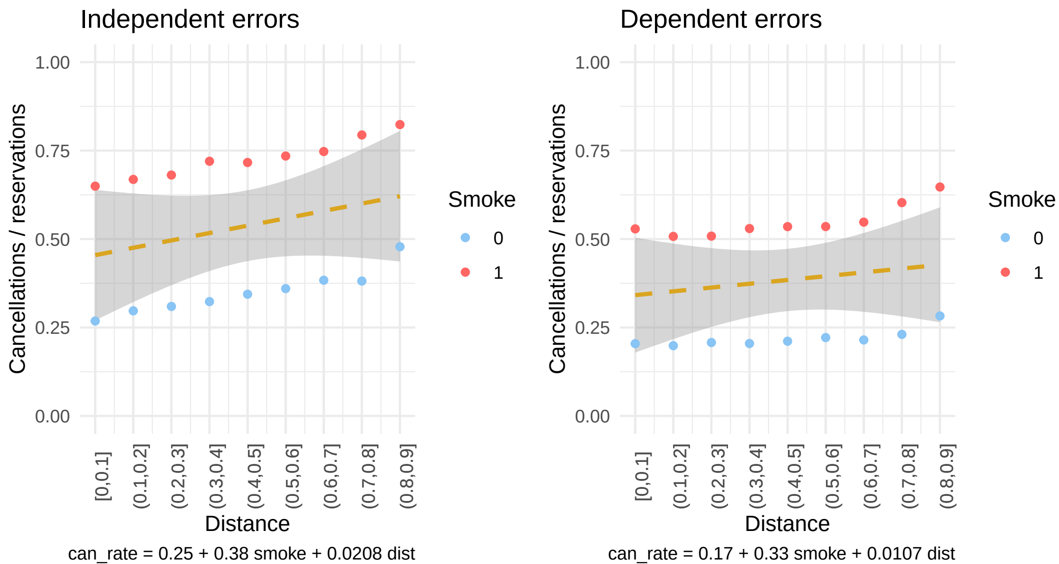


Table A.5: Example regression of distance on ε_{ij} in the full and selected sample.

	(1)	(2)
ε_{ij}	-0.0003	0.005^{**}
	(0.0004)	(0.001)
Intercept	0.398^{**}	0.384^{**}
	(0.001)	(0.001)
Observations	100,000	57,559
R^2	0.00001	0.001
Users	All users	Reservers
Note:		$^{*}p<0.05$; $^{**}p<0.01$.

Next we show that WTP estimates are only biased under a selected sample and with correlated preferences. We estimate a logit regression for the reservation and cancellation decisions, varying whether we use the full sample or the selected sample of reservers. In addition, we vary whether we use the dependent error υ_{ij}^{dep} or the independent error υ_{ij}^{ind} for the cancellation decision.

Table A.6 shows an example from one iteration of the Monte Carlo simulation. In column 1 we use the full sample for the reservation decision. In columns 2 and 3 we estimate the cancellation decision with both errors υ_{ij}^{ind} and υ_{ij}^{dep}, but with the full sample. These regressions show that the dependency of the error would not cause biased estimation if the counterfactual cancellation decision of the non-reservers were known. In column 4 we estimate the cancellation decision among only the selected sample but with an independent error υ_{ij}^{ind}. Regression 4 demonstrates that sample selection is not an issue if the user's preferences at cancellation are uncorrelated with their preferences at the time of reservation. Finally, column 5 shows that WTP estimates are biased when preferences are correlated and the sample is selected.

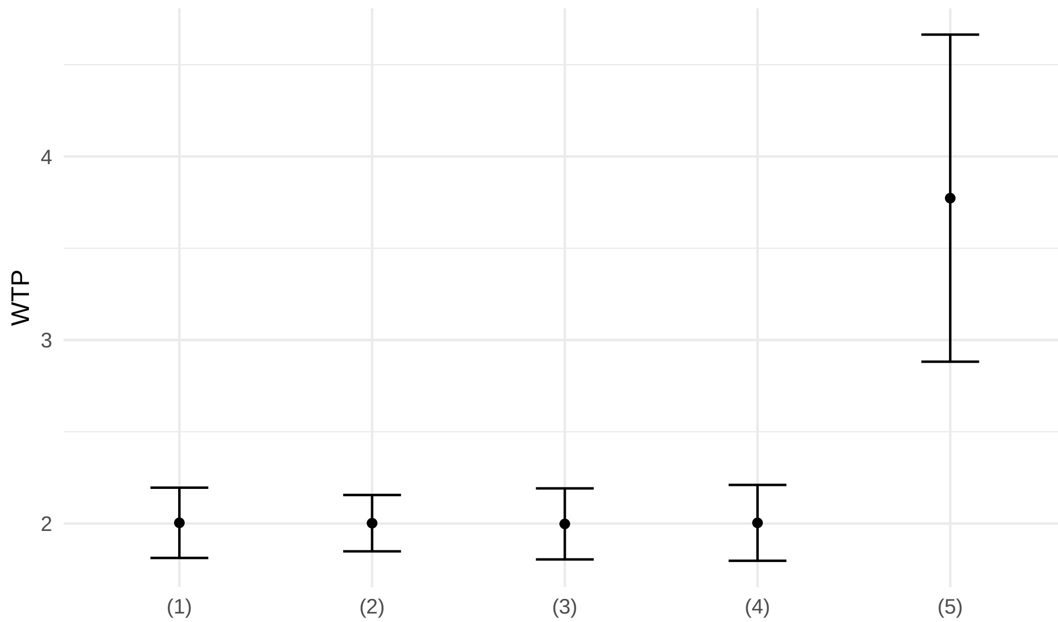
Table A.6 uses only one draw from the full set of 10,000 random draws. In Figure A.16 we show the same results over the full set of 10,000 draws. The logic holds: estimation of WTP is biased only under a selected sample with correlated preferences.

Table A.6: Example regressions of reservation and cancellation decisions under various samples and error structures.

	(1)	(2)	(3)	(4)	(5)
Distance	-0.7998**	-0.8131**	-0.5826**	-0.8261**	-0.2727**
	(0.0405)	(0.0426)	(0.0414)	(0.0563)	(0.0606)
$\mathbb{E}$[Smoke]	-1.5951**				
	(0.0515)				
Smoke		-1.5814**	-1.2402**	-1.6025**	-1.4407**
		(0.0160)	(0.0155)	(0.0211)	(0.0205)
Intercept	0.9988**	1.0091**	0.7576**	1.0190**	1.4310**
	(0.0214)	(0.0189)	(0.0183)	(0.0245)	(0.0266)
N	100,000	100,000	100,000	57,559	57,559
Dep. var.	R_{ij}	C_{ij}	C_{ij}	C_{ij}	C_{ij}
Users	All users	All users	All users	Reservers	Reservers
Error	ε_{ij}	υ_{ij}^{ind}	υ_{ij}^{dep}	υ_{ij}^{ind}	υ_{ij}^{dep}
WTP	1.99	1.95	2.13	1.94	5.28

Notes: True WTP = 2. * $p < 0.05$, ** $p < 0.01$.

Figure A.16: Monte Carlo 10,000 simulated regressions of reservation and cancellation decisions.



	(1)	(2)	(3)	(4)	(5)
WTP	2.00**	2.00**	2.00**	2.00**	3.77**
	(0.10)	(0.08)	(0.10)	(0.11)	(0.46)
Dep. var.	R_{ij}	C_{ij}	C_{ij}	C_{ij}	C_{ij}
Users	All users	All users	All users	Reservers	Reservers
Error	ε_{ij}	υ_{ij}^{ind}	υ_{ij}^{dep}	υ_{ij}^{ind}	υ_{ij}^{dep}

Notes: True WTP = 2. * $p < 0.05$, ** $p < 0.01$.

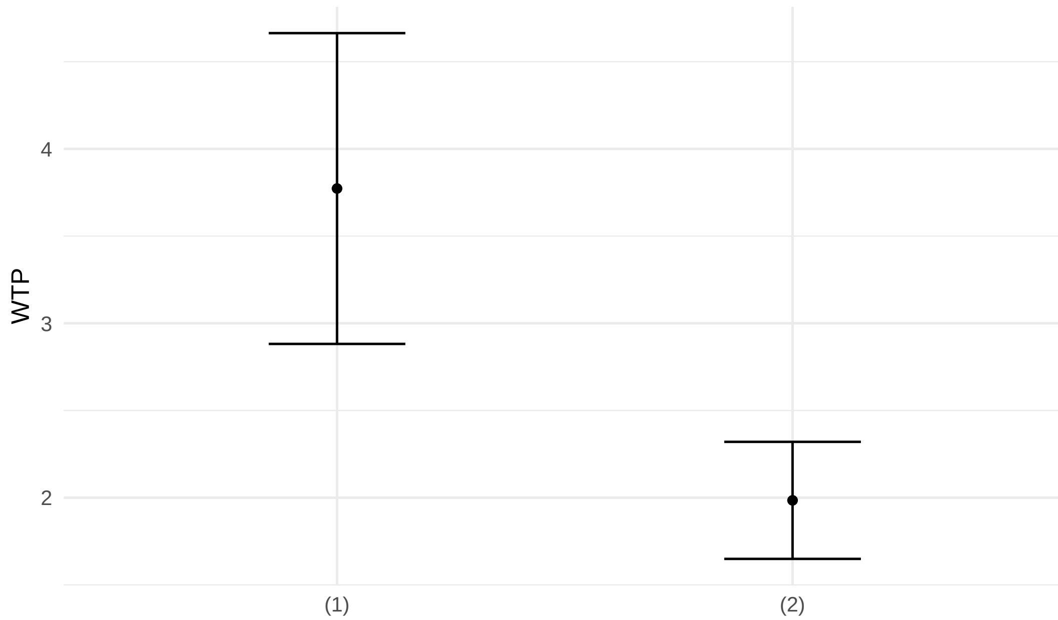
We next demonstrate the bias correction of the estimand $\tilde{\varepsilon}_{ij}$ derived in equation 1.13. We first estimate the reservation decision, then use the fitted values of $\mathbb{E}[V_{ij}]$ to form $\tilde{\varepsilon}_{ij}$. Table A.7 shows an example from one draw of the 10,000 simulations. In this example we see that the smoke coefficient is unaffected by the bias corrector. Instead, the value of the intercept is reduced and the value of the distance coefficient is inflated. In this single random draw the true WTP was not exactly recovered. However, over the full set of 10,000 simulations we see that the inclusion of $\tilde{\varepsilon}_{ij}$ results in unbiased estimation. Figure A.17 shows WTP results for the full set of 10,000 simulations. The inclusion of the $\tilde{\varepsilon}_{ij}$ estimator resulted in recovery of the true WTP. This result lends support to the use of this bias corrector in the empirical dataset.

Table A.7: Example regression of cancellation decision for reservers using bias correction.

	(1)	(2)
Intercept	1.4310**	0.7590**
	(0.0266)	(0.0813)
Smoke	-1.4407**	-1.4417**
	(0.0205)	(0.0205)
Distance	-0.2727**	-0.6088**
	(0.0606)	(0.0718)
$\tilde{\varepsilon}_{ijt}$		-0.6862**
		(0.0786)
N	57,559	57,559
WTP	5.28	2.37
2-step estimator	None	$\tilde{\varepsilon}_{ijt}$

Notes: True WTP = 2. * $p < 0.05$, ** $p < 0.01$.

Figure A.17: Monte Carlo 10,000 simulated regressions showing bias correction.



	(1)	(2)
WTP	3.77**	1.98**
	(0.45)	(0.17)
2-step estim.	None	$\tilde{\varepsilon}_{ij}$

Notes: True WTP = 2. * p < 0.05, ** p < 0.01.

There are several key assumptions from this exercise. First, the data generating process asserts that users react the same way to expected smoke as to realized smoke. That is, the coefficient for expected smoke and realized smoke is the same. This assumption may not hold for real users; it is reasonable to believe that decision makers may respond differently to expected conditions than to realized conditions. Still, the purpose of $\tilde{\varepsilon}_{ij}$ is to account for selection from the first stage and should therefore serve as an appropriate control function, regardless of whether the coefficients are identical between stages.

The second key assumption is that the decision maker selects from a single choice alternative. This setup matches our conceptual framework in Section 1.3, where we assumed a binary site choice. The main reason for this assumption is for computational tractability of the dataset, which features millions of users and nearly one thousand campgrounds over eight years. For an extended treatment of this matter see Appendix A.3.

A.5 Bootstrapped standard errors for $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$

In Section 1.4 we used a two stage sample selection correction to estimate $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$. Wooldridge (2015) recommends that researchers bootstrap standard errors when estimating two stage control functions. Because we cluster standard errors at the campground level, our bootstrap follows the process outlined by Cameron and Miller (2015) in a methods guide for clustered standard errors. Their process is as follows: for B bootstraps and G clusters, (1) sample with replacement G times from the original sample of clusters, (2) compute parameter estimates. The estimating dataset contains $G = 999$ clusters. The resampling occurs over entire clusters; in some bootstraps, some clusters will not be represented, whereas some clusters will have all of their observations appear multiple times in the estimating dataset. Cameron and Miller (2015) note that $B = 400$ should be "more than adequate" in most settings.

In this section we test that the bootstrapped coefficients follow a normal distribution, assessing whether $B = 400$ is an adequate number of bootstraps. Table A.8 reports W statistics from Shapiro-Wilk tests of normality for the smoke and travel cost coefficients from the main estimation of Table 1.4. We fail to reject the null hypothesis that the bootstrapped smoke and travel cost coefficients follow a normal distribution. These tests imply that 400 bootstraps are adequate for the analysis. Figures A.18 and A.19 plot the bootstrapped coefficients visually.

Table A.8: W statistics from Shapiro-Wilk test of normality for bootstrapped coefficients of $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ with sample selection correction. Parentheses indicate p values. The null hypothesis is that the coefficients are normally distributed.

	(1)	(2)	(3)	(4)
Smoke in week of arrival	0.996	0.998	0.998	0.994
	(0.450)	(0.979)	(0.852)	(0.084)
Travel cost (dollars)	0.990	0.996	0.995	0.995
	(0.006)	(0.343)	(0.291)	(0.255)
Campground FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Campground x week-of-year FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Figure A.18: Distribution of estimated smoke coefficient from models (1) through (4) in bootstrapped estimation of $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ with sample selection correction. Red line indicates mean.

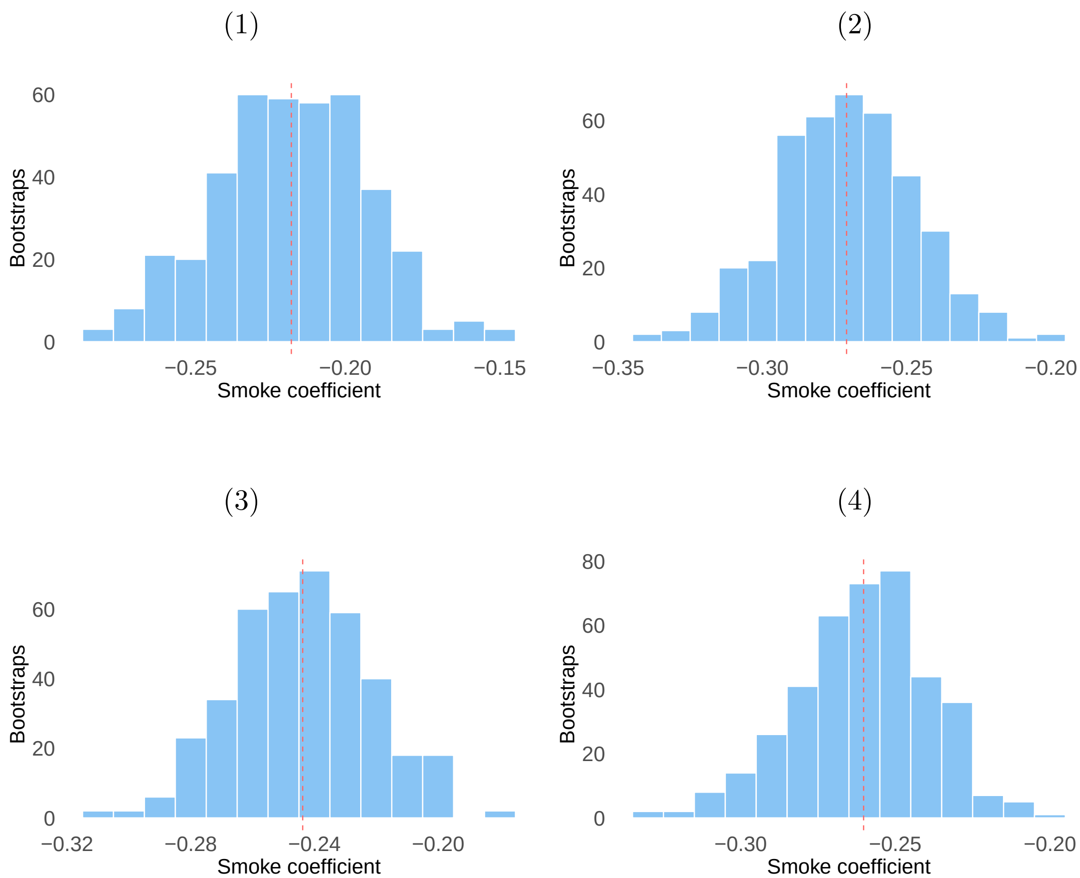
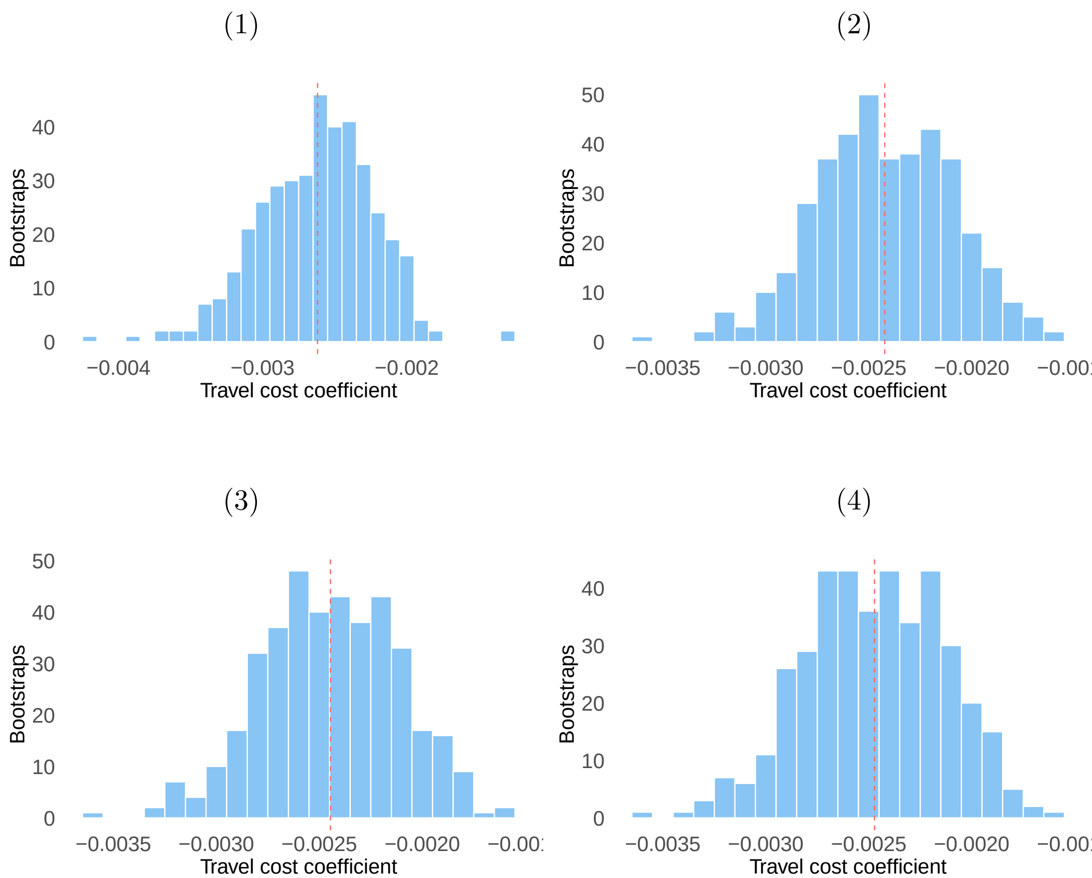


Figure A.19: Distribution of estimated travel cost coefficient from models (1) through (4) in bootstrapped estimation of $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ with sample selection correction. Red line indicates mean.



A.6 Testing the influence of no shows in cancellations

One may be concerned that some recreationists do not formally cancel their reservation when they decide not to complete a trip. Unreported no shows threaten the identification of any WTP that is based on cancellations, since it could potentially underestimate cancellations. While most of the campgrounds in the Recreation.gov dataset do not report check ins or no shows, a subset of campgrounds do.

In this section we compare estimates at these select campgrounds with and without the inclusion of no shows. We demonstrate that although no shows are not infrequent at these campgrounds, omitting them does not influence measures of responses to smoke and travel cost. This analysis should mitigate some concern that we understate avoidance behavior.

In total, just 36 out of 999 campgrounds (3.6%) report no shows. However, these campgrounds represent a large proportion of the reservations used in the cancellation estimation. Of the reservations made greater than a week ahead of time, 2,188,444 reservations were at non-no show facilities (80.3%), while 535,496 were reservations at facilities that report no shows (19.7%).

To gauge the importance of no shows in the cancellation estimation, Figure A.20 and Table A.9 report the share of all cancellations that are no shows at each campground. While most of the overall dataset is comprised of US Forest Service campgrounds, Table A.9 shows that many campgrounds reporting no shows are managed by the National Park Service and US Army Corps of Engineers. For most of these campgrounds, no shows represent less than 15% of all cancellations, though at some campgrounds no shows represent nearly a third of all cancellations.

Figure A.20: No shows as a proportion of all cancellations among campgrounds reporting no shows.

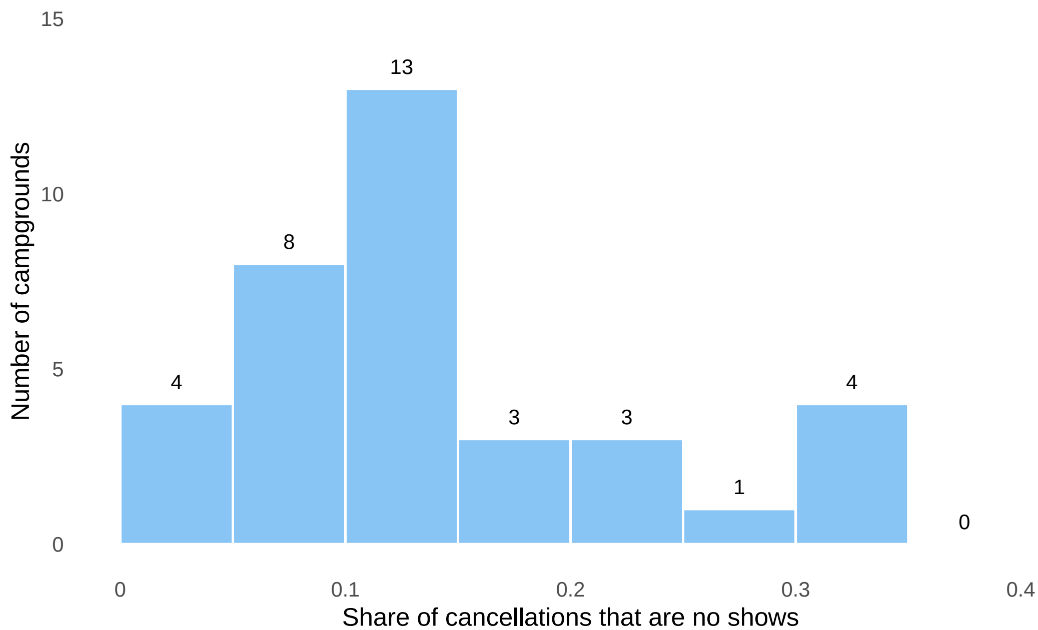


Table A.9: Campgrounds reporting no shows.

Campground	Recreation area	State	Agency	No show % of cancellations
Aspenglen	Rocky Mountain	CO	NPS	33.69
Glacier Basin	Rocky Mountain	CO	NPS	32.8
Moraine Park	Rocky Mountain	CO	NPS	32.51
Watchman	Zion	UT	NPS	32.36
Mather	Grand Canyon	AZ	NPS	27.59
Schwarz Park	Dorena Lake	OR	USACE	24.62
Buckhorn	Black Butte Lake	CA	USACE	23.37
Springy Point	Albeni Falls Dam	ID	USACE	20.44
Hood Park	McNary Lock And Dam	WA	USACE	18.51
Hodgdon Meadow	Yosemite	CA	NPS	18.49
Fishhook Park	Ice Harbor Lock	WA	USACE	15.09
Dinkey Creek	High Sierra RD	CA	USFS	14.86
Meeks Bay	Lake Tahoe Basin	CA	USFS	14.03
Serrano	Big Bear	CA	USFS	14.02
Crane Flat	Yosemite	CA	NPS	13.89
Riley Creek	Albeni Falls Dam	ID	USACE	13.83
Dogwood	Arrow Head	CA	USFS	13.24
Wawona	Yosemite	CA	NPS	13.2
Charbonneau Pk	Ice Harbor Lock	WA	USACE	12.74
Pine Meadows	Cottage Grove Lake	OR	USACE	12.65
North Rim	Grand Canyon	AZ	NPS	12.47
Kyen	Lake Mendocino	CA	USACE	10.83
Nevada Beach	Lake Tahoe Basin	CA	USFS	10.81
William Kent	Lake Tahoe Basin	CA	USFS	10.1
Lepage Park	John Day Lock	OR	USACE	9.74
Fish Creek	Glacier	MT	NPS	8.5
Rancheria	High Sierra RD	CA	USFS	7.61
Oh Ridge	Mono Lake RD	CA	USFS	7.19
Deer Creek	High Sierra RD	CA	USFS	7.1
Diamond Lake	Diamond Lake RD	OR	USFS	6.01
Downstream	Fort Peck Project	MT	USACE	5.68
Pinecrest	Summit RD	CA	USFS	5.47
Fallen Leaf	Lake Tahoe Basin	CA	USFS	4.56
Acorn	New Hogan Lake	CA	USACE	4.46
Lodgepole	Sequoia And Kings Canyon	CA	NPS	2.5
Dorst Creek	Sequoia And Kings Canyon	CA	NPS	2.33

We would like to use this subset of campgrounds to demonstrate that unreported no shows likely do not matter in the full sample. Table A.10 tests whether these campgrounds are systematically different than the full sample. The table shows that these no show campgrounds tend to have higher cancellation rates under both smoke and non-smoke conditions.

However, the estimates in Table A.11 should alleviate concerns that no shows are influential in cancellation estimates. We test four models with the same sets of fixed effects, but vary the estimating sample. In column 1 we include all campgrounds and estimate $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$. Column 2 removes no shows from the dataset, finding that WTP is unchanged. In column 3 we allow smoke and travel cost to respond differentially for no show and non-no show campgrounds, but include no shows in the dataset. This model shows that no show and non-no show campgrounds have different overall measures of WTP. Finally, column 4 removes no shows from the dataset. Comparing the WTP of no show campgrounds with and without the inclusion of no shows, WTP is virtually unchanged. This analysis should alleviate concerns that no shows influence the estimate of WTP in the full sample.

Table A.10: Cancellation rate mean by campground type and by smoke.

	All campgrounds	Non-no show campgrounds	No show campgrounds	t-statistic
Baseline	0.09	0.09	0.13	(9.44)
No. of res.	2,380,606	1,898,955	481,651	
Smoke	0.13	0.12	0.19	(2.02)
No. of res.	343,334	289,489	53,845	
t-statistic	(13.41)	(13.19)	(3.06)	

Notes: The righthand column gives the t-statistic for the difference in mean cancellation rates by campground type in either smoke or non-smoke conditions. The bottom row gives the t-statistic for the difference in mean cancellation rate for smoke and non-smoke days among the different campground types.

Table A.11: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, testing effect of no shows on cancellation.

	(1)	(2)	(3)	(4)
Smoke in week of arrival	-0.2613**	-0.2659**		
	(0.0215)	(0.0215)		
Smoke x 1(Non-no show campground)			-0.2608**	-0.2605**
			(0.0188)	(0.0188)
Smoke x 1(No show campground)			-0.2628**	-0.2846**
			(0.0689)	(0.0736)
Travel cost (dollars)	-0.0024**	-0.0025**		
	(0.0003)	(0.0004)		
Travel cost x 1(Non-no show campground)			-0.0025**	-0.0025**
			(0.0004)	(0.0004)
Travel cost x 1(No show campground)			-0.0023**	-0.0024**
			(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-7.8194**	-7.9970**	-7.8180**	-7.9907**
	(0.8239)	(0.8659)	(0.8223)	(0.8631)
High temp. (degrees C)	0.0306**	0.0308**	0.0306**	0.0308**
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Low temp. (degrees C)	-0.0252**	-0.0254**	-0.0252**	-0.0254**
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Precip. in week of arrival (mm)	-0.0057**	-0.0058**	-0.0057**	-0.0058**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0370**	-0.0370**	-0.0376**	-0.0373**
	(0.0126)	(0.0131)	(0.0134)	(0.0137)
WTP	107.95**	107.92**		
	(17.14)	(17.48)		
WTP, non-no show campgrounds			103.82**	103.9**
			(17.39)	(17.75)
WTP, no show campgrounds			116.66**	119.75**
			(32.1)	(33.5)
No shows included?	Yes	No	Yes	No
N	2,688,739	2,677,763	2,688,739	2,677,763
Campground FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
Campground x week-of-year FE	Yes	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes	Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

A.7 Alternative distance thresholds for sample restriction

The main estimates of this paper restrict the estimating sample to reservations from origins within driving distance of a site, which we define as 650 km of one-way driving distance, or approximately 400 miles. Figure 1.1 shows that this threshold admits approximately 85% of the total reservations into the estimation. In this section we show results from the main estimation using alternative distance thresholds of 350 km (approximately 217 miles) and 950 km (approximately 590 miles).

Figure A.21 illustrates how WTP estimates increase as the distance threshold is relaxed. Using a restrictive threshold of 350 km, WTP is estimated to be $79 per person per trip; with a wider threshold of 950 km, WTP is estimated to be $140 per person per trip. Tables A.12 and A.13 show full results for these estimations, which should be compared to the main estimates in Table 1.4.

Recall that WTP is calculated as the ratio of marginal disutility in smoke to marginal disutility in expenditure, i.e. the smoke coefficient divided by the travel cost coefficient. The choice of distance threshold does not alter the estimated smoke coefficient. Instead, the increasing WTP estimates are driven by a decline in the magnitude of the travel cost coefficient as the distance threshold is relaxed. The travel cost coefficient is estimated at -0.0034, -0.0025, and -0.0019 for thresholds of 350 km, 650 km, and 950 km, respectively. In other words, increasing the pool of potential reservers decreases the estimated response to travel cost. This phenomenon could from the inclusion of visitors at greater distances who chose not to cancel their reservations.

An additional difference across estimations is the magnitude of the coefficient for the $\tilde{\varepsilon}_{ijt}$ preference parameter, which is estimated at -0.0240, -0.0385, and -0.0390 for the respective distance thresholds of 350 km, 650 km, and 950 km. The magnitude of this coefficient is likely smaller at low distance restriction thresholds due to the correlation of preferences with travel cost; removing reservations made from larger distances eliminates some visitors with both high travel costs and high preferences. Figure A.22 shows that the fitted parameter $\tilde{\varepsilon}_{ijt}$ correlates with travel cost in both the 350 km sample and the 950 km sample.

Figure A.21: Summary of WTP measures using alternative distance thresholds for sample restriction of 350 km (217 miles) and 950 km (590 miles).

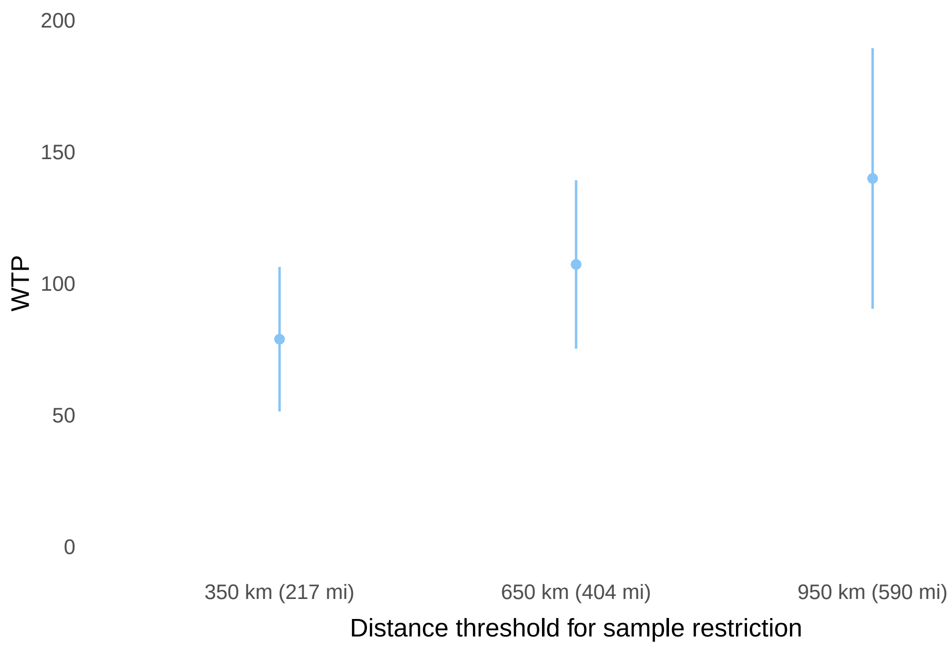


Figure A.22: Relationship between control function $\tilde{\varepsilon}_{ijt}$ and travel cost using model (4), using a distance threshold of: (A) 350 km (217 miles); (B) 950 km (590 miles). Compare to Figure 1.5.

(A) 350 km.

(B) 950 km.

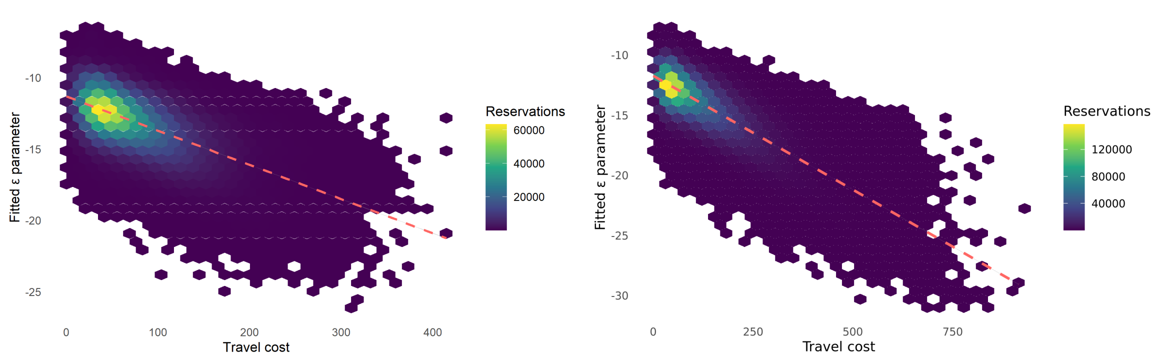


Table A.12: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ within one week, restricting sample distance to within 350 km (217 miles) of site.

	(1)	(2)	(3)	(4)
Smoke in week of arrival	-0.2227**	-0.2641**	-0.2329**	-0.2651**
	(0.0262)	(0.0342)	(0.0324)	(0.0241)
Travel cost (dollars)	-0.0039**	-0.0033**	-0.0033**	-0.0034**
	(0.0006)	(0.0005)	(0.0005)	(0.0005)
Inv. distance to wildfire (km^{-1})	-12.3006**	-14.1542**	-14.0303**	-8.9377**
	(1.0509)	(3.2997)	(3.3356)	(0.8670)
High temp. (degrees C)	0.0210**	0.0323**	0.0325**	0.0331**
	(0.0043)	(0.0027)	(0.0027)	(0.0025)
Low temp. (degrees C)	-0.0007	-0.0209**	-0.0217**	-0.0248**
	(0.0054)	(0.0029)	(0.0029)	(0.0028)
Precip. in week of arrival (mm)	-0.0045**	-0.0065**	-0.0066**	-0.0061**
	(0.0011)	(0.0010)	(0.0010)	(0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.0139	-0.0222	-0.0230	-0.0240
	(0.0344)	(0.0160)	(0.0162)	(0.0165)
N	2,085,985	2,047,894	2,047,894	2,044,062
WTP	57.42**	80.09**	69.86**	78.74**
	(11.65)	(17.61)	(15.7)	(14.02)
Campground FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Campground x week-of-year FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

A.8 Heterogeneous results by campground popularity

This section explores heterogeneous welfare damages based on the popularity of the campground. We define popularity based on the average number of visitors per year for years in which the campground was open. For reference, Table A.1 shows the top most-visited campgrounds, many of which belong to high profile National Parks such as Yosemite National Park, Grand

Table A.13: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ within one week, restricting sample distance to within 950 km (590 miles) of site.

	(1)	(2)	(3)	(4)
Smoke in week of arrival	-0.2128**	-0.2622**	-0.2354**	-0.2589**
	(0.0238)	(0.0269)	(0.0259)	(0.0206)
Travel cost (dollars)	-0.0021**	-0.0019**	-0.0019**	-0.0019**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Inv. distance to wildfire (km^{-1})	-10.9723**	-11.6811**	-11.5690**	-7.5899**
	(0.9010)	(2.2906)	(2.3049)	(0.8101)
High temp. (degrees C)	0.0198**	0.0280**	0.0286**	0.0300**
	(0.0046)	(0.0023)	(0.0022)	(0.0021)
Low temp. (degrees C)	-0.0053	-0.0199**	-0.0210**	-0.0249**
	(0.0058)	(0.0024)	(0.0024)	(0.0024)
Precip. in week of arrival (mm)	-0.0039**	-0.0058**	-0.0060**	-0.0056**
	(0.0011)	(0.0009)	(0.0009)	(0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0121	-0.0414**	-0.0424**	-0.0390**
	(0.0243)	(0.0122)	(0.0121)	(0.0128)
N	2,884,364	2,854,171	2,854,171	2,851,414
WTP	100.43**	137.19**	121.83**	139.83**
	(20.95)	(27.77)	(24.69)	(25.27)
Campground FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Campground x week-of-year FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

Canyon National Park, and Rocky Mountain National Park. The least popular campgrounds tend to be small, local, or regional US Forest Service campgrounds. We rerun the main estimation but allow the smoke and travel cost coefficients to vary by the quartile of campground popularity. Given 999 campgrounds, each quartile contains approximately 250 campgrounds.

Figure A.23 summarizes the point estimates for smoke responses, travel cost responses, and WTP. Full results are displayed in Table A.14. Across specifications, the magnitude for both the smoke and travel cost coefficients are lower at more popular campgrounds. These results suggest visitors are more willing to incur both higher travel costs and some environmental disamenity for highly desirable locations.

The translation of these responses to welfare impacts is less clear. Recall that WTP is estimated as the ratio of marginal disutility in smoke to marginal disutility in expenditure, i.e. the smoke coefficient divided by the travel cost coefficient. Because WTP is a ratio, WTP could be either higher or lower given reductions in both the smoke parameter (the numerator) and the travel cost parameter (the denominator). Figure A.23 shows that the reduction in the smoke parameter dominates, resulting in lower WTP at popular campgrounds. Table A.14 confirms that WTP is lower at popular campgrounds across all specifications. In general, welfare damages tend to be largest for the middle two quartiles of campground popularity.

Figure A.23: Point estimates for smoke response, travel cost response, and WTP by quartile of popularity using model (4). Visitors are less responsive to smoke and travel cost at more popular campgrounds.

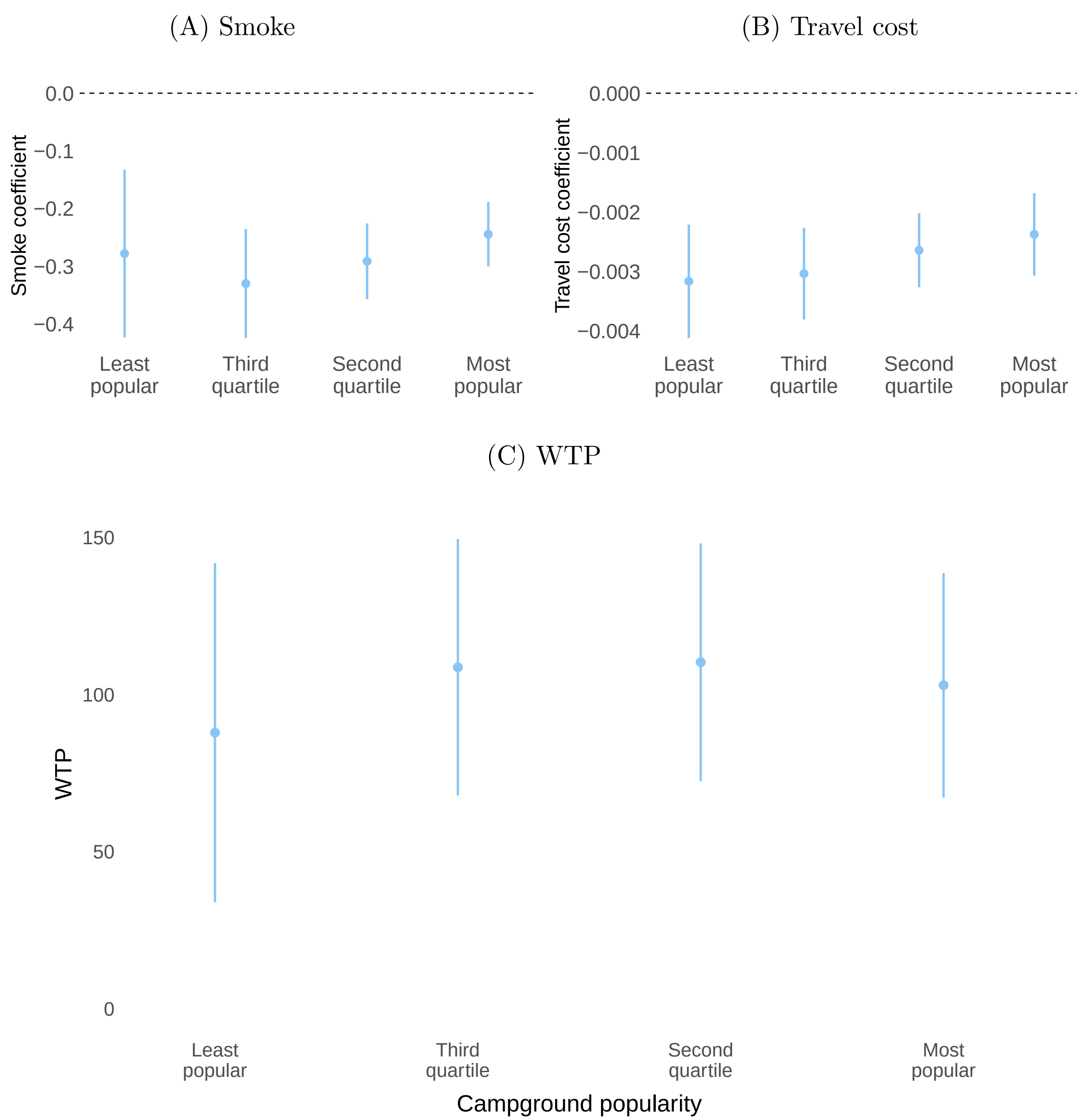


Table A.14: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, heterogeneity by campground popularity.

	(1)	(2)	(3)	(4)
Inv. distance to wildfire (km^{-1})	-11.0284**	-12.0844**	-11.9595**	-7.8196**
	(0.9225)	(2.4306)	(2.4448)	(0.8254)
High temp. (degrees C)	0.0187**	0.0289**	0.0293**	0.0307**
	(0.0044)	(0.0023)	(0.0023)	(0.0022)
Low temp. (degrees C)	-0.0012	-0.0204**	-0.0213**	-0.0252**
	(0.0055)	(0.0025)	(0.0025)	(0.0025)
Precip. in week of arrival (mm)	-0.0046**	-0.0059**	-0.0061**	-0.0057**
	(0.0010)	(0.0009)	(0.0009)	(0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0037	-0.0377**	-0.0387**	-0.0402**
	(0.0256)	(0.0120)	(0.0120)	(0.0122)
Smoke x first quartile (most popular)	-0.2208**	-0.2297**	-0.2035**	-0.2446**
	(0.0320)	(0.0345)	(0.0338)	(0.0286)
Smoke x second quartile	-0.2563**	-0.3296**	-0.3007**	-0.2915**
	(0.0425)	(0.0417)	(0.0407)	(0.0335)
Smoke x third quartile	-0.2364**	-0.3161**	-0.2889**	-0.3301**
	(0.0462)	(0.0482)	(0.0482)	(0.0482)
Smoke x fourth quartile (least popular)	-0.2488**	-0.3577**	-0.3457**	-0.2781**
	(0.0576)	(0.0673)	(0.0681)	(0.0743)
Travel cost x first quartile (most popular)	-0.0028**	-0.0023**	-0.0024**	-0.0024**
	(0.0004)	(0.0003)	(0.0003)	(0.0004)
Travel cost x second quartile	-0.0010*	-0.0027**	-0.0027**	-0.0026**
	(0.0005)	(0.0003)	(0.0003)	(0.0003)
Travel cost x third quartile	-0.0009	-0.0030**	-0.0030**	-0.0030**
	(0.0006)	(0.0004)	(0.0004)	(0.0004)
Travel cost x fourth quartile (least popular)	-0.0009	-0.0031**	-0.0031**	-0.0032**
	(0.0006)	(0.0005)	(0.0005)	(0.0005)
WTP: first quartile (most popular)	79.36**	98.63**	86.49**	102.87**
	(17.55)	(21.64)	(20.09)	(18.25)
WTP: second quartile	249.52	123.65**	112.36**	110.23**
	(136.76)	(22.99)	(21.6)	(19.31)
WTP: third quartile	253.55	106.16**	96.52**	108.62**
	(169.66)	(22.64)	(21.48)	(20.82)
WTP: fourth quartile (least popular)	272.18	116.18**	110.39**	87.8**
	(195.78)	(29.58)	(28.58)	(27.56)
N	2,723,034	2,691,655	2,691,655	2,688,739
Campground FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Campground x week-of-year FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

A.9 Total welfare estimate data construction

In Section 1.5 we report estimates for the total annual number of recreation visits affected by smoke in the west. To do so we combine the Recreation.gov data with overall visitation data from various federal and state agencies. In particular, we use total visitation numbers from the National Park Service, US Forest Service, Bureau of Land Management, US Army Corps of Engineers, and the National Association of State Park Directors. Each of these agencies reports visitation at varying spatial and temporal levels. For example, the National Park Service reports visitation at a park by month level; the US Forest Service reports at a forest by year level; and the state parks data is reported at a state by year level. For each data source we aggregate the daily Recreation.gov data to the most relevant spatial and temporal scale to determine the proportion of visits affected by smoke. We then multiply this proportion by the total visitation data. In this section we detail this process for each data source.

For the National Park Service we use the agency's Annual Summary Reports.[2] This dataset reports total monthly visitation at all National Parks, National Monuments, National Recreation Areas, and other lands managed by the National Park Service. In the western states, 27 National Parks are included in the Recreation.gov dataset, while 82 are not. For the 27 parks in the Recreation.gov dataset, we determine each park's monthly proportion of campers that were affected by wildfire smoke. We then multiply this proportion by each park's monthly visitation from the Annual Summary Reports to infer the total number of visits affected by smoke. For the 82 parks not in the Recreation.gov dataset, we calculate a statewide proportion of smoke-affected campers in the data. We multiply these state by month proportions by each park's visitation levels in the Annual Summary Reports based on its location.

To estimate smoke-affected visits at National Forests we use the US Forest Service's National Visitor Use Monitoring (NVUM) Program.[3] These data report visitation at all National Forests at an annual level. In the west, 70 National Forests are included in the Recreation.gov dataset,

[2]National Park Service. Annual Summary Report. `https://irma.nps.gov/STATS`.

[3]US Forest Service. National Visitor Use Monitoring Program. `https://www.fs.usda.gov/about-agency/nvum`.

while 8 are not. For the 70 forests in the Recreation.gov data we calculate each forest's annual proportion of campers affected by smoke and multiply it by the corresponding annual visitation totals in the NVUM data. For the 8 forests not in the Recreation.gov dataset, we use a statewide annual proportion of smoke-affected campers.

The Bureau of Land Management records visitation statistics as part of its Recreation Management Information System (RMIS).[4] We contacted the program administrator and received data on site by year visitation for all BLM sites.[5] Most visitation to BLM lands is not reservable and a large portion is considered backcountry. Therefore, the Recreation.gov dataset contains very few BLM campgrounds. We thus combine annual state level proportions of smoke-affected campers from the Recreation.gov data with annual site visitation from the RMIS.

For sites managed by the US Army Corps of Engineers we use data from the agency's Value to the Nation (VTN) reports.[6] For the study period of 2008 to 2017 the agency only has one year of recreation data, which is for the year 2016. We treat this year as representative of typical annual visitation over the study period. For each site we multiply the total number of visitors by the state level average of smoke-affected campers from the Recreation.gov data over all years.

Lastly, we estimate smoke impacts at state parks. We use visitation data from the National Association of State Park Directors which was compiled by Smith et al. (2019). For these data the unit of observation is a state by year. We again use annual state level proportions of smoke-affected campers from the Recreation.gov data multiplied by the NASPD data.

Having approximated total visitation, we multiply each agency's annual smoke-affected visits by the empirical estimate of per trip losses due to wildfire smoke. We estimate that more than 21.5 million recreation visits per year are affected by smoke in the west, with annual losses of $2.3 billion. For further discussion, see Section 1.5.

[4] Bureau of Land Management. Public Land Statistics. `https://www.blm.gov/about/data/public-land-statistics`.

[5] Ridenhour, L. & Leitzinger, K. Bureau of Land Management. Personal correspondence.

[6] US Army Corps of Engineers. Value to the Nation. `https://www.iwr.usace.army.mil/Missions/Value-to-the-Nation`.

Appendix B

Appendix to Chapter 2

B.1 Recreation dataset construction

This section discusses the construction of the recreation data in greater depth. In the raw Recreation.gov data, each record is a transaction. Transactions are grouped into orders, each of which with one or more transactions. For example, a single order might contain the following transactions, in order of transaction time: Registration/Walk-in, Make Payment, Change Number of Vehicles, Extend Stay Leave Later, Change Number of People, Checkout. Each transaction includes the date and time, campground or facility, unique user identifier (retained across orders), user's zip code of origin, arrival and departure dates for the order, group size, and campsite type. If the order contains a "Cancellation" transaction, then it is known that the order was cancelled.

For each date, we are able to determine the number of parties and the number of people present at each campground using information on the orders' arrival and departure dates. If the order was cancelled, voided, or listed as a no-show, it is not added to the number of occupied sites at a campground. Figure B.1 provides a visualization of the data. We plot the average number of campers present at Glacier along with the proportion of days with observed smoke conditions in the sample; smoke conditions in Glacier overlap with times of greater visitation.

One of our primary variables of interest is the occupancy rate of a campground i on a given day t, which we define as (occupied campsites$_{it}$)/(total number of campsites$_{it}$). The Recreation.gov data do not report the total number of campsites at each campground on a given date. While the data provide a list of campsites at each campground for 2017–18, the actual number of available campsites at some campgrounds varies from year to year. Some campgrounds, for example, were not yet open during the early years of the sample; others added or removed campsites over time. In some cases, campgrounds have shut down for entire seasons. To obtain the best possible estimate of the available campsites for each campground, we create an algorithm that predicts the number of campsites by year for each campground based on a combination of (i) the listed campsites in 2017–18, (ii) the maximum number of sites reserved on any given day in a given year, and (iii) the individual identification numbers for each site, to ensure that we capture as many of the available sites as possible. For each campground for each year, the algorithm proceeds in the following way:

1. If the maximum number of reserved sites in a year (item ii) matches the number of campsites listed in 2017–18 (item i), the algorithm applies that number.

2. If the maximum number of reserved sites does not match the number of campsites listed in 2017–18, the algorithm counts the number of times the within-year maximum number of occupants (item ii) was obtained. If it occurred three times or more, the algorithm applies that number for the yearly number of available campsites.

3. If step 2 fails (the within-year maximum number of occupants was not obtained at least three times), the algorithm checks how often the number of occupants matched the listed number of campsites in 2017–18 (item i). If it was more than three times, the algorithm applies that number for the yearly available campsites.

4. If both steps 2 and 3 fail, the algorithm checks if the maximum number of occupants in the preceding year and the following year matched, and if so it applies that number.

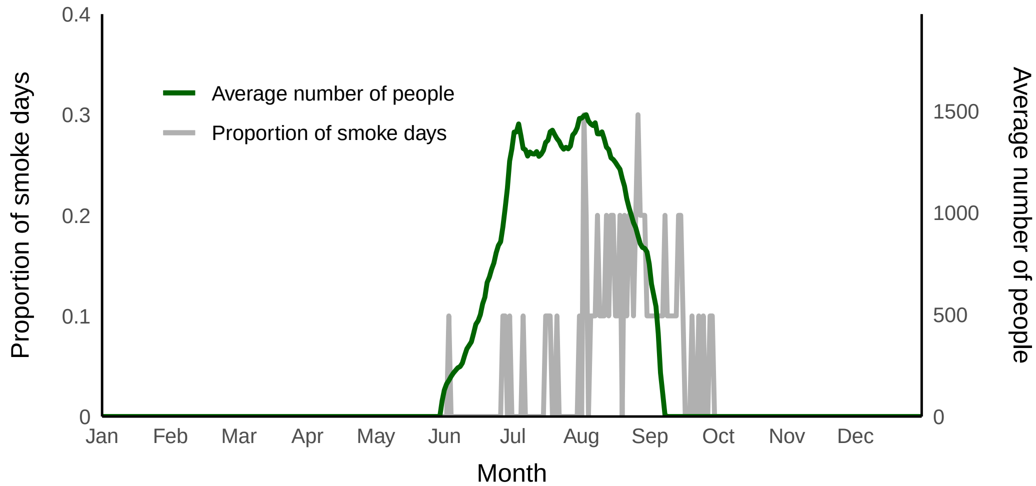
5. If none of these criteria are satisfied, the algorithm selects the number of sites available in 2017–18 (item i).

This algorithm accounts for many scenarios. If a campground had more available sites than was reported in 2017–18 (criterion i), then the yearly maximum would be achieved fairly frequently (item ii), providing a more accurate measure of campground size. If a campground was closed for an entire season, then the maximum number of sites reserved in a year (criterion ii) is 0, which occurs 365 times, so the number of available sites for that year would be set to 0. We manually assessed and corrected the results of this algorithm by examining a time series of the number of occupied sites for each campground and comparing against items (i), (ii), and (iii). Some campgrounds do not fill up, but by examining the individual identification numbers of each site (item iii), we can determine the number of available sites for each year.

Two other variables are of interest in regressions on campground use: the pre- and post-arrival cancellation rates. For the pre-arrival cancellation rate, for day t, we add the transactions of type "Cancellation," "Cancellation (Waive Penalty)," and "No-Show" for arrival date t if the cancellation was transacted within seven days (i.e., greater than or equal to t–7). We divide this sum by the total number of reservations scheduled to arrive on t. Formally, for campground i, this is $\frac{\text{cancellations}_{it} + \text{cancellations (waived penalty)}_{it} + \text{no shows}_{it}}{\text{reservations}_{it}}$. Intuitively, this measures the share of reservations for date t that were cancelled prior to arrival.

For post-arrival cancellations, we add transactions of type "Cancellation," "Cancellation (Waive Penalty)," and "Shorten Stay Leave Early" on day t if the date t falls between the scheduled arrival and departure date. We divide that sum by the number of occupants present at the campground on day t. Formally, for campground i, this is $(\text{cancellations}_{it} + \text{cancellations (waived penalty)}_{it} + \text{shorten stay leave early}_{it})/(\text{occupants}_{it})$, for midstay cancellations only.

Figure B.1: Occupancy and smoke at Glacier National Park. The average number of campers at Glacier National Park and the proportion of days it was affected by adverse smoke conditions in the study period.



B.2 Results with alternative fire and smoke variables

B.2.1 Campground and campground visitor-days affected by wildfire and smoke

The measurement of campground-days near actively burning wildfires or impacted by smoke varies depending on how we define affected days. In the main text, we define “near to an active fire” as being within 20 km of a burning wildfire. The upper panel of Table B.1 summarizes the number of campground-days and visitor-days affected when we instead use a 30 km bandwidth. The average number of days on which campgrounds experience a nearby fire increases from 1.5 to 2.8, and the percent of total visitor-days affected by a fire increases from 1.4 to 2.5. The distribution of fire days across regions is similar for both bandwidths.

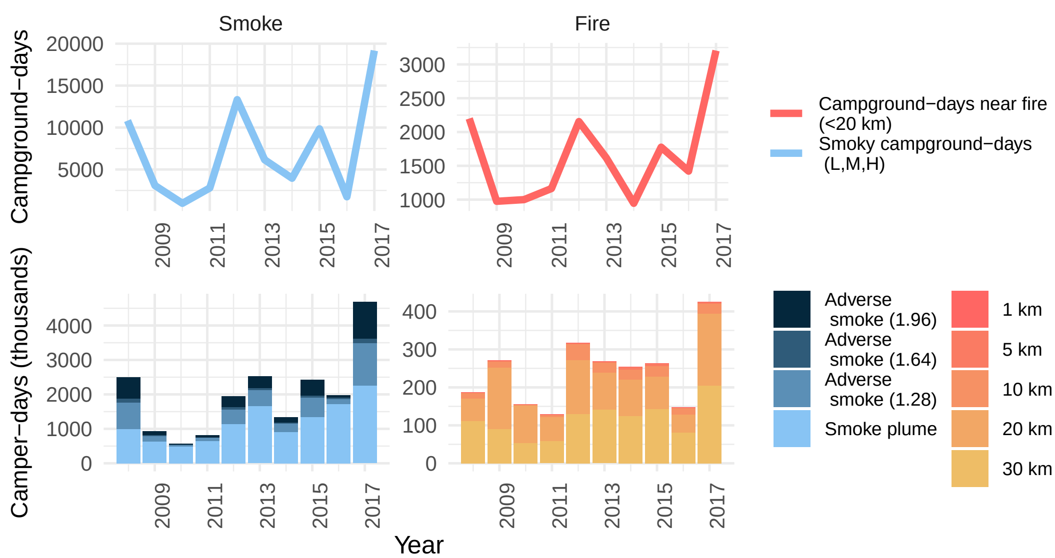
Table B.1: Annual campground- and camper-days near wildfires (within 30 km) and under smoke plumes, by region. Fire days are days in which a campground is 30 km or less from an active wildfire. Days under smoke plumes are days in which campgrounds intersected a NOAA HMS smoke plume. Each campground's available campground-days are calculated as the number of days each year that the campground had at least one occupant.

	Campground-days		Camper-days	
	Avg. annual days per campground	Percent total available campground-days	Avg. annual camper-days (thousands)	Percent total camper-days
I. Fire				
California	4.3	3.4	139	3.4
Pacific Northwest	3.1	4.3	26	1.8
Rocky Mountains	0.8	0.9	4	0.4
Great Basin	1	1.2	5	0.5
Southwest	4.1	3.8	29	3.8
Northern Rockies	3	3.7	15	2.2
Total	2.8	3	218	2.5
II. Smoke				
California	28	22	707	17
Pacific Northwest	31	44	345	24
Rocky Mountains	20	24	163	16
Great Basin	16	19	107	12
Southwest	14	13	54	7
Northern Rockies	34	43	211	32
Total	26	28	1588	18

The lower panel of Table B.1 shows how the number of campground-days and visitor-days affected by smoke changes when we define smoky days using only the NOAA HMS smoke plume data, without restricting impacted days to be those with on-the-ground air quality above the 95th percentile on nonsmoky days (our definition of adverse smoke conditions in our baseline results). Contrasting Table B.1 with Table 2.1, only approximately 26% of the days in which campgrounds were covered by smoke plumes had $PM_{2.5}$ levels above the 95th percentile.

Figure B.2 shows trends over time in the number of campground-days and visitor-days affected by fire and smoke. Though the frequency of large wildfires in the western United States has increased over the past several decades (Westerling 2016), we observe no clear trends in exposure to fire or smoke over the 10 years of our data set. It may be that year-to-year variation in the numbers and locations of wildfire events masks long-term trends, especially over the relatively short span of our data set.

Figure B.2: Prevalence of days near fire and with adverse smoke conditions over time. In the upper panel, campground smoke days are defined as days in which a campground was covered by a smoke plume and PM2.5 was more than 1.64 SD above the seasonal mean; campground fire days are defined as days in which a fire burned within 20 km. In the lower panel, definitions of adverse smoke conditions are varied, with standard deviations above the seasonal mean that PM2.5 must be for the campground to be considered to have impacted air quality given in parentheses. We also plot the number of days campgrounds were under a smoke plume, irrespective of PM2.5. Finally the lower right panel shows differences in the number of camper-days near fire by fire distance thresholds.



B.2.2 Behavioral responses to smoke and fire

In our regressions on campground use, we explore behavioral responses to smoke and wildfire. Equation 2.1 shows the main specification, where the dependent variable is a function of indicators for smoke, fire, and a series of location and time fixed effects. We test the effects of alternative definitions of the fire indicator and alternative sets of location and time fixed effects specifications in Figures B.3 through B.5.

Our preferred model sets the fire variable equal to 1 when an active fire burns within 20 km of a campground. In Figures B.3- B.5, we test distance bandwidths of 10 km and 30 km. The coefficient grows in magnitude as we narrow the bandwidth, indicating that campground use is affected more when fire is closer to the campground.

Figures B.3- B.5 also illustrate effects of our choice of fixed effect specifications. For each combination of smoke and fire variable, we show results of four specifications: (i) no fixed effects; (ii) campground and month $\times$ year fixed effects; (iii) campground, recreation area $\times$ month-of-year, and recreation area $\times$ year fixed effects; (iv) the same fixed effects as in (iii), but adding controls for holidays, week of year, and day of week; and (v) the same fixed effects as in (iv) but adding a control for the upcoming week's total precipitation.

In specification (i), standard errors are quite large and coefficients frequently do not have the expected sign. For example, the coefficient on smoke in the percent occupancy regression (Figure B.3) is positive, likely because recreation activity coincides with times of year with greater fire activity (see, for instance, Figure 2.1), emphasizing the importance of the fixed effects.

Specification (ii) greatly reduces standard errors. However, by including only campground and month $\times$ year fixed effects, the specification assumes seasonal variation in campground use is the same across campgrounds. The results of specification (ii) may be biased if time-varying, location-specific unobservables exist that are correlated with the independent variable of interest. In most cases, coefficients estimated from specification (ii) have the expected signs; however, we observe sign reversal in the smoke coefficient in the percent occupancy regressions.

Models (iii) and (iv) allow for different temporal effects by recreation area. The recreation area $\times$ month fixed effects allow for control of seasonality at the recreation area level, and the recreation area $\times$ year fixed effects control for differential trends across time for different recreation areas. These fixed effects take into account, for example, that different recreation areas peak at different times of year. For instance, the Grand Canyon in Arizona has different seasonal peaks than North Cascades National Park in northern Washington. Model (iv) additionally controls for seasonality, adding holiday indicators, day-of-week fixed effects, and week-of-year fixed effects. These controls distinguish the effects of weekdays from weekends and also account for popular times of the year, such as July 4 or Memorial Day. Including precipitation controls in model (v) does not have a substantial effect on coefficient estimates.

In summary, these sensitivity analyses reveal that results vary sensibly as definitions of the fire and smoke variables are altered. Fire and smoke coefficient estimates depend somewhat on the set of fixed effects we include in the regression, but results are consistent across specifications that account for recreation area-specific seasonal variation in visitation.

Figure B.3: Specification chart for regression of campground occupancy rate on fire and smoke. The coefficients of interest are on the y-axis. The baseline model is shown in blue.

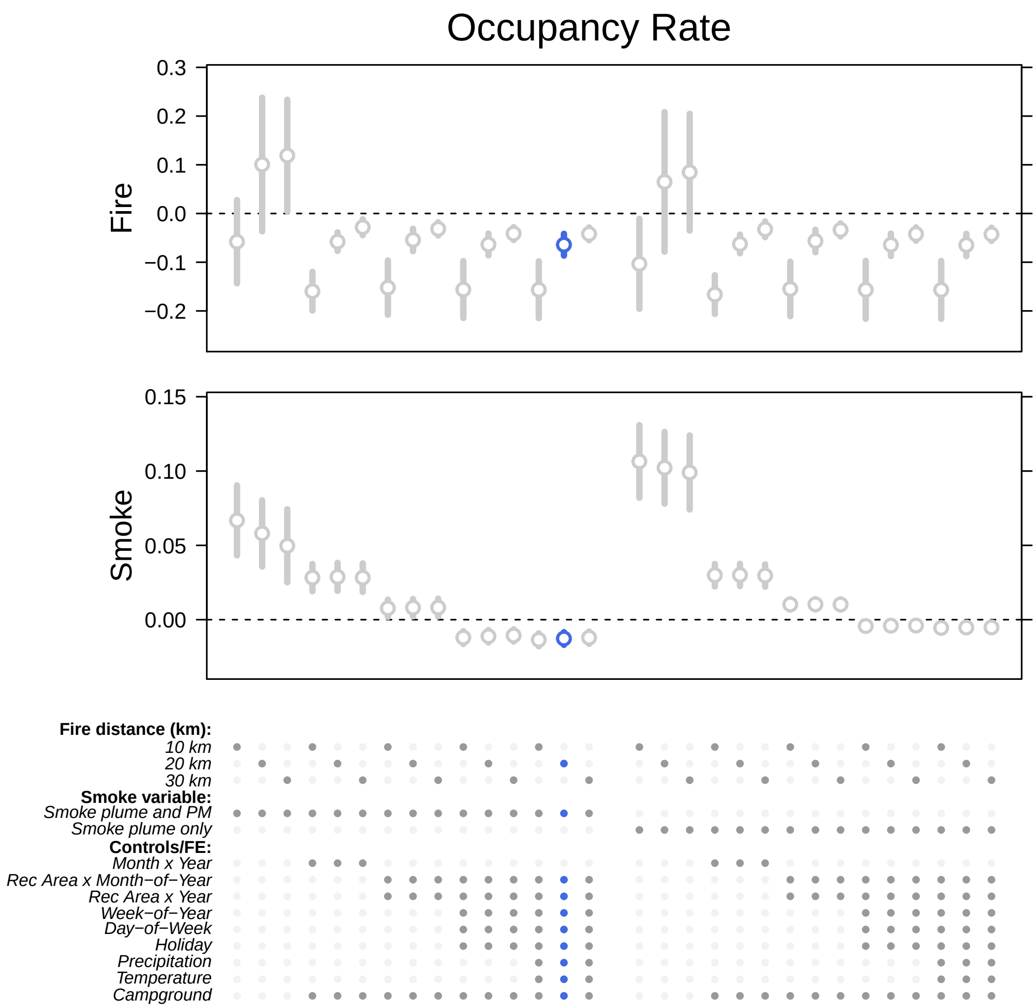


Figure B.4: Specification chart for regression of pre-arrival cancellation rate on fire and smoke. The coefficients of interest are on the y-axis. The baseline model is shown in blue.

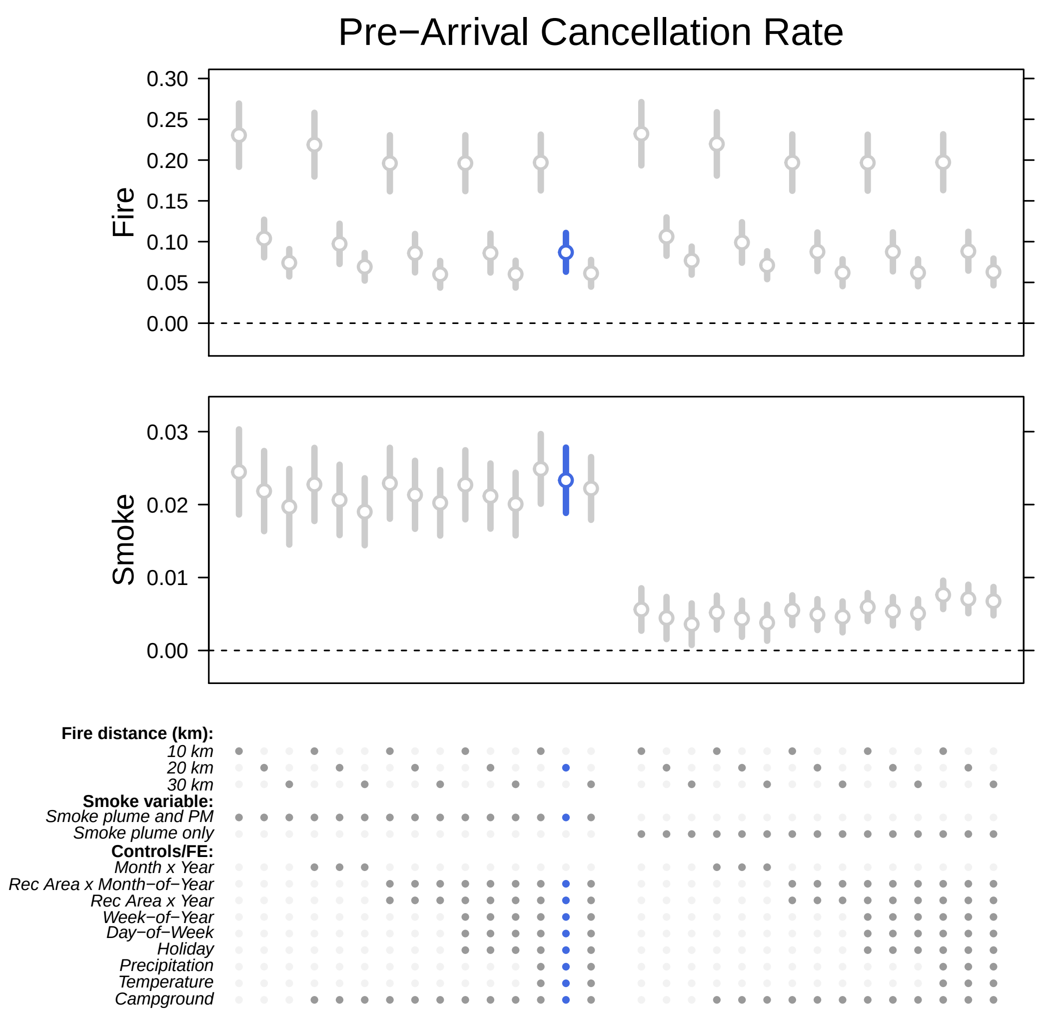
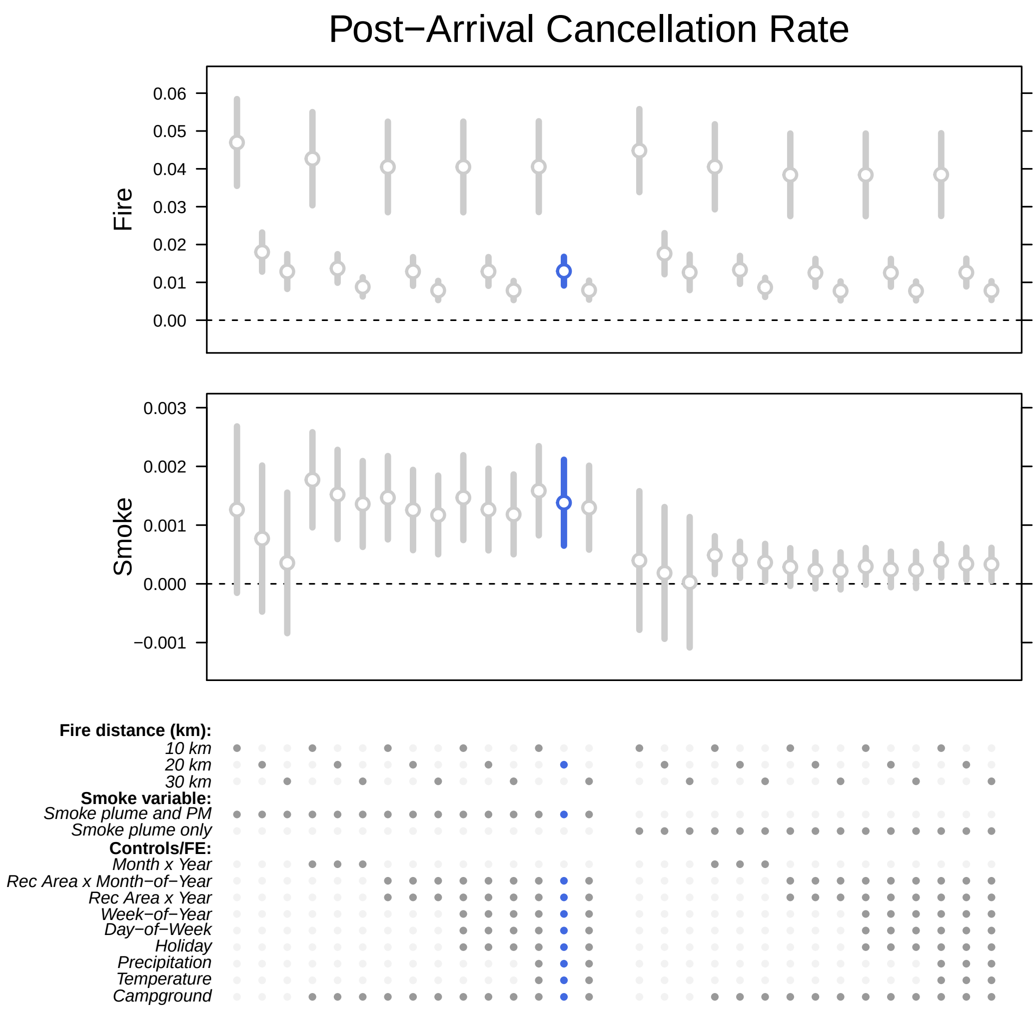


Figure B.5: Specification chart for regression of post-arrival cancellation rate on fire and smoke The coefficients of interest are on the y-axis. The baseline model is shown in blue.



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