



Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem



Welfare losses from wildfire smoke: Evidence from daily outdoor recreation data[☆]

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ARTICLE INFO

JEL classification:

Q26
Q51
Q53
Q54

Keywords:

Wildfire smoke
Wildfire
Air pollution
Recreation

ABSTRACT

Wildfire smoke pollution is growing in the western United States. Estimates of health impacts from smoke are numerous, but few revealed preference estimates of its damages exist. We study a setting where individuals are directly exposed to smoke and where avoidance behavior is measured with high frequency: outdoor recreation. We combine millions of administrative campground reservation records with satellite data on wildfire, smoke, and air pollution. The data allow us to model sequential recreation decisions under evolving information using a novel control function approach. We estimate wildfire smoke reduces welfare by \$107 per person per trip. These damages are larger when campgrounds are affected by consecutive days of smoke. Back-of-the-envelope calculations imply 21.5 million outdoor recreation visits in the western United States are affected by smoke every year, with annual welfare losses of \$2.3 billion. These findings contribute to a growing body of evidence on the costs of wildfire smoke.

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, 2018; Williams et al., 2019). This wildfire activity has generated considerable increases in smoke, which can cover large geographic areas and affect air quality hundreds of miles away. Wildfire smoke now accounts for up to half of particulate matter pollution in some areas of the western United States (Burke et al., 2021), and some literature has found that particulate emissions from smoke harm health more severely than those from other sources (Aguilera et al., 2021; Kochi et al., 2010). Empirical evidence on the negative effects of wildfire smoke is growing, with studies finding increased morbidity and mortality, negative effects on birth outcomes, reductions in academic performance, and impacts in labor markets (Borgschulte et al., 2024; Heft-Neal et al., 2023; Kochi et al., 2010; McCoy and Zhao, 2021; Miller et al., 2024; Reid et al., 2016; Wen and Burke, 2022).

Few estimates of the welfare costs of smoke exist, however, and those that do are based on stated preference or survey-based methods (Jones, 2017; Richardson et al., 2012, 2013) or were calculated by applying a value of statistical life (VSL) to changes in

☆ We thank Andrew Plantinga, Olivier Deschênes, Kelsey Jack, Max Moritz, Steve Dundas, Jeff Englin, David J. Lewis, Molly Robertson, Roger von Haefen, John Whitehead, and two anonymous referees for comments and suggestions on this paper. We are also grateful to seminar participants in the UCSB Environmental Economics group, AERE 2021 Summer Conference, Western Economics Association 2022 Conference, 2023 Occasional Workshop, 2023 AERE OSWEET, University of Alaska Anchorage, and the University of Nevada, Reno. In addition, we thank Jude Bayham and coauthors, who generously shared the gridded air quality data. This research was funded by a United States Department of Agriculture National Institute of Food and Agriculture (NIFA) Agriculture and Food Research Initiative (AFRI) grant, award number 2020-67023-33258.

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mortality (Miller et al., 2024). Welfare estimates derived from revealed preference methods are limited, perhaps because smoke is challenging to study in a revealed preference setting. In hedonic property value studies, it may be difficult to distinguish effects of long-run increases in wildfire smoke from other unobserved region-level changes to housing markets. In travel cost recreation studies, data at a high temporal resolution are needed to compare changes in behavior in response to transient smoke conditions.

We use high-frequency data on campground reservations in a travel cost framework to provide the first revealed preference estimates of welfare damages from wildfire smoke. Outdoor recreation is advantageous for studying responses to smoke for several reasons. First, because wildfire season and peak outdoor recreation season tend to coincide, the choice to recreate may frequently involve a decision about smoke exposure (Gellman et al., 2022). Second, visitors to recreation sites spend large amounts of time outdoors and tend to engage in vigorous activities, such as hiking, which may exacerbate the effects of exposure (Korrick et al., 1998; Richardson et al., 2012). Smoke can also reduce the visibility and amenity value from recreation trips. Third, structural modeling of outdoor recreation decisions using the travel cost framework can naturally yield welfare cost estimates (Parsons, 2017; Lupi et al., 2020).

Our approach uses millions of administrative campground reservation records from nearly 1000 federally managed campgrounds, which we combine with daily data on wildfire, smoke, and air pollution. The data include information on campsite reservations, which are typically made well in advance, and cancellations of planned trips. The cancellation data allow us to account for the short-term and transient nature of wildfire smoke by focusing on decisions made both before and after visitors have knowledge of air quality conditions at the site.

We model visitors' reservation and cancellation decisions as a two-stage discrete choice. In the first stage, a visitor chooses to reserve based on expected site conditions; in the second stage, they decide whether to cancel based on realized site conditions. A key feature of this setting is that reservations and cancellations are made in sequence; a visitor can only cancel if they have a reservation, meaning they have already demonstrated a preference for the site. This induces sample selection in the population holding reservations; if unaccounted for, this selection would bias welfare estimates of wildfire smoke. To correct for this bias, we develop a novel control function approach to link preferences across choices (Wooldridge, 2015). The control function uses estimated preferences from the first-stage reservation decision to remove selection bias in the second-stage cancellation decision. We demonstrate the effectiveness of this approach through numerical simulations.

We find that wildfire smoke imposes welfare costs of \$107 per person per trip. Without accounting for sample selection using the control function, the analysis would have implied damages of \$154 per person per trip, overstating welfare impacts by 44 percent. Damage estimates vary by the number of smoke-affected days in the week leading up to arrival. When a campground is affected by smoke on only one day in the week of arrival, estimated damages are as low as \$32 per person per trip; but when it is affected on all seven days, losses are as high as \$432 per person per trip. The heterogeneity in our estimates is consistent with greater perceived likelihood of experiencing smoke during weeks with more frequent smoke, more severe smoke impacts, or potentially both. We report additional heterogeneity and robustness checks, including a placebo for smoke, a test of the influence of uncancelled no-shows, and heterogeneous responses by type of recreation site.

The overall magnitude of welfare losses from wildfire smoke is large. We find that in the western United States, an average of 21.5 million outdoor recreation visits per year (approximately 4.2 percent of all annual visits), which includes both camping and non-camping trips, 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 state park systems. Under an assumption that our empirical estimates are representative of outdoor recreation more generally, a back-of-the-envelope calculation implies welfare losses of \$2.3 billion per year. This estimate is likely conservative, as consumer surplus values for camping tend to lower than for other forms of recreation (Rosenberger et al., 2017).

Our study adds to the growing literature on wildfire and wildfire smoke. Several studies have examined short-run consequences of smoke, finding that it increases emergency room visits (Heft-Neal et al., 2023) and mortality (Miller et al., 2024), decreases labor earnings (Borgschulte et al., 2024), and worsens expressed sentiment on social media (Burke et al., 2022; Loureiro et al., 2022). Some researchers have used survey evidence to estimate welfare impacts of smoke. Based on US life satisfaction survey data, for example, Jones (2017) estimates a willingness to pay (WTP) of \$373 to avoid one wildfire smoke day per six-month period. Richardson et al. (2012) employ a defensive expenditure approach using survey data on air purifier purchases to estimate a WTP to reduce one smoke-induced health symptom day of \$84 (in 2009 dollars). Using a stated preference contingent valuation survey, Richardson et al. (2013) estimate a WTP to avoid one smoke-induced symptom day of \$95, which they compare to an \$87 WTP estimate based on a cost-of-illness approach (both figures in 2009 dollars).

We measure the welfare damages of smoke exposure using cancellations of planned recreation trips; our estimate of \$107 per trip roughly translates to \$38 per day. This value is in line with estimates from Richardson et al. (2012, 2013) but considerably lower than the estimate from Jones (2017). Compared to our aggregate welfare estimate of \$2.3 billion per year, Miller et al. (2024) value damages from mortality among elderly Medicare recipients in the United States at \$4.8 billion. Borgschulte et al. (2024) find annual lost labor earnings of \$125 billion per year due to wildfire smoke.

Measuring the cost of wildfire smoke is crucial to informing public policy. The federal government spent an average of \$2.8 billion per year on fire suppression between 2017 and 2021, and the State of California spent an average of \$900 million per year from 2018 to 2022.^{1,2} California has proposed spending \$1.2 billion over fiscal years 2022–23 and 2023–24 on wildfire mitigation

¹ National Interagency Fire Center. Suppression Costs. <https://www.nifc.gov/fire-information/statistics/suppression-costs>

² California Department of Forestry and Fire Protection. Suppression Costs. <https://www.fire.ca.gov/stats-events>

measures, including vegetation management, prescribed burns, and home hardening.³ These activities are consistent with the state's recently declared goal to treat 1 million acres of hazardous fuels per year.⁴ Together, the 2021 Infrastructure Investment and Jobs Act (P.L. 117-58) and the Inflation Reduction Act of 2022 (P.L. 117-169) provided \$24 billion for federal wildfire programs (Goldman et al., 2022). Understanding the welfare costs of wildfire and smoke is critical to assessing the benefit of these public expenditures.

We also contribute to the recreation demand literature by using novel methods and data sources. We value a transient environmental disamenity in a setting where users make decisions under evolving sets of information. The two-stage choice structure that links preferences across decisions is informed by literature on sample selection correction in nonlinear models (Greene, 2012; Terza, 2009) and 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 nonlinear or discrete-choice settings. It could also be applied to recreation studies valuing other short-lived environmental amenities, such as temperature and precipitation extremes 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 regions (Dundas and von Haefen, 2020; English et al., 2018; Kolstoe and Cameron, 2017; Parthum and Christensen, 2022).

The remainder of this paper is organized as follows. In Section 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 3 describes the modeling approach, including a conceptual framework and a description of the estimating dataset. In Section 4, we turn to estimation, describing various sets of results. Section 5 approximates the total annual welfare damages of wildfire smoke in the western United States. Section 6 concludes.

2. Data

We combine data on recreation behavior, travel costs, wildfire smoke, air pollution, wildfire activity, and weather into 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 climate normals and local daily measurements of smoke, wildfire activity, pollution, and weather. 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 to measure daily reservation activity by distance from each campground.

2.1. Recreation

We obtained data on campground use from Recreation.gov,⁵ the primary web portal for reserving sites at 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 A1 in Appendix A displays the 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 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 is known. For the 999 campgrounds, 84 percent of transactions were made online, 9 percent over the phone, and 7 percent on-site (such as walk-ins or early checkouts).

2.2. Travel costs

We calculate travel costs based on the distance and travel time between origin zip codes and destination campgrounds with GraphHopper, an open source routing engine that uses Djikstra's algorithm and OpenStreetMap data.^{6,7} We calculate nearly 5.4 million routes representing 5379 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 the coordinates of each user's zip code, we match zip codes to Census Zip Code Tabulation Areas (ZCTAs) and find the centroid of each ZCTA.^{8,9} Figure A2 in Appendix A displays an example route.

³ California Legislative Analyst's Office. The 2022–23 Budget Wildfire and Forest Resilience Package. <https://lao.ca.gov/Publications/Report/4495>

⁴ 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>

⁵ Recreation.gov. <https://www.recreation.gov>

⁶ GraphHopper. <https://www.graphhopper.com>

⁷ GraphHopper GitHub. <https://github.com/crazycapivara/graphhopper-r>

⁸ Health Resources and Services Administration, John Snow, Inc., and American Academy of Family Physicians. Uniform Data System. <https://udsmapper.org/zip-code-to-zcta-crosswalk>

⁹ Because ZCTA centroids may not be located along roads, we snapped them to the nearest road using Census TIGER/Line shapefiles and used the nearest points along roads as origin points.

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

$$c_{zjt} = \frac{p_{zt}^D D_{zj}}{n} + p_{zt}^T T_{zj}, \quad (1)$$

for travel distance D_{zj} , travel time T_{zj} , and group size n . The per-kilometer cost of traveling between ZCTA z and campground j is given by p_{zt}^D and includes gasoline costs, per-kilometer vehicle maintenance, and per-kilometer marginal 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.^{10,11} We use per-kilometer vehicle maintenance costs and marginal depreciation from AAA data, as in English et al. (2018).^{12,13} Lastly, we measure hourly costs of travel time p_{zt}^T as one-third of the average household income in ZCTA z divided by 2080 h worked per year (English et al., 2018). All numbers are inflation-adjusted to 2020 US dollars.

2.3. Smoke and air pollution

Our measure of smoke impacts combines satellite-derived wildfire smoke plume data and gridded ground-level PM_{2.5} monitoring data. For each day, we record whether a campground was covered by smoke based on daily observations of smoke plumes from the National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (Schroeder et al., 2008).¹⁴ Each day, NOAA analysts manually trace the perimeters of 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., 2024; Burke et al., 2021, 2022; Burkhardt et al., 2019; Gellman et al., 2022; Heft-Neal et al., 2022; Miller et al., 2024; Preisler et al., 2015).

Satellite photography does not reveal where in the air column a smoke plume is: it could be at the ground level or high in the atmosphere. If the latter, it may not reflect on-the-ground conditions. To address this challenge, we code an area as smoke-affected only if it is covered by a smoke plume and its ground-level PM_{2.5} is at least 1.64 standard deviations above the location-specific seasonal mean for non-smoke days, which represents the 95th percentile of a normal distribution.¹⁵ This definition follows from binary measures of on-the-ground smoke air quality impacts used in previous papers (Burkhardt et al., 2019; Gellman et al., 2022), and is similar in spirit to the continuous measure of smoke's contribution to overall PM_{2.5} produced by Childs et al. (2022). Figure A3 in Appendix A displays an example of this measure using kriged PM_{2.5} data from Burkhardt et al. (2019). The map shows that although many areas were covered by smoke, only some had air quality poor enough to be coded as smoke-affected. In Appendix F we test the sensitivity of the main results to smoke measures based on alternative critical values.

2.4. Wildfire activity

At each campground, we measure the daily distance to an actively burning fire. We combine NASA MODIS fire detection points with the United States Geological Survey (USGS) 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 US wildfires. 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 fire's final perimeter and its start and containment dates to filter MODIS points. Figure A4 in Appendix A demonstrates an example of this process for the western United States.

2.5. Temperature and precipitation

To control for weather conditions, we gather daily precipitation (mm) and maximum 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 that reflect average conditions over the period 1980 to 2010.

¹⁰ Energy Information Administration. Weekly Retail Gasoline and Diesel Prices. https://www.eia.gov/dnav/pet/pet_pri_gnd_a_epmr_pte_dpgal_m.htm

¹¹ Bureau of Transportation Statistics. Average Fuel Efficiency of US Light Duty Vehicles. <https://www.bts.gov/content/average-fuel-efficiency-us-light-duty-vehicles>

¹² For example: AAA. Your Driving Costs 2016. <https://publicaffairsresources.aaa.biz/wp-content/uploads/2016/03/2016-YDC-Brochure.pdf>

¹³ Marginal depreciation cost is calculated by taking the difference in “reduced depreciation” and “increased depreciation” between 10,000 and 20,000 miles, divided by 10,000 miles, as in English et al. (2018). Some literature has argued that depreciation functions as a fixed cost rather than a marginal cost, in which case inclusion would cause an overstatement of travel cost (Hang et al., 2016).

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

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>

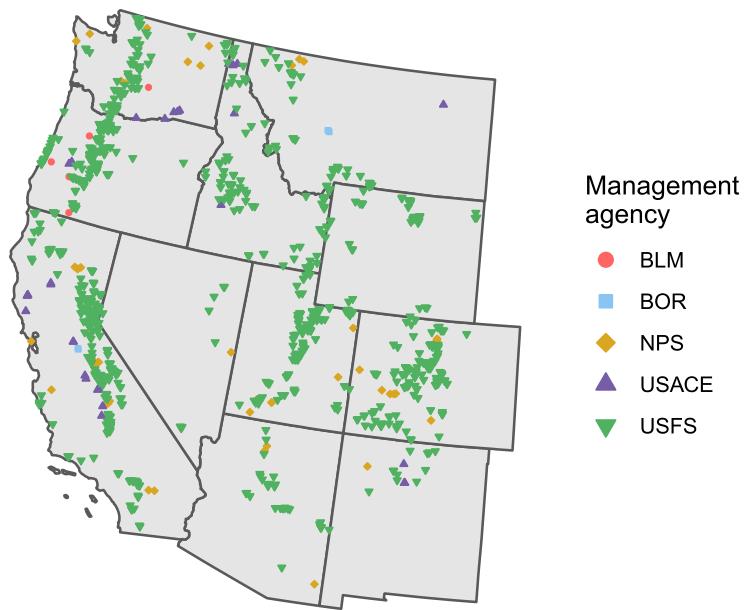


Fig. 1. Map of campgrounds in dataset.

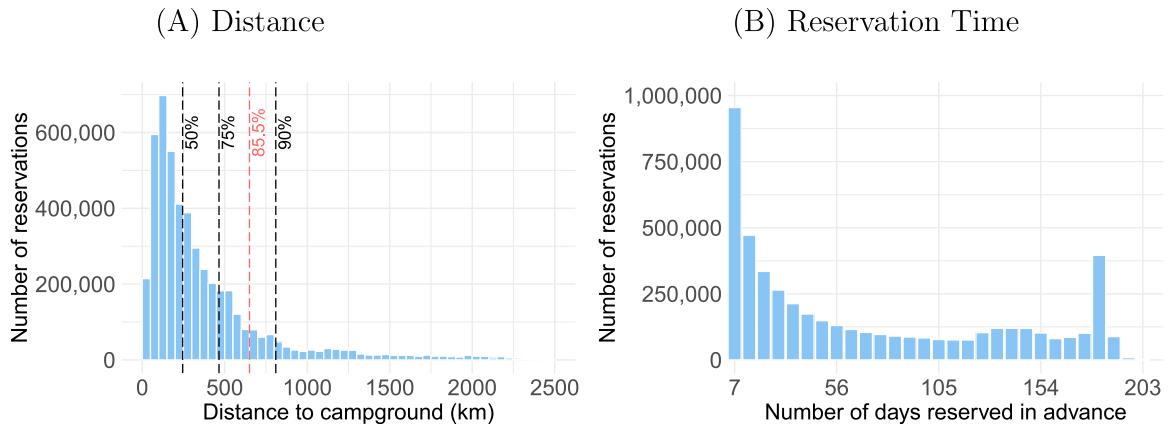


Fig. 2. Driving distance and time between reservation and scheduled arrival.

Notes: Panel A shows the one-way driving distance of reservations from the destination campground, where the red line indicates a 650 km cutoff. Panel B displays the distribution of time reserved in advance of arrival date. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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. Fig. 1 plots a map of the campgrounds in the dataset. Although the Forest Service manages most of the campgrounds, the most-visited locations tend to be in national parks. Table A1 in Appendix A reports the most-visited campgrounds.

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). 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 to the calculation of travel cost. Exclusion of trips from far distances can also eliminate multipurpose trips. Panel A of Fig. 2 shows that the 650 km restriction results in including more than 85 percent of reservations in the dataset. Half of the observed trips come from within 250 km (155 miles), and three-quarters come from within 450 km (280 miles). In Appendix E we report the main results using alternative driving distance thresholds.

The timing of a reservation is also key for our setting. Wildfire smoke is a random event, meaning that visitors who reserve far in advance do not know whether their chosen campground will be smoke-affected during their visit. Panel B of Fig. 2 shows that most

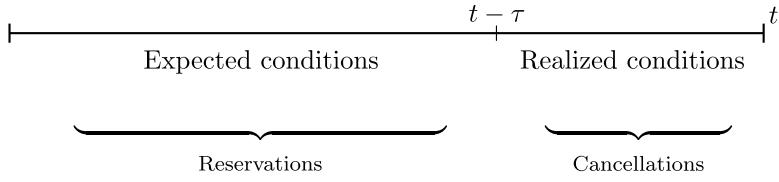


Fig. 3. Timing of decisions.

visitors reserve far in advance, 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, a significant mass appears 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.

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 of this setting is that smoke is ephemeral; it is not a permanent feature of site quality but may impact air quality suddenly and without warning for several days or weeks. Given this feature, one estimation strategy might be to contrast reservation rates during smoke and non-smoke periods. However, because demand for campgrounds is high, campers must often make reservations far in advance, before smoke conditions are known. As campgrounds are often completely full shortly before a given date, rates of new reservations may not be responsive to smoke.¹⁹

We therefore consider the cancellation decisions of visitors who reserved ahead of time. The population that is eligible to cancel consists of those that already hold a reservation; thus, the sample is selected due to their demonstrated preference for the site. We account for selection bias induced by the reservation decision using a control function approach that explicitly models and estimates the “first-stage” reservation decision, in which visitors choose whether to reserve based on expected site conditions. In the second stage, close to the arrival date, they decide whether to cancel based on realized site conditions. Fig. 3 illustrates the timing of these decisions, where t gives the arrival date and τ denotes a bandwidth sufficiently close to the arrival date. For the reservation decision we use a pooled zonal travel cost model to construct the control function for the second stage, trip-level model of cancellations. The control function uses preference parameters estimated in the first stage to remove selection bias in the second stage.

3.1. Reservations

Define utility from visiting site j at time t as:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} + v_{ijt}, \quad (2)$$

where V_{ijt} gives the observable portion of utility to household i from visiting campground j on date t , ε_{ijt} represents fixed unobserved preferences of household i for visiting site j at time t , and v_{ijt} represents unobserved shocks to preferences that occur between time $t - \tau$ and time t . Let V_{ijt} be specified according to:

$$V_{ijt} = \begin{cases} \delta c_{ijt} + \phi s_{jt} + X'_{jt}\gamma + \psi_{jt}, & j \in \{1, 2, \dots, J\}; \\ 0, & j = 0, \end{cases} \quad (3)$$

where c_{ijt} gives the travel cost for person i to site j at time t , and s_{jt} represents smoke conditions at campground j on date t . The vector X_{jt} includes time-varying, campground-level conditions, such as precipitation, temperature, and proximity to an active wildfire. Additional variables include ψ_{jt} , which account for site- and time-specific fixed effects. Campground-related fixed effects capture location-specific unobservables, such as quality or desirability. Time fixed effects, such as for year, week-of-year, or day-of-week, account for seasonality and trends in preferences over time. The parameter of interest is the WTP to avoid smoke, which is found by taking the ratio of marginal disutility of smoke ϕ to the marginal disutility of expenditure δ , $\text{WTP} = \phi/\delta$.

When making a reservation at an early date, person i knows their fixed unobserved preference for the site ε_{ijt} , but not what site conditions or the shock v_{ijt} will be. Therefore, they choose based on ε_{ijt} and an expectation of V_{ijt} ; in expectation, v_{ijt} is 0. Denoting the expectation of variable Y at the time of reservation as \bar{Y} , write the expectation of V_{ijt} as:

$$\bar{V}_{ijt} = \begin{cases} \delta^R c_{ijt} + \phi^R \bar{s}_{jt} + \bar{X}'_{jt}\gamma^R + \psi_{jt}^R, & j \in \{1, 2, \dots, J\}; \\ 0, & j = 0. \end{cases} \quad (4)$$

¹⁹ For example, during May to September, 21 and 25 percent of Fridays and Saturdays, respectively, were completely booked as of one week in advance, and approximately 28 percent are completely unbooked; this low degree of variation in reservation rates would suppress identifying variation on smoke and non-smoke days.

Thus, at the time of reservation, an individual's expected utility from visiting site j at time t is $\bar{V}_{ijt} + \varepsilon_{ijt}$.

The reservation decision is estimated using a pooled zonal travel cost model; because of the zonal structure, this implicitly assumes a binary choice set for a representative individual from each zone. Let $R_{ijt} = 1$ if an individual chooses to make a reservation to visit site j at time t . Individuals choose $R_{ijt} = 1$ if the expected utility of doing so exceeds the utility of their outside option, the observable portion of which we normalize to 0. Under the assumption that ε_{ijt} is distributed iid type I extreme value, the probability an individual makes a reservation is given by:

$$\mathbb{P}(R_{ijt} = 1) = \mathbb{P}(\varepsilon_{i0t} - \varepsilon_{ijt} \leq \bar{V}_{ijt}) = \frac{\exp(\bar{V}_{ijt})}{1 + \exp(\bar{V}_{ijt})}. \quad (5)$$

For each campground j and day t , we sum the number of reservers and non-reservers in concentric zones z around a campground. The former (denoted N_{zjt}^1) is 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 (N_{zjt}^0) 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 $R_{ijt} \in \{0, 1\}$. Let ω^R denote the set of parameters $\{\delta^R, \phi^R, \gamma^R, \psi_{jt}^R\}$. Summing the individual log-likelihood function over all reservers and non-reservers in each zone and for each campground and date, the log-likelihood function is given by:

$$\ell^R(\omega^R) = \sum_{z=1}^Z \sum_{j=1}^J \sum_{t=1}^T N_{zjt}^1 \log(\mathbb{P}(R_{i(z),j,t} = 1 | \omega^R)) + N_{zjt}^0 \log(1 - \mathbb{P}(R_{i(z),j,t} = 1 | \omega^R)), \quad (6)$$

for Z zones, T choice occasions, and J sites. Maximizing Eq. (6) yields utility parameters for a representative individual i from zone z .

We use a zonal approach for the reservation decision for several reasons. The primary purpose of this first-stage reservation estimation is to construct a control function that accounts for preferences in the cancellation estimation. A person can only cancel a trip if they held a reservation. Therefore, preferences from the reservation decision likely play a role in the cancellation. The zonal reservation model accounts for these preferences and provides computational advantages over a multinomial logit approach. In this setting, we have more than 1200 arrival dates to define choice occasions, nearly 5 million reservations, nearly 5400 zip codes to account for the non-reserving individuals, and 999 campgrounds to form the choice set. It would be infeasible to use all the data in a multinomial logit model of individual site choice. We 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 that 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. 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 computationally less expensive than a contraction mapping method (Berry et al., 1995). This computational speed makes a difference when bootstrapping standard errors in the two-stage model.

3.2. Cancellations

For the second-stage cancellation decision, we model a binary choice at the level of the individual trip.²⁰ At time $t - \tau$, site conditions are realized and approximately known to the individual, resulting in random shock $e_{ijt} \equiv V_{ijt} - \bar{V}_{ijt} + v_{ijt}$ to the utility of site visitation. The shock e_{ijt} includes realization of the actual (V_{ijt}) as opposed to mean (\bar{V}_{ijt}) smoke and other weather conditions, as well as a random idiosyncratic and individual-specific taste shock (e.g., illness) represented by v_{ijt} . Like ε_{ijt} , we assume v_{ijt} is distributed type I extreme value. However, we allow its standard deviation to differ from the standard deviation of ε_{ijt} by a scale factor of ρ , letting $v_{ijt} \equiv \rho \eta_{ijt}$, where η_{ijt} is distributed standard type I extreme value.

Conditional on having a reservation, individual i follows through on their reservation if:

$$\bar{V}_{ijt} + \varepsilon_{ijt} + e_{ijt} \geq \varepsilon_{i0t} + e_{i0t}. \quad (7)$$

Using the definition of e_{ijt} , and letting C_{ijt} be a binary variable equal to 1 if individual i cancels their reservation within τ days of arrival, the probability that i follows through is:

$$\begin{aligned} \mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1) &= \mathbb{P}(V_{ijt} + \varepsilon_{ijt} + v_{ijt} \geq \varepsilon_{i0t} + v_{i0t}) \\ &= \mathbb{P}(\eta_{i0t} - \eta_{ijt} \leq \bar{V}_{ijt} - \rho(\varepsilon_{i0t} - \varepsilon_{ijt})), \end{aligned} \quad (8)$$

where the second line follows from the definition of v_{ijt} and where $\bar{V}_{ijt} = \rho V_{ijt}$, a rescaling.

Eq. (8) presents challenges for the econometrician. The variables ε_{i0t} and ε_{ijt} are unobserved. However, omitting these variables will bias parameter estimates because they are correlated with V_{ijt} , as only households with high taste for the site (ε_{ijt}) will have

²⁰ An alternative would have been to model a choice to cancel and rebook at another campground. However, very few users rebook after cancelling. In the estimating dataset, only 1.7 percent of all cancellations make a new reservation to a different campground for the same week of arrival as the initial reservation; in terms of later bookings, 12.5 percent of cancellations make a reservation for any new date within the next six months. Therefore, modeling cancellations as a binary decision is likely a reasonable representation of a visitor's choice.

made a reservation. Specifically, ε_{ijt} is correlated with travel cost in the selected sample; for individuals with a high travel cost c_{ijt} , selection into the group of reservers implies a higher ε_{ijt} . Without sample selection correction, this relationship downward biases estimates of the travel cost parameter δ in the cancellation decision and thus inflates estimates of WTP = ϕ/δ . Section 3.4 explores this relationship using a numerical example. We show that the bias arises only when unobserved preferences from the first stage affect the second-stage decision ($\varepsilon_{i0t} - \varepsilon_{ijt} \neq 0$ in Eq. (8)) and when we can only observe the cancellation decision for the selected sample of reservers ($R_{ijt} = 1$).

3.3. Control function

To correct for this bias, we develop a 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:

$$\begin{aligned} f(\tilde{\varepsilon}_{ijt} | R_{ijt} = 1) &= f(\tilde{\varepsilon}_{ijt} | \tilde{\varepsilon}_{ijt} \leq \bar{V}_{ijt} - \bar{V}_{i0t}) \\ &= \frac{f(\tilde{\varepsilon}_{ijt}) \cdot \mathbb{1}\{\tilde{\varepsilon}_{ijt} \leq \bar{V}_{ijt} - \bar{V}_{i0t}\}}{F(\bar{V}_{ijt} - \bar{V}_{i0t})} \\ &= \frac{f(\tilde{\varepsilon}_{ijt}) \cdot \mathbb{1}\{\tilde{\varepsilon}_{ijt} \leq \bar{V}_{ijt}\}}{\mathbb{P}(R_{ijt} = 1)}, \end{aligned} \quad (9)$$

where the first line follows from the reservation condition in Eq. (5), the second from the definition of a truncated density, and the third by noting that $V_{i0t} = 0$ and that $F(\bar{V}_{ijt}) = \mathbb{P}(R_{ijt} = 1)$.

An estimand for $\tilde{\varepsilon}_{ijt}$ is given by:

$$\begin{aligned} \mathbb{E}[\tilde{\varepsilon}_{ijt} | \tilde{\varepsilon}_{ijt} \leq \bar{V}_{ijt}] &= \int_{-\infty}^{\bar{V}_{ijt}} \tilde{\varepsilon}_{ijt} f(\tilde{\varepsilon}_{ijt} | \tilde{\varepsilon}_{ijt} \leq \bar{V}_{ijt}) d\tilde{\varepsilon}_{ijt} \\ &= \frac{\int_{-\infty}^{\bar{V}_{ijt}} \tilde{\varepsilon}_{ijt} f(\tilde{\varepsilon}_{ijt}) d\tilde{\varepsilon}_{ijt}}{\mathbb{P}(R_{ijt} = 1)} \\ &= \frac{\bar{V}_{ijt} \cdot \frac{\exp(\bar{V}_{ijt})}{1+\exp(\bar{V}_{ijt})} - \log(1 + \exp(\bar{V}_{ijt}))}{\mathbb{P}(R_{ijt} = 1)} \\ &= \frac{\bar{V}_{ijt} \cdot \mathbb{P}(R_{ijt} = 1) - I_{ijt}}{\mathbb{P}(R_{ijt} = 1)} \\ &= \bar{V}_{ijt} - \frac{I_{ijt}}{\mathbb{P}(R_{ijt} = 1)}. \end{aligned} \quad (10)$$

The first line follows from the definition of a conditional expectation, the second by substituting in Eq. (9), the third by evaluating the definite integral, the fourth by substituting Eq. (5) and defining $I_{ijt} \equiv \log(1 + \exp(\bar{V}_{ijt}))$, and the last through simplification.

Eq. (10) contains familiar terms. The \bar{V}_{ijt} term gives the expected utility of the site choice from the reservation decision. The second term contains the inclusive value I_{ijt} , which is equivalent to the expected maximal utility a visitor could anticipate from holding the reservation, including the value of either the trip or the cancellation (Train, 2009). The I_{ijt} term is scaled by the inverse of the probability that they would reserve at the site.

Including $\tilde{\varepsilon}_{ijt}$ as a control function in Eq. (8) provides an estimate of the unobserved preferences of individual i and allows for unbiased estimation of the travel cost parameter in the cancellation problem. As 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 Eq. (8). In Section 3.4, we illustrate the bias correction of this control function 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 Eq. (6), for reservations made earlier than $t - \tau$ and using expected site conditions. Then, we use the parameters to create a fitted value $\hat{\varepsilon}_{ijt}$ 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. In this second stage, the independent variables in V_{ijt} use realized rather than expected site conditions, as users approximately know the site conditions close to the arrival date. Let ω denote the set of parameters $\{\delta, \phi, \gamma, \psi_{jt}\}$. For individual i , the log-likelihood function for the cancellation decision is:

$$\ell^C(\omega, \rho) = \sum_{i=1}^N \sum_{j=0}^J \sum_{t=1}^T (1 - C_{ijt}) \log(\mathbb{P}(C_{ijt} = 0 | \omega, \rho, R_{ijt} = 1)) + C_{ijt} \log(1 - \mathbb{P}(C_{ijt} = 0 | \omega, \rho, R_{ijt} = 1)). \quad (11)$$

Because of the two-stage estimation, we bootstrap the main estimates to obtain appropriate standard errors (Cameron and Miller, 2015; Wooldridge, 2015).

Table 1Numerical example for 10,000 Simulations of Cancellation Estimation, Bias, and Bias Correction from $\tilde{\epsilon}_{ijt}$ Control Function.

	(1)	(2)	(3)	(4)
WTP	2.01** (0.14)	2.01** (0.15)	6.70 (8.52)	2.00** (0.25)
Sample	All users	Reservers	Reservers	Reservers
Second-stage errors	$\epsilon_{ijt} + \frac{1}{\rho} \eta_{ijt}$	$\frac{1}{\rho} \eta_{ijt}$	$\epsilon_{ijt} + \frac{1}{\rho} \eta_{ijt}$	$\epsilon_{ijt} + \frac{1}{\rho} \eta_{ijt}$
Control function	No	No	No	Yes

Notes: True willingness to pay (WTP) = 2. WTP values are means (with standard errors in parentheses) across estimates from M = 10,000 simulations with N = 100,000. * p < 0.05, ** p < 0.01.

3.4. Numerical example

To illustrate the source of bias in naïve cancellation estimates, and the ability of the control function to correct for this bias, we test our estimator on simulated data. We simulate 10,000 draws with $N = 100,000$ users (individuals i) who make sequential reservation and cancellation decisions. We assign each user random travel costs, smoke conditions, and unobserved preferences ϵ_{ijt} and v_{ijt} . We assert an arbitrary true WTP to avoid smoke of $\phi/\delta = 2$. Appendix B provides additional details.

Table 1 summarizes results from the simulation and illustrates two dimensions of the identification challenge. First, we test the role of sample selection, using the fact that in simulated data, we can observe the counterfactual cancellation decisions of users who never held a reservation. In Column 1, we estimate WTP based on the full sample of reservers and non-reservers. With no sample selection (i.e. when the sample is not limited to reservers), our estimate approaches 2, the true WTP. In Column 2, the sample is limited to reservers, but we model cancellation and reservation decisions as independent, conditional on observables. That is, unobserved preferences affecting reservation decisions do not affect cancellation decisions, and second-stage unobserved preferences are equal to $\frac{1}{\rho} \eta$ rather than $\epsilon_{it} + \frac{1}{\rho} \eta$. Under this assumption, our estimate is again nearly equal to the true WTP. It is only in Column 3, when the sample is selected and preferences in the first and second stages are not conditionally independent, that WTP is biased. In Appendix B, 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 4, we maintain both assumptions from Column 3 but also introduce the control function for $\tilde{\epsilon}_{ijt}$. 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 B.

4. Results

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 to cancellations close to arrival. [Fig. 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 [Fig. 3](#), and who decided whether to cancel within a week of the arrival date. We therefore exclude reservations that 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. Last, we limit attention to trips coming from within 650 km (400 miles), as described in [Section 2.6](#). These restrictions result in a sample of 2,723,940 reservations.²¹

4.1. Identification

Identification comes from one of two sources, depending on the parameter. In the case of the travel cost parameter, identification comes from the relationship between the rate at which populations make reservations or cancellations and the distance they have to travel. An implicit assumption, as in most travel cost models, is that preferences are homogeneous and do not vary with distance to the site. If individuals do sort according to their preference for campgrounds, this could upward bias WTP estimates.²² This concern is somewhat mitigated by the fact that we model household choices over trips to a large number of destinations, and, as [Section 4.2](#) details, we control for unobservables with a large number of site-specific and time-specific fixed effects. For campground characteristics, identification comes from within-season and across-campground differences in reservation or cancellation rates.

As well, we make the standard travel cost assumption that trips are made for the sole purpose of visiting the campground and any nearby recreation sites. Multipurpose trips would likely bias estimates upwards, since households traveling from long distances to visit multiple destinations would be less likely to cancel their trip. We can investigate this assumption in the data by checking for reservations at multiple campgrounds by the same user near in time to one another. Though it does not rule out the possibility of multipurpose trips taken for reasons other than camping, chained trips to campgrounds are uncommon in the data; about 1.18 percent of trips are reserved by the same user at another recreation area within one week of another trip. In addition, the choice to restrict the preferred sample to those traveling from nearer than 650 km (400 miles) – made to avoid the complications of measuring travel cost from air travel – has the added benefit of reducing the likelihood of chained trips.

²¹ A “reservation” or “trip” is composed of multiple “transactions”, which could include an initial booking, payment, check-in, cancellation, or refund.

²² This bias is because the model would attribute lower probability of reserving or greater likelihood of cancelling to travel cost, when it would have actually owed to lower preference for the site.

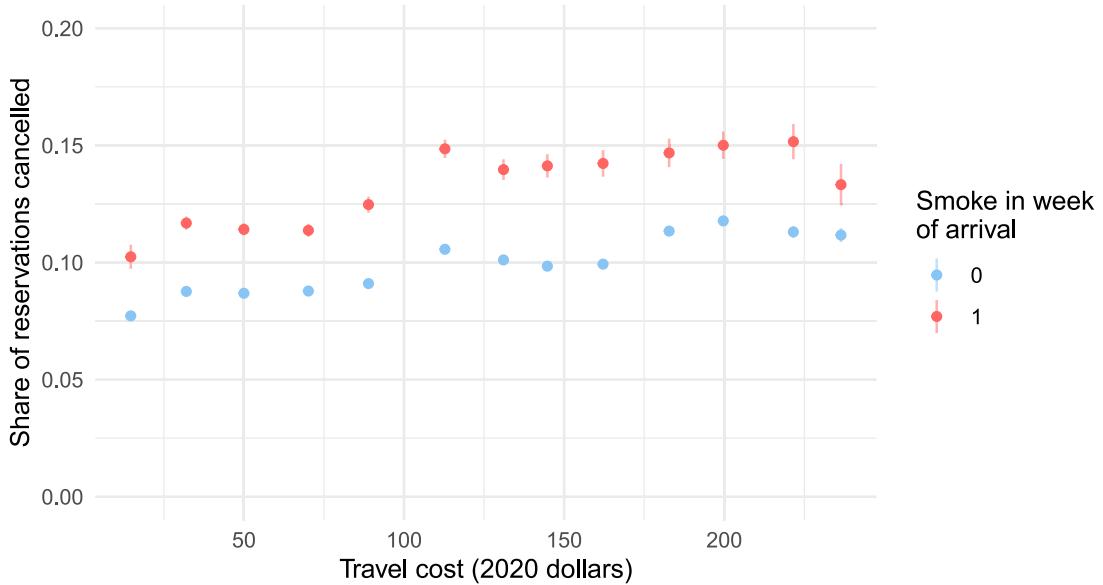


Fig. 4. Cancellation rate close to arrival. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2. Cancellations close to arrival

Fig. 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. 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. Visually, the slope between cancellation rate and travel cost appears shallow. As explored in Section 3 and Appendix B, 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 someone with a similar travel cost who did not reserve, such that $\mathbb{E}[\epsilon_{ijt} c_{ijt} | R_{ijt} = 1] > 0$. 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 Fig. 4.

Table 2 reports results for biased estimation of cancellations $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ using the trip-level maximum likelihood function of Eq. (11). These estimates ignore the correlation between ϵ_{ijt} and travel cost among the set of users who chose to reserve. WTP is computed by taking the ratio between marginal disutility of smoke to that of expenditure (the smoke coefficient divided by the travel cost coefficient). Standard errors for WTP are computed using the delta method. In all estimations, the observations are weighted using frequency weights because a single reservation might represent, for example, two or eight visitors.

In Column 1, we display results that include covariates such as daily high or low temperature, but without controlling for campground or seasonal fixed effects. Columns 2 through 4 add fixed effects. We include a campground-by-week fixed effect to control for unobserved location-specific site quality and seasonality, such as seasonal natural phenomena. We also account for differences in reservation rates based on the day of the week, as weekends see higher reservation activity. 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 because $WTP = \phi/\delta$, and we expect the travel cost parameter δ to be attenuated.

To correct for the biased WTP in Table 2, we use the control function described in Eq. (10), $\tilde{\epsilon}_{ijt} = \bar{V}_{ijt} - \frac{I_{ijt}}{\mathbb{P}(R_{ijt}=1)}$. The first step is to estimate the probability of reservation earlier than one week based on expected site conditions and using a pooled zonal travel cost model. Then, we fit the parameters from the reservation estimation to form an estimate for $\tilde{\epsilon}_{ijt}$. 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 the PRISM data source, which represent average weather conditions for 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 3 shows results from the first-stage reservation decision $\mathbb{P}(R_{ijt} = 1)$ implied by Eq. (6). Counterintuitively, users appear 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, moving the WTP close to 0. Campground by week-of-year fixed effects absorb the

Table 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	-0.220** (0.024)	-0.262** (0.028)	-0.235** (0.027)	-0.262** (0.022)
Travel cost (dollars)	-0.002** (0.0003)	-0.002** (0.0001)	-0.002** (0.0001)	-0.002** (0.0001)
Inv. distance to wildfire (km^{-1})	-11.128** (0.927)	-12.039** (2.429)	-11.917** (2.443)	-7.800** (0.829)
High temp. (degrees C)	0.020** (0.005)	0.029** (0.002)	0.029** (0.002)	0.031** (0.002)
Low temp. (degrees C)	-0.003 (0.006)	-0.021** (0.003)	-0.021** (0.003)	-0.025** (0.003)
Precip. in week of arrival (mm)	-0.004** (0.001)	-0.006** (0.001)	-0.006** (0.001)	-0.006** (0.001)
N	2,723,830	2,692,468	2,692,468	2,689,216
WTP	91.1** (12.36)	153.4** (21.06)	137.35** (19.85)	154.04** (15.43)
Campground x week-of-year FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

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

Table 3

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

	(1)	(2)	(3)	(4)
Smoke exp.	0.926** (0.004)	0.251** (0.042)	0.103** (0.036)	0.082* (0.032)
Travel cost (dollars)	-0.020** (0.000)	-0.024** (0.001)	-0.024** (0.001)	-0.024** (0.001)
Inv. distance to wildfire exp. (km^{-1})	39.690** (0.074)	6.057** (1.745)	6.159** (1.571)	6.786** (1.465)
High temp. exp. (degrees C)	0.019** (0.0001)	0.060** (0.013)	0.061** (0.013)	0.059** (0.013)
Low temp. exp. (degrees C)	-0.019** (0.0001)	-0.082** (0.015)	-0.084** (0.015)	-0.081** (0.015)
Precip. exp. in week of arrival (mm)	-0.013** (0.0001)	0.007** (0.003)	0.007* (0.003)	0.007* (0.003)
N	15,209,187	12,668,366	12,668,366	12,298,572
WTP	-45.93** (0.18)	-10.31** (1.72)	-4.23** (1.45)	-3.37* (1.31)
Campground x week-of-year FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

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

seasonal variation in average expected smoke, meaning the remaining variation is due to across-year differences in expected smoke within a given campground and week of year; we hypothesize that there may be a positive relationship between reservations and remaining variation in expected smoke due to a reserve of unmet demand for campgrounds that experienced smoke in previous years. Nevertheless, the primary purpose to estimate the likelihood of reservation $\mathbb{P}(R_{ijt} = 1)$ is as an input for the control function $\tilde{\epsilon}_{ijt}$ in the estimation of $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, and we expect that the sign of the expected smoke coefficient will have a minor effect on fitted control function values.

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. We expect that preferences and travel costs are correlated in the selected sample, $\mathbb{E}[c_{ijt}\epsilon_{ijt} | R_{ijt} = 1] > 0$, so our control function should be inversely correlated with travel cost, $\mathbb{E}[c_{ijt}(\epsilon_{i0t} - \epsilon_{ijt}) | R_{ijt} = 1] < 0$. Figure A5 in Appendix A illustrates this correlation empirically using the fitted values of $\tilde{\epsilon}_{ijt}$ and the travel cost for the sample of reservers. This empirical result is consistent with the prediction of the theory and numerical exercise in Section 3 and Appendix B.

Table 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 $\tilde{\epsilon}_{ijt}$. The coefficient for $\tilde{\epsilon}_{ijt}$ is significant, suggesting that preferences at the time of reservation are an important determinant of the cancellation decision. In addition, comparing to Table 2, the travel cost coefficient was the only parameter to change when including $\tilde{\epsilon}_{ijt}$, which is consistent with sample selection bias operating through correlation with travel cost. Overall, the WTP

Table 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	-0.218** (0.025)	-0.271** (0.024)	-0.244** (0.022)	-0.260** (0.022)
Travel cost (dollars)	-0.003** (0.0004)	-0.002** (0.0003)	-0.002** (0.0003)	-0.003** (0.0003)
Inv. distance to wildfire (km^{-1})	-11.102** (0.858)	-10.888** (1.428)	-10.707** (1.429)	-7.814** (0.792)
High temp. (degrees C)	0.020** (0.004)	0.028** (0.002)	0.029** (0.002)	0.031** (0.002)
Low temp. (degrees C)	-0.004 (0.005)	-0.020** (0.003)	-0.021** (0.003)	-0.025** (0.003)
Precip. in week of arrival (mm)	-0.004** (0.001)	-0.006** (0.001)	-0.006** (0.001)	-0.006** (0.001)
$\tilde{\epsilon}_{ijt}$	-0.011 (0.028)	-0.036** (0.011)	-0.037** (0.011)	-0.039** (0.011)
N	2,723,034	2,691,655	2,691,655	2,688,739
WTP	85.23** (17.82)	113.91** (18.48)	101.50** (16.50)	107.14** (16.33)
Campground x week-of-year FE		Yes	Yes	Yes
Day-of-week 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. * $p < 0.05$, ** $p < 0.01$.

estimates are reduced to \$107 per person per trip of lost utility. By comparison, the biased results in [Table 2](#) were \$154 per person per trip, which is 44 percent higher.

[Wooldridge \(2015\)](#) recommends bootstrapping standard errors for control functions because of the two-stage estimation process. For the main estimates in [Table 4](#), we follow the clustered bootstrapping process of [Cameron and Miller \(2015\)](#), drawing with replacement at the campground level for 400 bootstraps. In Appendix C, 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.

4.3. Relationship of damages to smoke duration

In this section, we investigate how estimated welfare losses vary according to one measure of the severity of smoke impacts: the number of smoke days in the week of arrival. We hypothesize that welfare impacts could vary with this measure for two reasons. First, it is likely that sites experiencing a greater number of smoke days in close succession also experience a larger degradation in air quality. Second, additional smoke days in the week of arrival communicate a higher likelihood of smoke on the actual arrival date.²³

To investigate heterogeneity in estimated welfare impacts, we respecify $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ to allow for differential effects based on the number of smoke-affected days in the week of arrival. [Fig. 5](#) plots the resulting WTP estimates.²⁴ Damages monotonically increase in the number of smoke days, giving confidence that the estimates reflect damages from smoke. 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. Estimated welfare impacts are likely greater during more smoke-affected weeks due to worse air quality conditions or because the perceived likelihood of smoke during the visit is greater.

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 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, more than 375,000 placebo reservations are created.

[Table 5](#) displays results from the placebo test. Across the main specifications, we find null responses to the two smoke placebos. Comparing to [Table 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.

²³ Table A2 in Appendix A reports results from a regression of $\mathbb{1}\{\text{campground is smoke-affected}\}$ 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. For instance, compared to a week with no smoke days, a week with two days raises the probability by 0.301; a week with six days raises it by 0.739.

²⁴ Full results are included in Table A3 in Appendix A.

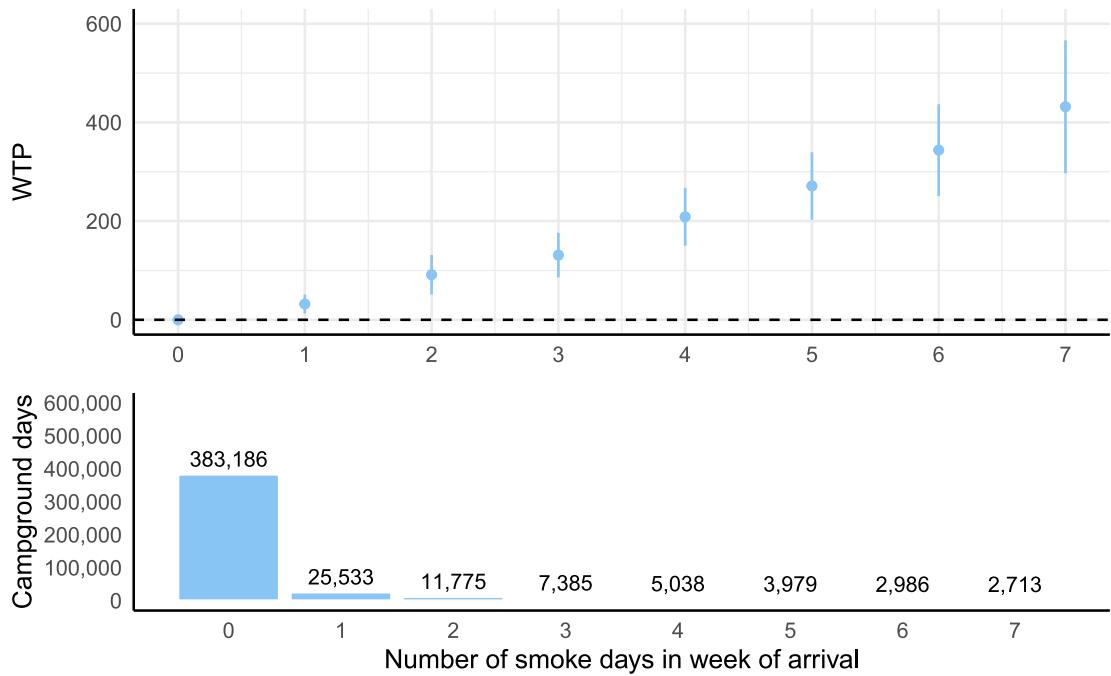


Fig. 5. Greater welfare damages for weeks that were more smoke-affected, consistent with either more severe events or increased certainty of smoke conditions.

Table 5
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	0.087** (0.019)	0.025 (0.016)	0.023 (0.016)	0.007 (0.016)
Smoke two weeks after arrival	0.078** (0.023)	0.004 (0.015)	0.003 (0.015)	-0.004 (0.016)
Travel cost (dollars)	-0.003** (0.0004)	-0.003** (0.0003)	-0.003** (0.0003)	-0.003** (0.0003)
Inv. distance to wildfire (km^{-1})	-8.592** (0.837)	-7.323** (0.900)	-7.241** (0.882)	-5.205** (0.780)
High temp. (degrees C)	0.020** (0.004)	0.029** (0.002)	0.029** (0.002)	0.030** (0.002)
Low temp. (degrees C)	-0.001 (0.006)	-0.018** (0.003)	-0.018** (0.003)	-0.022** (0.003)
Precip. in week of arrival (mm)	-0.004** (0.001)	-0.006** (0.001)	-0.006** (0.001)	-0.006** (0.001)
$\tilde{\epsilon}_{ijt}$	-0.009 (0.026)	-0.033** (0.012)	-0.034** (0.012)	-0.035** (0.012)
N	2,379,842	2,344,620	2,344,620	2,340,894
Campground x week-of-year FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	Yes
State x year FE			Yes	
Campground x year FE				Yes

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

4.5. Additional results and robustness checks

We report several additional results and robustness checks in the appendices. The first group of analyses assesses heterogeneity and robustness by campground characteristics, including an assessment of the role of no-shows in the estimation of cancellation probability. A second set of exercises varies the spatial and temporal thresholds that define the sample restriction. Lastly, we perform sensitivity analyses for various measures of smoke and air pollution.

One concern when studying cancellations is whether an individual will simply not show up without formally cancelling. For most campgrounds, we do not observe whether an individual checks in. However, campers have an incentive to cancel their reservation. For cancellations made more than 24 h before the arrival date, visitors are reimbursed for the full cost less a \$10 cancellation fee;

when cancelling within 24 h of arrival, they are reimbursed for the full trip less the \$10 fee and the price of the first night's stay. Still, we explore this question in Appendix D. For a small subset of campgrounds, we are able to observe no-shows. In this sample, we test recoding no-shows as arrivals, which would mirror what the data would report at campgrounds that do not record no-shows. This recoding does not change the estimates for the smoke or travel cost coefficients, suggesting unreported no-shows should not affect the results of the main estimates.

We also 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, versus small, primarily local US Forest Service campgrounds. Appendix D reports heterogeneous results by campground popularity, where popularity is defined by annual visitation. We find that visitors are less responsive to both smoke and 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.

Appendix D reports additional heterogeneity, including by region and managing agency. These analyses reveal that California and the Pacific Northwest experience the largest per-trip welfare losses. We also incorporate campground features, such as the availability of electric hookups, RV versus tent-only sites, terrain diversity, and proximity to water bodies. Among many results, we find that RV users have the strongest responses to smoke, which could reflect health-related sensitivity among older visitors. See Appendix D for a discussion.

In further analyses, we explore alternative thresholds for sample restriction. In the main results, we limit attention to reservations made within 650 km of one-way driving distance, or approximately 400 miles. Fig. 2 shows that this distance restriction includes more than 85 percent of all reservations. Appendix E 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 difference may be due to the inclusion of visitors traveling from greater distances, some of whom could be on multipurpose trips and were therefore less likely to cancel. As a result, the estimated welfare damages increase as the distance threshold is relaxed.

Similarly, we vary the threshold value for τ in Fig. 3. The main estimation considers cancellation decisions within $\tau = 7$ days of arrival, but Appendix E reports results for alternative thresholds of 3, 5, and 9 days. Welfare estimates are larger for shorter bandwidths of τ . For $\tau = 3$, we find estimates of \$137 per person per trip; for $\tau = 9$, we find estimates of \$92 per person per trip. These results point to a similar mechanism as in Section 4.3. During shorter time windows, the occurrence of smoke communicates a greater likelihood of smoke on the actual arrival date. An information effect is consistent with greater smoke avoidance closer to the arrival date.

Lastly, in Appendix F we perform sensitivity analyses related to smoke and air pollution. The presence of smoke at a visitor's home zip code serves as a useful check on whether smoke influences the value of the outside option $j = 0$ in cancellation decisions. In addition, we test alternative definitions of the PM_{2.5} threshold used to define a campground as smoke-affected, an issue that is discussed in Section 2.3. Finally, we investigate how WTP varies based on the level of smoke-induced PM_{2.5}, adopting a binning approach. See Appendix F for details.

5. Total welfare losses

In the preceding sections, we estimated per-trip damages of wildfire smoke. We now use those estimates to approximate annual welfare damages of smoke 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 damage of smoke. We also calculate the value of lost visitation based on estimated cancellation rates. Together, these measures approximate the total annual welfare loss due to smoke. One potential limitation of this analysis is that the 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. Rosenberger et al. (2017) found that, for studies conducted through 2015, camping had slightly lower consumer surplus values than other forms of recreation. Under the assumption that welfare impacts of smoke would be greater for higher value activities, our back-of-the-envelope calculation provides a conservative estimate of total annual smoke damages for outdoor 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. Most damages are incurred by inframarginal trips that are taken in spite of smoke; lost visitation represents only about 1 percent of total damages, in line with earlier descriptive work in the literature (Gellman et al., 2022).

To arrive at these estimates, we use total visitation numbers from the National Park Service,²⁵ US Forest Service,²⁶ Bureau of Land Management,²⁷ US Army Corps of Engineers,²⁸ and National Association of State Park Directors (Smith et al., 2019) for 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

²⁵ National Park Service. Annual Summary Report. <https://irma.nps.gov/STATS>

²⁶ US Forest Service. National Visitor Use Monitoring Program. <https://www.fs.usda.gov/about-agency/nvum>

²⁷ Bureau of Land Management. Public Land Statistics. <https://www.blm.gov/about/data/public-land-statistics>

²⁸ US Army Corps of Engineers. Value to the Nation. <https://www.iwr.usace.army.mil/Missions/Value-to-the-Nation>

Table 6
Smoke-affected recreation visits and welfare losses for the western United States, 2008 to 2017.

	Total visits/year (millions)	Smoke-affected visits/year (millions)	Lost visits/year (millions)	Proportion visits smoke-affected	Welfare loss/year (millions)
Panel A: Agency					
National Park Service	102.6	2.3	0.05	0.023	\$250.2
US Forest Service	108.0	4.8	0.11	0.044	\$515.8
Bureau of Land Management	59.8	2.5	0.06	0.042	\$269.6
US Army Corps of Engineers	46.4	2.4	0.05	0.051	\$253.9
State Parks	194.5	9.6	0.21	0.049	\$1030.9
Total	511.4	21.5	0.48	0.042	\$2320.4
Panel B: State					
Arizona	33.0	0.4	0.01	0.013	\$46.7
California	162.7	6.1	0.14	0.037	\$655.2
Colorado	55.3	2.1	0.05	0.037	\$222.9
Idaho	19.6	1.3	0.03	0.065	\$137.9
Montana	18.3	1.1	0.03	0.062	\$122.9
New Mexico	13.7	0.6	0.01	0.041	\$61.5
Nevada	20.2	0.3	0.01	0.014	\$30.1
Oregon	69.9	4.4	0.10	0.062	\$470.3
Utah	32.1	0.8	0.02	0.025	\$85.5
Washington	64.8	3.3	0.07	0.051	\$354.9
Wyoming	21.9	1.2	0.03	0.056	\$132.7
Total	511.4	21.5	0.48	0.042	\$2320.4

Notes: Welfare losses combine per-trip smoke damages and the value of lost visitation. See Appendix G.

smoke. These proportions are measured based on visitors' dates of visit and length of stay, which we link to daily smoke conditions at each campground. For more information on the estimation of smoke-affected visitation, see Appendix G.

Table 6 displays estimates of total visitation, smoke-affected visitation, lost 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 smoke-affected, or 4.2 percent. When multiplied by the per-trip estimate of \$107, we find annual welfare losses of approximately \$2.3 billion. Nearly half of 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 because much of that agency's visitation (nearly 40 percent) occurs at lakes and reservoirs in the Pacific Northwest, a region that has seen particularly high wildfire smoke impacts relative to other regions (Burke et al., 2021; Gellman et al., 2022).

The losses from reduced visitation are much lower. Using the smoke coefficient from Table 4, we estimate that smoke causally increases the probability of cancellation by 0.022, which is close to the value of 0.023 from a linear probability model of cancellation in Gellman et al. (2022). Following the approach of Dundas and von Haefen (2020), we multiply the predicted number of lost trips by the average value of a trip. We estimate that approximately 0.48 million visits per year are lost due to smoke, representing about 1 percent of total damages. These calculations are detailed in Appendix G.

Welfare losses vary by region. Some states saw high smoke damages due to high baseline levels of visitation, whereas damages in other regions were driven by a high proportion of smoke-affected visits. Panel B of Table 6 reports losses by 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, such as Idaho, Montana, and Wyoming, damages are driven by a high share of smoke-affected days despite lower total visitation. Figure A6 in Appendix A maps the results to contrast proportional versus total impacts.

The version of the Recreation.gov dataset used for this analysis covers the years 2008 to 2017, but losses from smoke are likely to have grown in recent years. For example, 2018 had several prolonged wildfire smoke events, particularly in areas with high visitation in Northern California. If we were to assume that visitation patterns followed the same distribution as 2017 and extend the above analysis to 2018, this single year would raise the average per-year losses to approximately \$3 billion. As smoke impacts are expected to grow over the coming century (Burke et al., 2023), these findings suggest a high future cost of wildfire smoke for outdoor recreation in the western United States.

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, consistent with either greater smoke impacts or greater perceived likelihood of a smoke-affected visit. 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.

This paper provides several contributions to the literature. First, we use novel methods and data. We value a temporary environmental bad, wildfire smoke, in a context where visitors face changing sets of information. We develop a two-stage decision structure that links preferences using a control function. This model draws on work from economists concerned with sample selection in nonlinear models (Greene, 2012; Terza, 2009) and 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.²⁹ Or, it could be used in applications of cancellations for intended visits (Whitehead et al., 2018). The model also relates strongly to prior work investigating environmental valuation when visitors have imperfect information about site quality (Leggett, 2002); here, we explicitly model individuals' perceptions of likely environmental quality at the time of reservation. Lastly, our use of administrative data complements recent literature using large or innovative datasets to study recreation across multistate regions (Cameron and Kolstoe, 2022; Dundas and von Haefen, 2020; English et al., 2018; Parthum and Christensen, 2022).

We also add to the 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 or healthcare costs, or valued changes in mortality using 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, including expenditures on air purifiers, as well as health outcomes and risk perceptions. They derive WTP to avert one wildfire-induced symptom day of \$84 in 2009 dollars. We estimate 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 of 2.84 days.

We can also compare the aggregated, total welfare results to the literature. We estimate welfare losses of approximately \$2.3 billion per year for recreation on federal and state lands in the western United States. Miller et al. (2024) combined a VSL with estimates of mortality among elderly Medicare recipients due to wildfire smoke. They found approximately \$4.8 billion in annual damages, in 2019 dollars. These results rely on assumptions about remaining years of life, as their sample is comprised largely of elderly individuals. Borgschulte et al. (2024) 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; Heft-Neal et al., 2023; Wen and Burke, 2022).

These cost estimates 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.^{30,31} Wildfires destroy thousands of structures per year, which has cost tens of billions of dollars in recent years (Baylis and Boomhower, 2022, 2023; Buechi et al., 2021). Both states and the federal government have pledged to increase fuel 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 year³² and proposed to spend \$1.2 billion across fiscal years 2022–23 and 2023–24 for fire mitigation activities, such as vegetation management and home hardening.³³ 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.

CRediT authorship contribution statement

Jacob Gellman: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Margaret Walls:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Matthew Wibbenmeyer:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: This research was funded by a United States Department of Agriculture National Institute of Food and Agriculture (NIFA) Agriculture and Food Research Initiative (AFRI) grant, award number 2020-67023-33258. The grant provider was not involved in the study design. Besides the aforementioned funding source, we have not received financial support in the form of consultant fees, retainers, or other grants. We have no paid or unpaid positions to disclose as officer, director, or board member of relevant non-profit organizations or profit-making entities. These statements also apply to close relatives and partners of the authors. A version of this article appeared as working paper number 23-31 for Resources for the Future, and in Jacob Gellman's PhD dissertation, but it is not

²⁹ Two early examples of discrete choices that indirectly consider sample selection include Adamowicz (1994) and Erdem (1996), both of which are highlighted in a discussion of dynamic discrete choices in Train (2009). Adamowicz (1994) modeled a covariate denoting the number of times an alternative had been chosen in the past. Erdem (1996) similarly used the attributes of an individual's previous choices as covariates.

³⁰ National Interagency Fire Center. Suppression Costs. <https://www.nifc.gov/fire-information/statistics/suppression-costs>

³¹ California Department of Forestry and Fire Protection. Suppression Costs. <https://www.fire.ca.gov/stats-events>

³² 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>

³³ California Legislative Analyst's Office. The 2022–23 Budget Wildfire and Forest Resilience Package. <https://lao.ca.gov/Publications/Report/4495>

under submission at any peer-reviewed journal besides the present one. In the acknowledgments section we thank Andrew Plantinga, Olivier Deschenes, Kelsey Jack, Max Moritz, Steve Dundas, Jeff Englin, David J. Lewis, Molly Robertson, Roger von Haefen, and John Whitehead for comments and suggestions on this paper. We are also grateful to seminar participants in the UCSB Environmental Economics group, AERE 2021 Summer Conference, Western Economics Association 2022 Conference, 2023 Occasional Workshop, 2023 AERE OSWEET, University of Alaska Anchorage, and the University of Nevada, Reno. In addition, we thank Jude Bayham and coauthors, who generously shared the gridded air quality data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.jeem.2025.103166>.

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Appendix A: Additional figures

Figure A1: Recreation.gov Web Interface

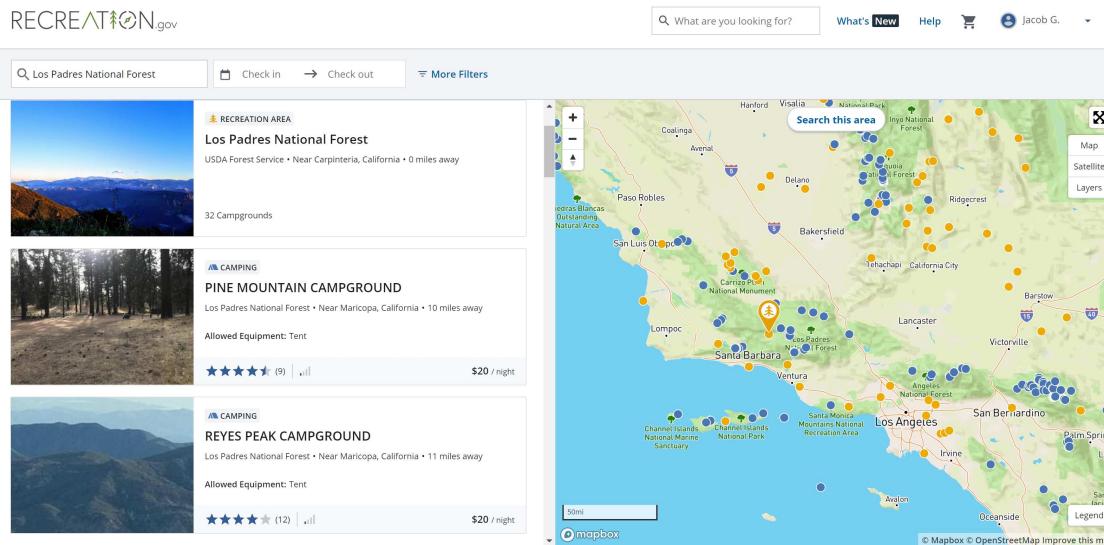
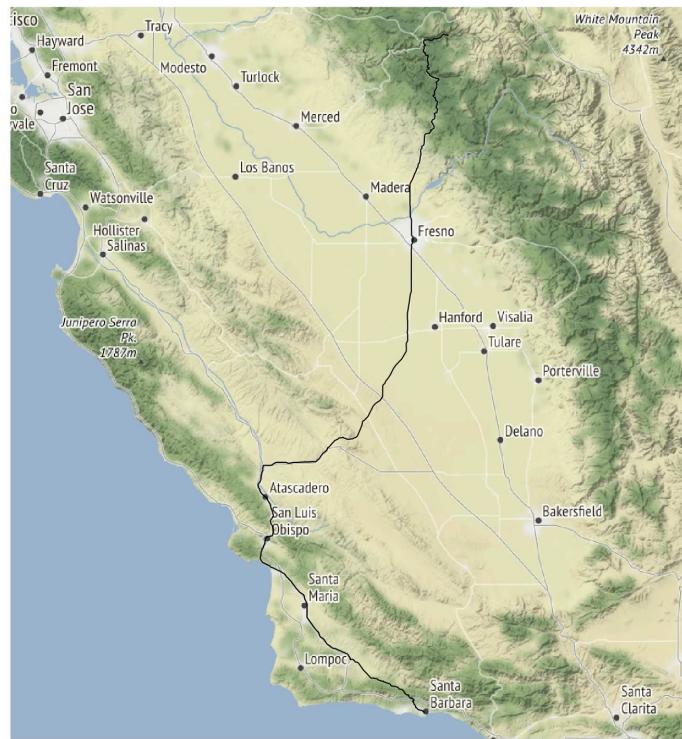


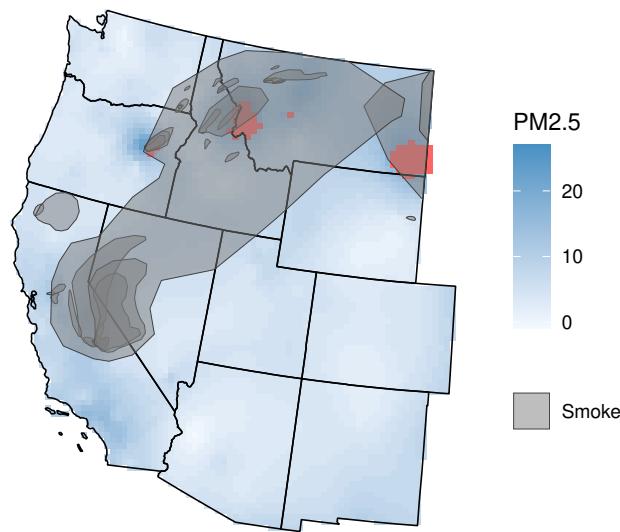
Figure A2: Automobile Route from Santa Barbara, California to Yosemite National Park



A2

Figure A3: NOAA Smoke Plumes and PM_{2.5}

September 1, 2015



Notes: Red areas are affected by smoke and poor air quality.

Figure A4: Fire Detection Points and Fire Perimeters

Fire perimeters and fire detections, 2015

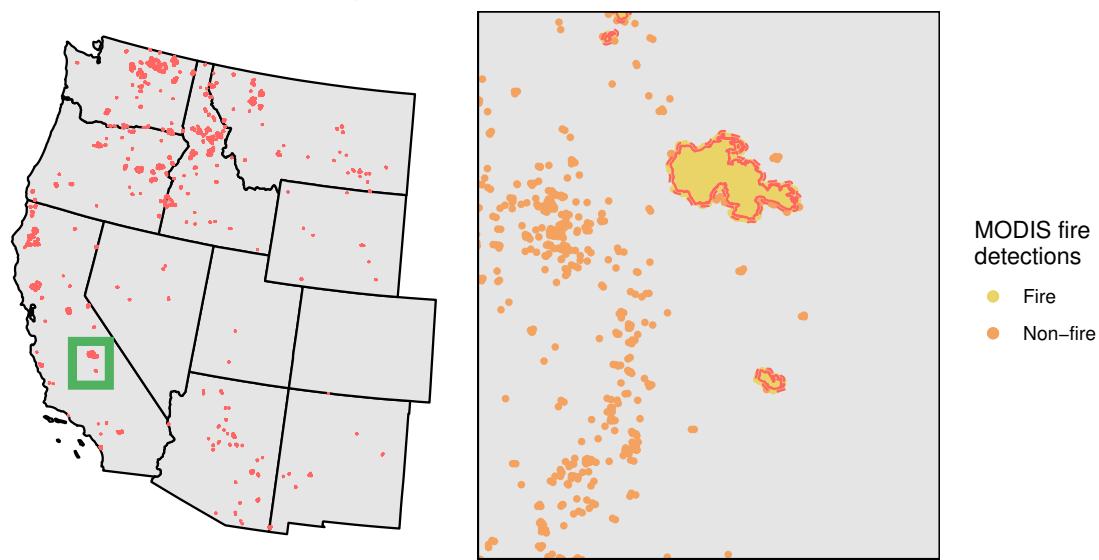


Table A1: Most Visited Federally Managed Campgrounds

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 A5: Relationship Between Control Function $\tilde{\varepsilon}_{ijt}$ and Travel Cost Using Model (4) of Table 4 Showing Correlation Between Preferences and Travel Cost in the Selected Sample of Reservers

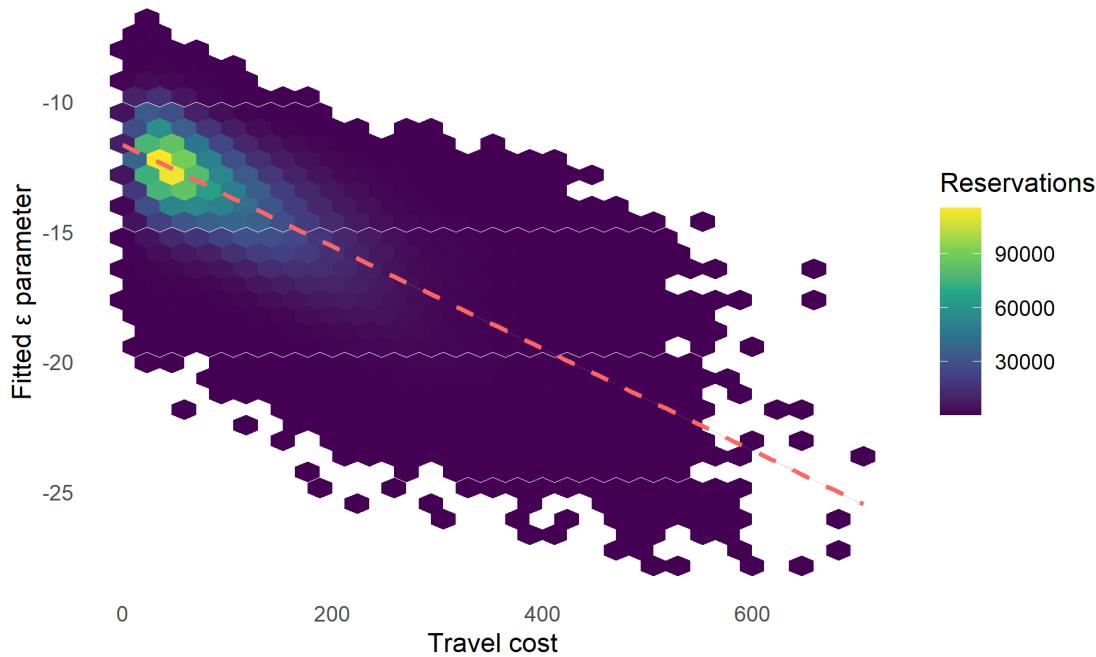


Figure A6: Total Estimated Welfare Losses and Proportion of Visits Affected by Smoke per Year

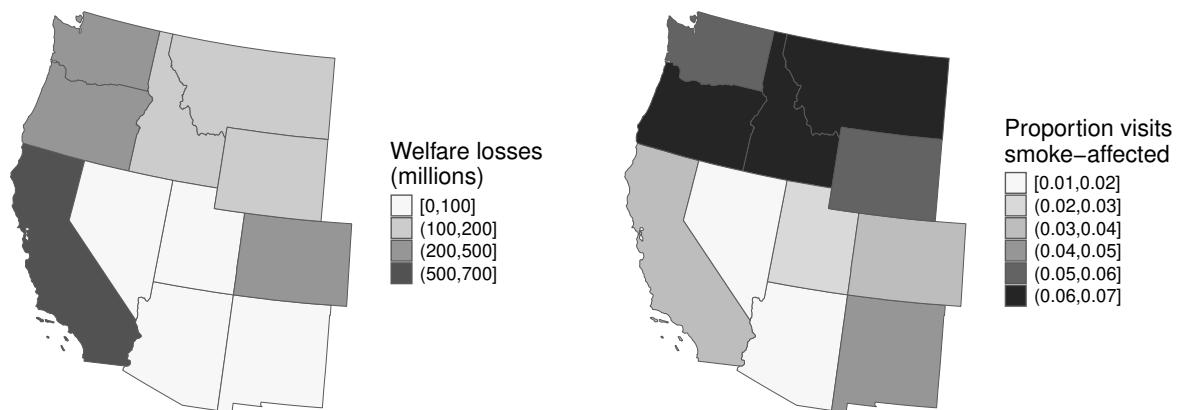


Table A2: Predicted Probability Campground Will Be Smoke-Affected, by Number of Smoke Days in the Preceding Week

	1{Campground is smoke-affected}
Intercept	0.0000 (0.0001)
1{Smoke days in week of arrival = 1}	0.2013** (0.0005)
1{Smoke days in week of arrival = 2}	0.3009** (0.0008)
1{Smoke days in week of arrival = 3}	0.3798** (0.0010)
1{Smoke days in week of arrival = 4}	0.4850** (0.0012)
1{Smoke days in week of arrival = 5}	0.6108** (0.0013)
1{Smoke days in week of arrival = 6}	0.7390** (0.0016)
1{Smoke days in week of arrival = 7}	1.0000** (0.0018)
N	1,528,470

Notes: * $p < 0.05$, ** $p < 0.01$.

Appendix B: Numerical example of sample selection correction

In Section 3.3, we propose a control function approach to account for unobserved preferences $\tilde{\varepsilon}_{ijt}$ that 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 willingness to pay (WTP), and correction using a control function. We show that WTP is only biased when preferences for the reservation decision influence the cancellation decision (i.e., given selection) and when the counterfactual cancellation decision of non-reservers is unobserved. Furthermore, the bias operates through correlation between preferences and travel cost:

Table A3: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, Heterogeneity by Smoke Days in Week Before Arrival

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

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

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, inflating WTP estimates. Finally, we demonstrate bias correction using the control function for $\tilde{\varepsilon}_{ijt}$ given in Equation 10.

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 uniformly. 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 uniformly. 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 $U_{ij}^R = \alpha_j + \delta c_{ij} + \phi \mathbb{E}[s_j] + \varepsilon_{ij}$, where α_j is an intercept, c_{ij} is the travel cost, s_j denotes smoke conditions at the site, and ε_{ij} is the individual's preferences from reservation. 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 values 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 $R_{ij} = 1 \iff U_{ij}^R \geq U_{i0}^R$.

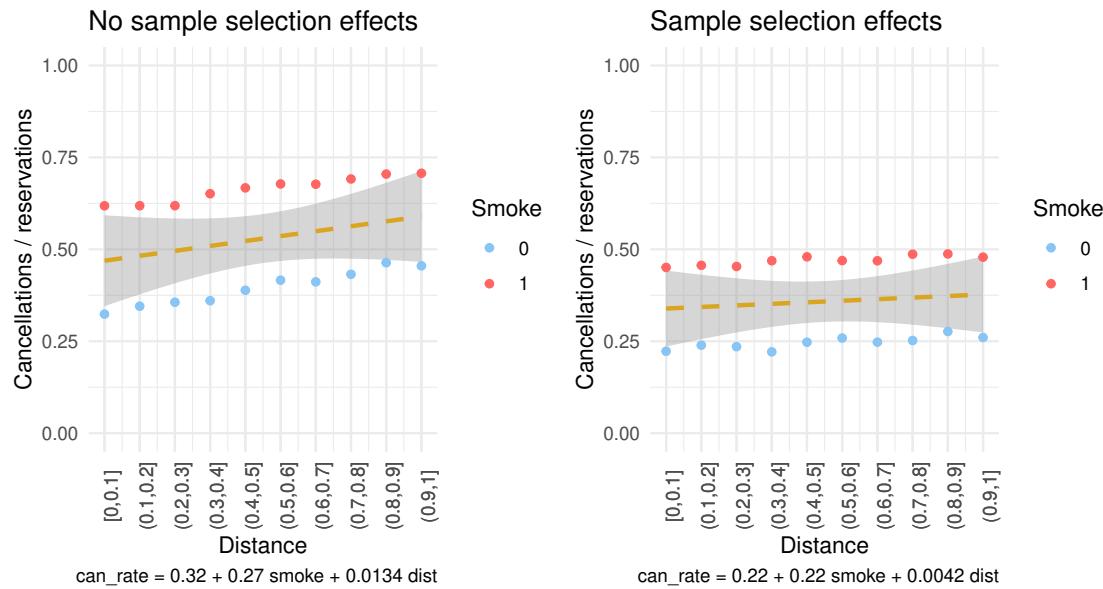
For the cancellation decision, the user decides based on realized smoke conditions. Let the utility from cancellation be $U_{ij}^C = \alpha_j + \delta c_{ij} + \phi s_j + v_{ij}$. Realized smoke s_j is drawn from $\{0, 1\}$ with $\mathbb{P}(s_j = 1) = 0.25$ for each user to create variation based on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

We consider two types of error structures v_{ij} in the cancellation decision. The first is an independent error, $v_{ij}^{ind} = \frac{1}{\rho} \eta_{ij}$, where $\eta_{ij} \sim$ type I extreme value, which assumes that the user's preferences in the decision are completely unrelated to their choice to have reserved. The second is a dependent error, $v_{ij}^{dep} = \varepsilon_{ij} + \frac{1}{\rho} \eta_{ij}$, which allows preferences at the time of reservation to affect the 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 decisions under both v_{ij}^{ind} and v_{ij}^{dep} , which we denote as 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 reservers. However, under the Monte Carlo simulation, we can also examine the counterfactual decision of the non-reservers to see if they “would have” cancelled. We show that, even with a dependent error v_{ij}^{dep} , estimation of $\mathbb{P}(C_{ij} = 0)$ on the full sample (reservers and non-reservers) without observing ε_{ij} will still recover the true WTP because no selection effect exists. That is, the biased estimation of $\mathbb{P}(C_{ij} = 0|R_{ij} = 1)$ is because ε_{ij} and c_{ij} are correlated in the selected sample, not the full sample.

Figure B1 illustrates the effects of selection by contrasting cancellation rates with and without selection effects, illustrating several key points. First, the overall cancellation rate is lower in the presence of selection, as indicated by the intercept of the fitted gold line. Users who 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 both with and without sample selection effects. Third, the effect of travel cost, which is the slope of the gold fitted line, is attenuated when preferences at the time of reservation affect the cancellation decision. This attenuation illustrates that the selection effect likely operates through positive correlation between ε_{ij} and travel cost.

Figure B1: Example Cancellation Rate to Illustrate the Effects of Selection



Next, we show that WTP estimates are only biased under a selected sample and when

preferences at the time of reservation affect the cancellation decision. We estimate a logit regression for the reservation and cancellation decisions, varying whether we use the full sample or selected sample of reservers and the dependent error v_{ij}^{dep} or the independent error v_{ij}^{ind} for the cancellation decision.

Table B1 shows results from 10,000 draws. 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 v_{ij}^{ind} and v_{ij}^{dep} but with the full sample. These regressions show that the selection effects 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 v_{ij}^{ind} (i.e., assuming no selection effects). Regression 4 demonstrates that sample selection is not an issue if the user's preferences at the time of reservation are unrelated to their cancellation decision. Biased estimation arises in Column 5 when there is both sample selection and when the reservation preferences affect the cancellation decision. Finally, Column 6 shows that inclusion of a control function corrects for the bias of Column 5. This result lends support to the use of this bias corrector in the empirical dataset.

Table B1: Monte Carlo 10,000 Simulated Regressions of Reservation and Cancellation Decisions

	(1)	(2)	(3)	(4)	(5)	(6)
WTP	2.00** (0.10)	2.01** (0.11)	2.01** (0.14)	2.01** (0.15)	6.70 (8.52)	2.00** (0.25)
Dep. var.	R_{ij}	C_{ij}	C_{ij}	C_{ij}	C_{ij}	C_{ij}
Users	All users	All users	All users	Reservers	Reservers	Reservers
Error	ε_{ij}	v_{ij}^{ind}	v_{ij}^{dep}	v_{ij}^{ind}	v_{ij}^{dep}	v_{ij}^{dep}
Control function		No	No	No	No	Yes

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

Appendix C: Bootstrapped standard errors for $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$

In Section 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: for B bootstraps and G clusters, (1) sample with replacement G times from the original sample of clusters, and (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 adequate. Table C1 reports W statistics from Shapiro-Wilk tests of normality for the smoke and travel cost coefficients from the main estimation of Table 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 C1 and C2 plot the bootstrapped coefficients visually.³⁴

³⁴One single iteration of the bootstrap produced abnormally large coefficient estimates, where, for example, the travel cost coefficient was estimated as -23 trillion. Still, that iteration produced a WTP in line with the other iterations; the WTP was equal to \$74, suggesting that despite the abnormal magnitude of the coefficients, the ratios of coefficients to one another were proper. Nevertheless, we remove this single outlier from Figures C1 and C2, and from the analysis in the main text.

Table C1: 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 (0.450)	0.998 (0.979)	0.998 (0.852)	0.994 (0.084)
Travel cost (dollars)	0.990 (0.006)	0.996 (0.343)	0.995 (0.291)	0.995 (0.255)
Campground x week-of-year FE		Yes	Yes	Yes
Day-of-week FE		Yes	Yes	Yes
Year FE		Yes		
State x year FE			Yes	
Campground x year FE				Yes

Figure C1: Distribution of Estimated Smoke Coefficient from Models (1) to (4) in Bootstrapped Estimation of $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ with Sample Selection Correction (red line indicates mean)

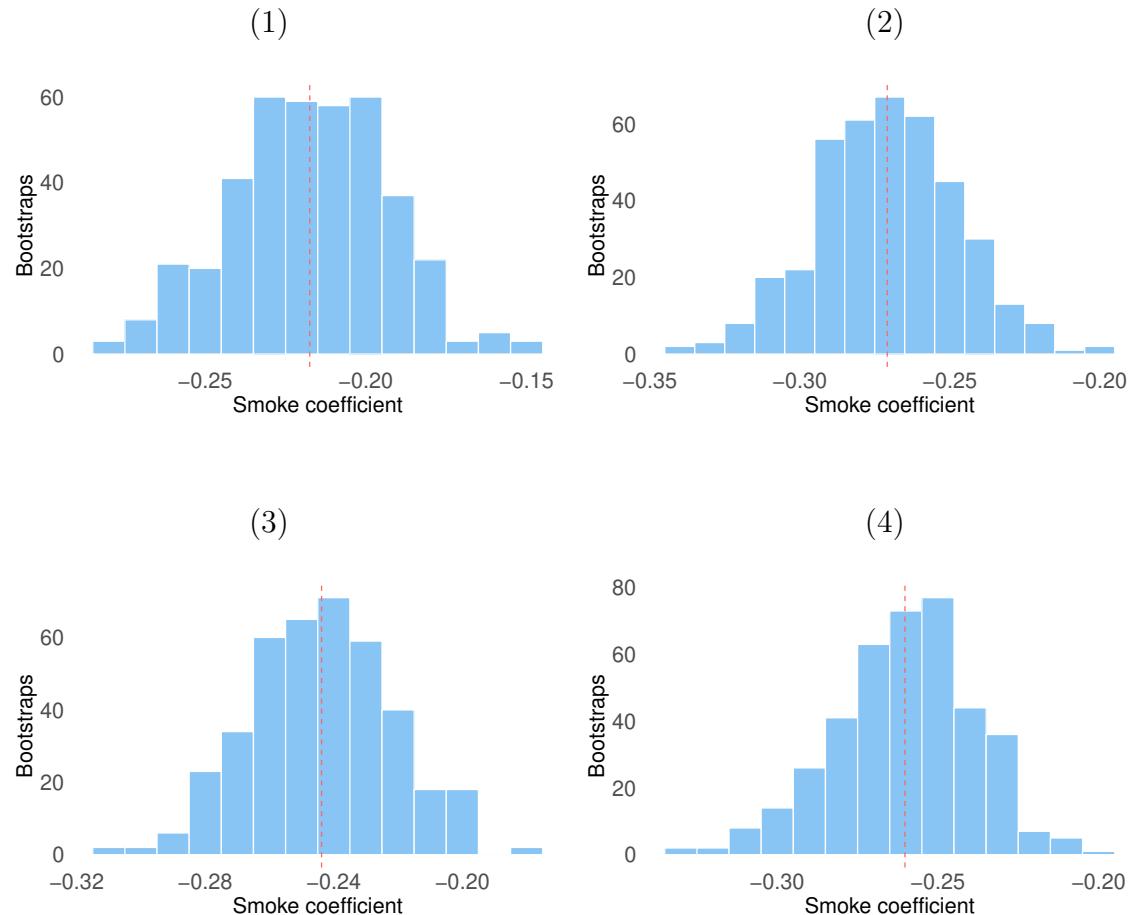
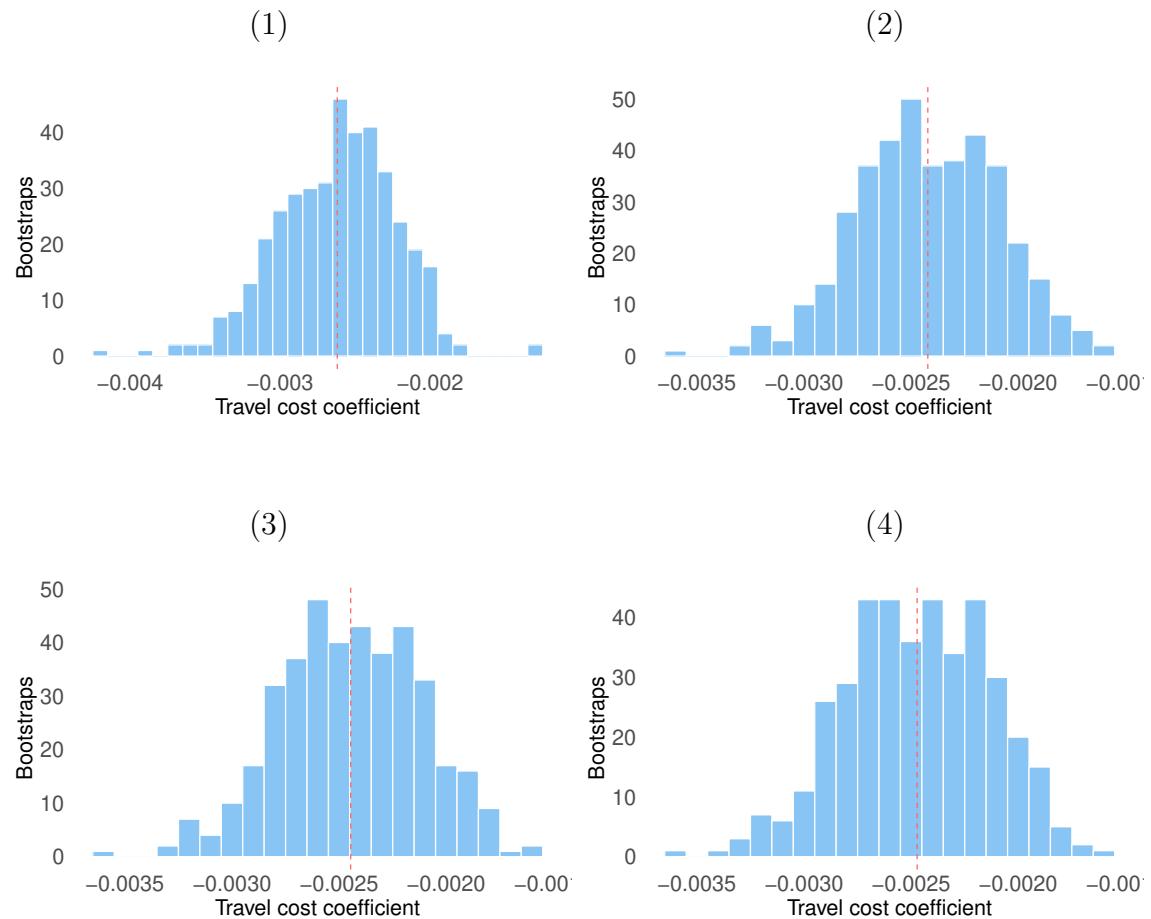


Figure C2: Distribution of Estimated Travel Cost Coefficient from Models (1) to (4) in Bootstrapped Estimation of $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ with Sample Selection Correction (red line indicates mean)



Appendix D: Heterogeneity and robustness by campground characteristics

In this section we explore a series of robustness checks and heterogeneity analyses. These include a test of the influence of no-shows on cancellation estimates. We also provide results by various campground characteristics, including visitation levels, region, managing agency, and site amenities. Lastly, we explore temporal aspects of demand, including heterogeneity by time of booking and by holiday weekend.

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D1 Testing the influence of no-shows in cancellations

One may be concerned that recreationists do not formally cancel their reservation when they decide not to complete a trip. Unreported no-shows threaten the identification of any willingness to pay (WTP) that is based on cancellations, as it could underestimate them. Although most of the campgrounds in the Recreation.gov dataset do not report check-ins or no-shows, a subset do. Just 36 out of 999 campgrounds (3.6 percent) report no-shows, but they represent 19.7 percent of the reservations used in the cancellation estimation. Overall, no-shows represent approximately 14.1 percent of all cancellations at the campgrounds which report no-shows.

As a robustness check, we recode no-shows at the reporting campgrounds to arrivals, which would reflect what the data would show at non-reporting campgrounds. If there is no difference in WTP when recoding no-shows, then it suggests that no-shows do not threaten the results of the main analysis.

Table D1 tests two models. Column 1 allows smoke and travel cost to respond differentially for no-show and non-no-show campgrounds. This model shows that no-show and non-no-show campgrounds have different overall measures of WTP. In Column 2 we recode no-shows as arrivals for the campgrounds that report no-shows. Comparing the WTP of no-show campgrounds with and without recoding (\$116.66 and \$118.44), WTP is virtually unchanged and is not statistically different. This analysis should alleviate concerns that no-shows influence the estimate of WTP in the full sample.

Table D1: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, Testing Effect of No-Shows on Cancellation by Recoding No-Shows as Arrivals

	(1)	(2)
Smoke x 1(Non-no-show campground)	-0.2608** (0.0188)	-0.2605** (0.0188)
Smoke x 1(No-show campground)	-0.2628** (0.0689)	-0.2786** (0.0730)
Travel cost x 1(Non-no-show campground)	-0.0025** (0.0004)	-0.0025** (0.0004)
Travel cost x 1(No-show campground)	-0.0023** (0.0003)	-0.0024** (0.0003)
Inv. distance to wildfire (km^{-1})	-7.8180** (0.8223)	-7.9904** (0.8606)
High temp. (degrees C)	0.0306** (0.0022)	0.0306** (0.0022)
Low temp. (degrees C)	-0.0252** (0.0025)	-0.0253** (0.0025)
Precip. in week of arrival (mm)	-0.0057** (0.0009)	-0.0058** (0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0376** (0.0134)	-0.0368** (0.0136)
WTP, non-no-show campgrounds	103.82** (17.39)	104.32** (17.8)
WTP, no-show campgrounds	116.66** (32.1)	118.44** (33.75)
No-shows recoded as arrivals?	No	Yes
N	2,688,739	2,688,582
Campground x week-of-year FE	Yes	Yes
Day-of-week FE	Yes	Yes
Campground x year FE	Yes	Yes

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

D2 Campground popularity

This section explores heterogeneous welfare damages based on the popularity of a campground. We define popularity based on the average number of visitors per year for years in which it was open. For reference, Table A1 shows the most-visited campgrounds, many of

which belong to high-profile national parks, such as Yosemite, Grand Canyon, and Rocky Mountain. The least popular 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 popularity. Given 999 campgrounds, each quartile contains approximately 250 locations.

Table D2 displays full results, including point estimates for smoke responses, travel cost responses, and WTP. 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. WTP is estimated as the ratio of marginal disutility in smoke to that in expenditure (the smoke coefficient divided by the travel cost coefficient). Because WTP is a ratio, it could be either higher or lower given reductions in both the smoke parameter (the numerator) and the travel cost parameter (the denominator). Table D2 shows that the reduction in the smoke parameter dominates, resulting in lower WTP at popular campgrounds. In general, welfare damages tend to be largest for the middle two quartiles of popularity.

D3 Campground characteristics and amenities

In this section, we consider heterogeneous responses by campground characteristics. First, we test for heterogeneous responses by managing agency. We run separate regressions only on the set of campgrounds managed by each agency. Table D3 displays results. This analysis suggests that the welfare costs of smoke are higher for National Park Service locations and lower for US Forest Service locations. We do not obtain statistically significant results for the US Army Corps of Engineers, Bureau of Land Management, or Bureau of Reclamation locations, likely due to being statistically underpowered. As noted in Section 2.6, the data feature 908 US Forest Service campgrounds and 50 National Park Service campgrounds, but only 31 US Army Corps of Engineers, 5 Bureau of Land Management, and 5 Bureau of

Table D2: $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$, Heterogeneity by Campground Popularity

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

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

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4 Reclamation campgrounds.
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6 Next, we assess regional heterogeneity. Two components are important to understand
7 regional differences in smoke impacts. One component is how the frequency of smoke differs,
8 which is in part addressed in the total welfare analysis in Table 6 and Figure A6. A second
9 component of regional heterogeneity is the potentially differential responses to smoke by
10 region. We run separate regressions by region to explore these responses. Table D4 shows
11 that per-trip welfare losses are highest for California, the Pacific Northwest, and the Great
12 Basin; they are lowest for the Rocky Mountains and Northern Rocky Mountains.
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15 We also investigate heterogeneity by campground characteristics. The Recreation.gov
16 data report the site type that individuals have reserved, where a site is a reservable location
17 within a campground. These site types include RV sites, “standard” sites, tent-only sites,
18 and “walk to/hike to” sites, the last of which are accessible only by hiking in. Ex-ante,
19 responses to smoke could differ for RV users because they are arguably less exposed to
20 smoke than tent-only or walk to/hike to sites; on the other hand, RV users could be older
21 and more health-sensitive. Results are reported in Table D5. We find that RV users have
22 the strongest responses to smoke, resulting in higher welfare losses for these individuals.
23 According to the RV Industry Association, about 66 percent of RV owners are aged 55 or
24 older, so these results could reflect health-related sensitivity to wildfire smoke.³⁵ The other
25 site types, such as tent-only or walk to/hike to, might be visited most by users who are
26 younger or more able-bodied. Separately, in Column 2, we find no differences by electric or
27 non-electric sites.
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30 Lastly, we test the influence of desirable environmental amenities. We collect water body
31 data from the USGS National Hydrography Dataset and elevation data from the USGS
32 National Elevation Dataset. We draw 1 km boundaries around campground centroids and
33 measure heterogeneity by the proportion of area that is a water body, the maximum elevation,
34 and the range in elevation (maximum minus minimum), the last of which is a measure of
35 terrain diversity. Column 1 of Table D6 shows that people are more tolerant of smoke if
36 there are water bodies nearby, which is an element of campground desirability. Column 2
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³⁵RV Industry Association. Go RVing RV Owner Demographic Profile: Class A Motorhomes. <https://www.rvia.org/news-insights/go-rving-rv-owner-demographic-profile-class-motorhomes>.

shows that people are more tolerant of smoke at higher elevations, which could correspond to mountainous locations. Column 3, which reports responses by terrain diversity, shows no clear trend.

Table D3: $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ Within One Week, Results by Managing Agency

	(1)	(2)	(3)	(4)	(5)
Smoke in week of arrival	-0.300** (0.0250)	-0.177** (0.0410)	-0.105* (0.041)	0.121 (0.238)	-0.129 (0.125)
Travel cost (dollars)	-0.003** (0.0003)	-0.001** (0.0004)	-0.007** (0.002)	-0.001 (0.003)	-0.004 (0.002)
Inv. distance to wildfire (km^{-1})	-9.835** (0.905)	-4.990** (1.090)	-11.551** (4.291)	-2.243 (1.914)	-32.845** (6.836)
High temp. (degrees C)	0.033** (0.003)	0.033** (0.004)	0.005 (0.006)	0.034** (0.011)	0.038 (0.035)
Low temp. (degrees C)	-0.026** (0.003)	-0.029** (0.005)	-0.011 (0.011)	-0.056** (0.015)	-0.033 (0.029)
Precip. in week of arrival (mm)	-0.005** (0.001)	-0.007** (0.003)	-0.005** (0.002)	-0.001 (0.001)	-0.001 (0.006)
$\tilde{\varepsilon}_{ijt}$	-0.049** (0.009)	-0.094* (0.040)	-0.143** (0.036)	-0.007 (0.071)	-0.040 (0.100)
Agency	USFS	NPS	USACE	BLM	BOR
WTP	91.24** (10.32)	119.12** (42.02)	14.03 (7.64)	-112.82 (477.86)	35.85 (49.65)
N	2,017,300	507,282	128,772	17,155	18,230
Campground x week-of-year FE	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes	Yes	Yes

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

Table D4: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within One Week, Results by Region

	(1)	(2)	(3)	(4)	(5)	(6)
Smoke in week of arrival	-0.276** (0.0360)	-0.222* (0.090)	-0.138** (0.041)	-0.378** (0.044)	-0.177** (0.041)	-0.195* (0.077)
Travel cost (dollars)	-0.002** (0.0004)	-0.003** (0.001)	-0.004** (0.001)	-0.005** (0.001)	-0.003** (0.001)	-0.002** (0.001)
Inv. distance to wildfire (km^{-1})	-7.837** (1.0130)	-2.934 (5.243)	-14.647** (1.439)	-5.331** (1.806)	-17.844** (4.670)	-7.643** (1.841)
High temp. (degrees C)	0.039** (0.0030)	0.026** (0.008)	0.035** (0.004)	0.020** (0.003)	0.020** (0.006)	0.022* (0.010)
Low temp. (degrees C)	-0.029** (0.0040)	-0.015 (0.009)	-0.032** (0.006)	-0.017** (0.004)	-0.037** (0.006)	-0.017* (0.009)
Precip. in week of arrival (mm)	-0.003* (0.0010)	-0.006** (0.002)	-0.008** (0.001)	-0.004** (0.001)	-0.013** (0.002)	-0.002 (0.001)
$\tilde{\varepsilon}_{ijt}$	-0.025 (0.0170)	-0.033 (0.020)	-0.076* (0.037)	-0.106** (0.018)	-0.053* (0.022)	-0.039 (0.023)
Region	California CA	Great Basin NV, UT	Northern Rockies ID, MT	Pacific Northwest OR, WA	Rocky Mountains CO, WY	Southwest AZ, NM
WTP	129.2** (25.84)	78.3* (35.93)	38.35* (17.04)	83.17** (12.73)	53.39** (11.71)	79.44 (41.72)
N	1,213,510	212,033	182,722	548,514	388,211	143,749
Campground x week-of-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table D5: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within One Week, Results by Site Type

	(1)	(2)
Travel cost (dollars)	-0.002** (0.0003)	-0.002** (0.0003)
Inv. distance to wildfire (km^{-1})	-7.824** (0.8240)	-7.818** (0.8240)
High temp. (degrees C)	0.031** (0.0020)	0.031** (0.0020)
Low temp. (degrees C)	-0.025** (0.0020)	-0.025** (0.0020)
Precip. in week of arrival (mm)	-0.006** (0.0010)	-0.006** (0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.037** (0.0130)	-0.037** (0.0130)
Smoke x RV Site	-0.347** (0.0510)	
Smoke x Standard Site	-0.264** (0.0220)	
Smoke x Tent Only Site	-0.237** (0.0410)	
Smoke x Walk To/Hike To Site	-0.215** (0.0550)	
Smoke x Electric Site		-0.251** (0.0470)
Smoke x Nonelectric Site		-0.262** (0.0220)
WTP: RV Site	143.26** (28.01)	
WTP: Standard Site	108.99** (16.64)	
WTP: Tent Site	98** (22.64)	
WTP: Walk To/Hike To Site	88.86** (26.31)	
WTP: Electric Site		103.72** (24.53)
WTP: Nonelectric Site		108.24** (17.26)
N	2,688,739	2,688,739
Campground x week-of-year FE	Yes	Yes
Day-of-week FE	Yes	Yes
Campground x year FE	Yes	Yes

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

Table D6: $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ Within One Week, Results by Terrain Within 1 km: Proportion of Area that is Water, Max Elevation, and Max Elevation Min Elevation

	(1)	(2)	(3)
Travel cost (dollars)	-0.002** (0.0003)	-0.002** (0.0004)	-0.002** (0.0004)
Inv. distance to wildfire (km^{-1})	-7.813** (0.8250)	-7.841** (0.8400)	-7.853** (0.8350)
High temp. (degrees C)	0.031** (0.0020)	0.030** (0.0020)	0.030** (0.0020)
Low temp. (degrees C)	-0.025** (0.0020)	-0.024** (0.0020)	-0.024** (0.0020)
Precip. in week of arrival (mm)	-0.006** (0.0010)	-0.006** (0.0010)	-0.006** (0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.037** (0.0130)	-0.038** (0.0130)	-0.038** (0.0130)
Snow x Prop. Water = 0	-0.287** (0.0280)		
Snow x Prop. Water in 0-0.01	-0.183 (0.1000)		
Snow x Prop. Water in 0.01-0.02	-0.260** (0.0730)		
Snow x Prop. Water in 0.02-0.03	-0.234** (0.0490)		
Snow x Prop. Water in 0.03-1	-0.215** (0.0480)		
Snow x Max Elev. in -10-1000 m		-0.289** (0.0460)	
Snow x Max Elev. in 1000-2000 m		-0.329** (0.0410)	
Snow x Max Elev. in 2000-3000 m		-0.207** (0.0340)	
Snow x Max Elev. in 3000-4000 m		-0.262** (0.0410)	
Snow x Elev. Diff. in 0-150 m			-0.199** (0.0330)
Snow x Elev. Diff. in 150-300 m			-0.286** (0.0430)
Snow x Elev. Diff. in 300-400 m			-0.365** (0.0770)
Snow x Elev. Diff. in 400-1200 m			-0.241** (0.0340)
WTP: Lowest bin	118.58** (21.88)	118.69** (26.96)	81.65** (26.96)
WTP: Second bin	75.77 (42.74)	134.78** (26.42)	117.12** (26.42)
WTP: Third bin	107.44** (33.92)	84.82** (18.09)	149.48** (18.09)
WTP: Highest bin	96.59** (18.96)	107.4** (23.65)	98.84** (23.65)
N	2,688,739	2,654,110	2,654,110
Campground x week-of-year FE	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes

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

D4 Time of booking, choice set, and campground quality

One consequence of campground quality, whether measured by popularity as in Appendix D2 or by physical amenities as in Appendix D3, is that some desirable campgrounds may get completely booked and become unavailable for visitors who reserved at a later time. The model of Figure 3 implies a one-stage choice for the reservation decision. The assumption of this model is that the window of opportunity to book at a location is between one week and six months in advance; someone who booked only one month in advance could have booked at an alternative site earlier, but chose not to. This choice is endogenous.

Nevertheless, it is reasonable to wonder if congestion at desirable sites might distort welfare estimates for late reservers whose first choice was not available. A check on this possibility is to estimate welfare differentially according to how far in advance an individual reserved. Six months ahead of time, an individual should have a full choice set. Figure D1 displays welfare estimates from such an exercise, allowing smoke and travel cost coefficients to vary with 30 day bins that group the time of reservation. Full results are listed in Table D7.

Figure D1: Welfare Estimates by Time of Reservation

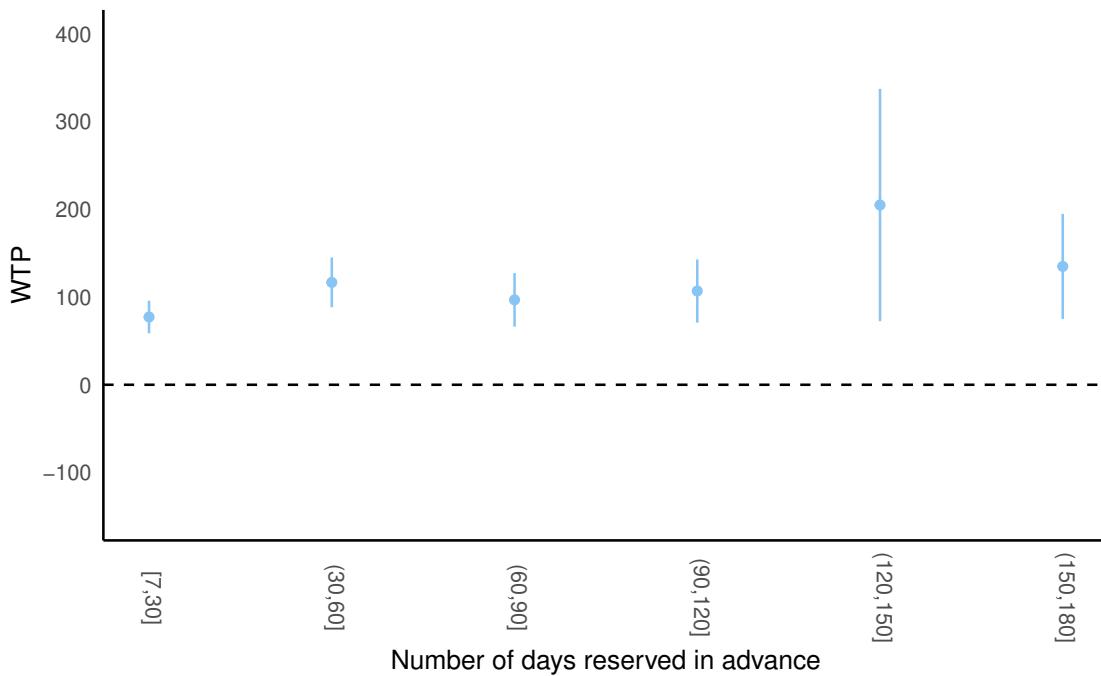


Table D7: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, Heterogeneity by Time of Reservation

	(1)
Inv. distance to wildfire (km^{-1})	-7.619** (0.822)
High temp. (degrees C)	0.032** (0.002)
Low temp. (degrees C)	-0.026** (0.003)
Precip. in week of arrival (mm)	-0.006** (0.001)
$\tilde{\varepsilon}_{ijt}$	-0.037** (0.010)
Solid line	
Smoke x [7,30] days ahead	-0.229** (0.024)
Smoke x (30,60] days ahead	-0.324** (0.028)
Smoke x (60,90] days ahead	-0.262** (0.034)
Smoke x (90,120] days ahead	-0.280** (0.037)
Smoke x (120,150] days ahead	-0.294** (0.029)
Smoke x (150,180] days ahead	-0.216** (0.032)
Dashed line	
Travel cost x [7,30] days ahead	-0.0030** (0.0002)
Travel cost x (30,60] days ahead	-0.0028** (0.0002)
Travel cost x (60,90] days ahead	-0.0027** (0.0003)
Travel cost x (90,120] days ahead	-0.0026** (0.0003)
Travel cost x (120,150] days ahead	-0.0014** (0.0005)
Travel cost x (150,180] days ahead	-0.0016** (0.0003)
Other	
N	2,417,246
Campground x week-of-year FE	Yes
Day-of-week FE	Yes
Campground x year FE	Yes

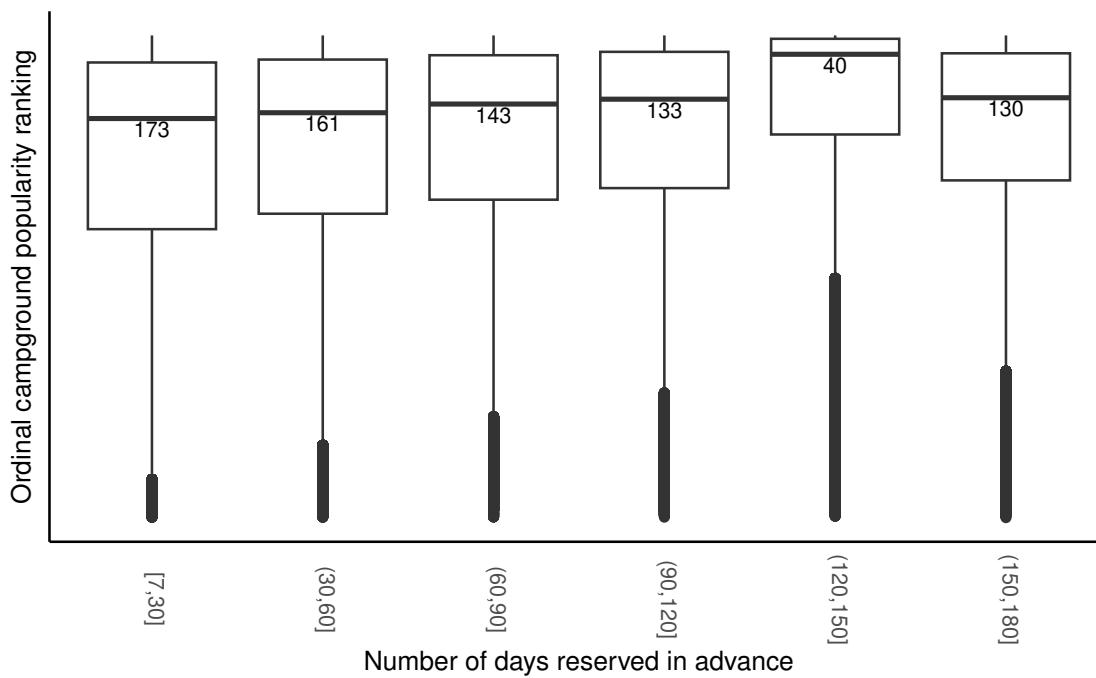
Notes: Std. err. clustered at campground level. * $p < 0.05$, ** $p < 0.01$.

The welfare values of Figure D1 include the main estimate of \$107 in their confidence intervals, mitigating concerns for the estimates in the main text. However, one feature of Figure D1 is that welfare damages are somewhat higher for the two earliest bandwidths, at

\$205.02 ([72.50, 337.54]) and \$134.98 ([75.06, 194.90]). This relationship could be driven by unobservable differences in preferences for early planners. It could also be due to differences in the quality of the campgrounds that are reserved ahead of time, since Appendix D2 and Appendix D3 showed that quality is consequential for welfare estimates. In particular, Table D2 showed lower welfare values for the least popular locations. In addition, Table D2 and Table D7 showed lower magnitude travel cost coefficients for popular campgrounds and earlier reservers, respectively, which is suggestive of composition effects.

Figure D2 shows the distribution of campground popularity by time of reservation using the ordinal rankings developed in Appendix D2. According to this figure, while popular campgrounds are still selected in later months, the distribution of reservations in earlier months includes fewer low-popularity sites. These composition effects could help explain the patterns observed in Figure D1 and Table D7.

Figure D2: Earlier Reservations For More Popular Campgrounds, With Median Popularity Rank Denoted



D5 Temporal demand and holiday weekends

Demand to camp varies temporally. For instance, holiday weekends are known to be popular times to visit national parks.³⁶ The heterogeneity analyses of Appendix D have found that welfare estimates can differ by the desirability of a location; this relationship may also hold for desirable arrival times.

To explore this issue, we test for heterogeneity on holiday weekends. We define days of arrival as falling on a holiday weekend if the weekend, including Friday and Monday, includes the US federal holidays of Memorial Day, Independence Day, or Labor Day. Table D8 displays results from this estimation. We find that welfare losses are larger on federal holiday weekends, both due to increased sensitivity to smoke and decreased sensitivity to travel cost. These results add to the evidence on the upper-bound welfare losses from wildfire smoke.

Table D8: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, Heterogeneity by Holiday Weekend

	(1)
Inv. distance to wildfire (km^{-1})	-7.812** (0.8250)
High temp. (degrees C)	0.031** (0.0020)
Low temp. (degrees C)	-0.025** (0.0020)
Precip. in week of arrival (mm)	-0.006** (0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.037** (0.0130)
Travel cost x Holiday weekend = 0	-0.0025** (0.0003)
Travel cost x Holiday weekend = 1	-0.0020** (0.0004)
Smoke x Holiday weekend = 0	-0.256** (0.0210)
Smoke x Holiday weekend = 1	-0.310** (0.0580)
WTP: Non-holiday weekend	103.12** (16)
WTP: Holiday weekend	152.86** (44.13)
N	2,688,739
Campground x week-of-year FE	Yes
Day-of-week FE	Yes
Campground x year FE	Yes

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

³⁶National Park Service. Visiting During the Busy Season. <https://www.nps.gov/jotr/planyourvisit/visiting-during-the-busy-season.htm>.

Appendix E: Alternative thresholds for sample restriction

We make two sample restrictions in the main text. First, we restrict attention to individuals within 650 km (400 miles) of one-way driving distance, which is meant to reduce the possibility of chained trips or air travel (English et al. 2018). We also define cancellations close to the arrival date as those made within seven days. In this section we provide sensitivity analyses for these threshold definitions.

E1 Distance restrictions

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 2 shows that this threshold admits approximately 85 percent 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).

Table E1 illustrates how willingness to pay (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. Column 2 reports the main estimates, identical to Table 4. The main estimate of \$107 is included in the confidence interval of the 950 km estimate ([90.30, 189.36]), and falls narrowly outside the confidence interval for the more restrictive 350 km estimate ([51.26, 106.22]).

As the distance threshold is relaxed, the increasing WTP estimates are driven by a decline in the magnitude of the travel cost coefficient. In other words, increasing the pool of potential reservers decreases the estimated response to travel cost. This phenomenon could result from including 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. The magnitude is likely smaller at lower thresholds due to the corre-

lation of preferences with travel cost; removing reservations from larger distances eliminates some visitors with both high travel costs and high tastes for the chosen site.

Table E1: $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$ Within One Week, Restricting Sample Distance to Within 350 km (217 miles), 650 km (404 miles), or 950 km (590 miles) of Site

	350 km	650 km	950 km
Smoke in week of arrival	-0.2651** (0.0241)	-0.2603** (0.0218)	-0.2589** (0.0206)
Travel cost (dollars)	-0.0034** (0.0005)	-0.0025** (0.0003)	-0.0019** (0.0003)
Inv. distance to wildfire (km^{-1})	-8.9377** (0.8670)	-7.8141** (0.7920)	-7.5899** (0.8101)
High temp. (degrees C)	0.0331** (0.0025)	0.0306** (0.0023)	0.0300** (0.0021)
Low temp. (degrees C)	-0.0248** (0.0028)	-0.0252** (0.0025)	-0.0249** (0.0024)
Precip. in week of arrival (mm)	-0.0061** (0.0010)	-0.0057** (0.0009)	-0.0056** (0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0240 (0.0165)	-0.0385** (0.0106)	-0.0390** (0.0128)
N	2,044,062	2,688,739	2,851,414
WTP	78.74** (14.02)	107.14** (16.33)	139.83** (25.27)
Campground x week-of-year FE	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes

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

E2 Heterogeneous results within τ days of arrival

The main estimation considers the cancellation decisions of users within $\tau = 7$ days of arrival, where τ is defined in Figure 3. In this section, we explore heterogeneous results for alternative temporal thresholds. We reconstruct the dataset to estimate visitors' probability of cancellation within $\tau = 3, 5, 7$, and 9 days of arrival. The variable of interest is an indicator equal to 1 if a smoke-affected day occurred within the τ day threshold. We consider only standing, uncancelled reservations as of τ days before arrival.

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 4 Table E2 reports these results.³⁷ For $\tau = 3, 5, 7$, and 9 days, we find welfare damages of
 5 \$137, \$129, \$107, and \$92 per person per trip, respectively. These results are consistent with
 6 an information mechanism, which was explored in Section 4.3. For smaller values of τ , the
 7 occurrence of one smoke day corresponds to a greater likelihood of smoke on the actual day
 8 of arrival. Visitors may have a greater propensity to cancel when observing smoke closer to
 9 the date of arrival. The travel cost coefficient is largely stable as τ decreases; greater WTP
 10 is driven by a growth in the magnitude of the smoke coefficient. Overall, however, the main
 11 estimate of \$107 is included in the confidence interval of the estimates from each model.
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20 Table E2: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within τ Days of Arrival
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τ	3 days	5 days	7 days	9 days
Smoke	-0.2961** (0.0536)	-0.2929** (0.0241)	-0.2603** (0.0218)	-0.2281** (0.0207)
Travel cost (dollars)	-0.0022** (0.0004)	-0.0023** (0.0004)	-0.0025** (0.0003)	-0.0025** (0.0003)
Inv. distance to wildfire (km ⁻¹)	-12.2894* (4.9610)	-7.9469** (0.8285)	-7.8141** (0.7920)	-7.7057** (0.8411)
High temp. (degrees C)	0.0384** (0.0026)	0.0343** (0.0023)	0.0306** (0.0023)	0.0284** (0.0020)
Low temp. (degrees C)	-0.0310** (0.0029)	-0.0279** (0.0026)	-0.0252** (0.0025)	-0.0235** (0.0023)
Precip. (mm)	-0.0052** (0.0009)	-0.0054** (0.0008)	-0.0057** (0.0009)	-0.0055** (0.0009)
$\tilde{\varepsilon}_{ijt}$	-0.0291* (0.0147)	-0.0353** (0.0136)	-0.0385** (0.0106)	-0.0380** (0.0126)
N	2,917,431	2,783,520	2,688,739	2,602,897
WTP	136.73** (37.43)	128.9** (22.22)	107.14** (16.33)	91.69** (15.03)
Campground x week-of-year FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
Campground x year FE	Yes	Yes	Yes	Yes

51 Notes: Std. err. clustered at campground level. * p < 0.05, ** p < 0.01.
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53 ³⁷In addition, refer to Table 4 in the main text for results when $\tau = 7$.
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Appendix F: Smoke and air pollution sensitivity analysis

This section provides several sensitivity analyses related to the measurement of smoke and air pollution. These include an exploration of smoke at the home zip code, alternative definitions of the smoke indicator variable, and heterogeneous responses by smoke-induced PM_{2.5} levels.

A natural question in travel cost models concerns the outside option $j = 0$. Smoke in the week of arrival could make alternative activities more or less desirable, which would threaten the stable unit treatment value assumption (SUTVA). We note in Section 3.2 that it is uncommon for individuals to cancel and rebook at other sites in the dataset, but we cannot observe activities in the $j = 0$ choice. Since the $j = 0$ choice is generally treated as a “stay-at-home” option, an empirical test to explore possible SUTVA violations is the presence of smoke at the home zip code.

In Table F1 we test two definitions of “smoke at the home zip code” using either the week of arrival or the day of arrival. The weekly definition of the variable in Column 1 yields insignificant coefficients. Using a daily definition in Column 2, we find that smoke at the home zip code has no effect on cancellation if the destination is unaffected; however, when both the home and destination are affected, visitors are more likely to cancel their reservation. This effect could be due to either greater information about or salience of smoke on days when it is also smoky at the visitor’s home zip code. Alternatively, the result could be driven by correlation between the intensity of smoke and the likelihood that both the destination site and the home location are affected. However, the result goes against the initial SUTVA concern, since we would have expected that smoke at the home location would decrease, rather than increase, the likelihood of cancellation by reducing the quality of the $j = 0$ option.

Next, we test alternative PM_{2.5} cutoffs to define a day as smoke-affected. As noted in Section 2.3, we count days as smoke-affected if there is an observed smoke plume and PM_{2.5} levels are greater than 1.64 standard deviations above the location-specific seasonal mean for days without smoke, following Burkhardt et al. (2019). The goal of this measure is to ensure that smoke plumes observed using satellite photography reflect on-the-ground

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4 conditions. This exercise is similar in spirit to continuous measures for smoke-specific PM_{2.5}
5 by Childs et al. (2022). Still, we explore sensitivity to this definition. Table F2 varies the
6 threshold to qualify as a smoke-affected day. Column 1 displays results using only observed
7 smoke plumes irrespective of PM_{2.5}, which includes observations where smoke may have been
8 high in the air column. Columns 2 through 4 use threshold cutoffs of the 90th percentile,
9 the 95th percentile, and the 97.5th percentile for on-the-ground PM_{2.5}. The strength of the
10 smoke coefficient grows as the cutoff becomes more restrictive, resulting in higher willingness
11 to pay (WTP) estimates.
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14 Elaborating on this analysis, we test a binned PM_{2.5} approach. We develop a continuous
15 measure of smoke-specific PM_{2.5} following a similar method to Childs et al. (2022). For
16 every campground, we define smoke-specific PM_{2.5} as:
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$$PM_{jt}^S = \max \{ 0, \mathbb{1}\{\text{smoke_plume}\}_{jt} \times (PM_{jt} - \overline{PM}_{j,m(t)}) \}, \quad (12)$$

19 where $\mathbb{1}\{\text{smoke_plume}\}_{jt}$ is an indicator variable if any smoke plume covered campground j
20 on day t , PM_{jt} is the overall PM_{2.5} level on day t , and $\overline{PM}_{j,m(t)}$ is the campground-specific
21 seasonal mean PM_{2.5} on non-smoke days.³⁸
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24 Table F3 tests two binned approaches to explore how welfare estimates vary with smoke-
25 specific PM_{2.5}. We define the bin cutoffs as 0, 9, and 35 $\mu\text{g}/\text{m}^3$, levels which roughly
26 correspond to EPA Air Quality Index thresholds for “Good,” “Moderate,” and “Unhealthy
27 for Sensitive Groups” or “Unhealthy.” The 35 $\mu\text{g}/\text{m}^3$ level is also the EPA 24-hour standard
28 for fine particulate matter pollution. Column 1 interacts the main smoke indicator, i.e.
29 smoke in the arrival week as defined in Section 2.3, with weekly mean smoke PM_{2.5}. Column
30 2 instead takes the weekly maximum smoke PM_{2.5}, since peaks in pollution could be as
31 important as the mean in this context. In both cases we find evidence of increasing welfare
32 losses with greater PM_{2.5} pollution.
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³⁸For additional discussion of data, refer to Section 2.3.

Table F1: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within One Week, Effects of Smoke at Home Zip Code

	(1)	(2)
Smoke at site, week of arrival	-0.211** (0.0300)	-0.237** (0.0230)
Smoke at home zip, week of arrival	-0.035 (0.0220)	
Smoke at site x smoke at home zip (week of arrival)	-0.072 (0.0440)	
Smoke at home zip, day of arrival		-0.024 (0.0450)
Smoke at site x smoke at home zip (day of arrival)		-0.127* (0.0520)
Travel cost (dollars)	-0.002** (0.0003)	-0.002** (0.0003)
Inv. distance to wildfire (km^{-1})	-7.845** (0.8280)	-7.809** (0.8240)
High temp. (degrees C)	0.031** (0.0020)	0.031** (0.0020)
Low temp. (degrees C)	-0.025** (0.0020)	-0.025** (0.0020)
Precip. in week of arrival (mm)	-0.006** (0.0010)	-0.006** (0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.036** (0.0130)	-0.036** (0.0130)
N	2,688,739	2,688,739
Campground x week-of-year FE	Yes	Yes
Day-of-week FE	Yes	Yes
Campground x year FE	Yes	Yes

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

Table F2: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ Within One Week, Alternative PM_{2.5} Cutoffs for Smoke

	Smoke plume	Smoke x 90th pctl PM	Smoke x 95th pctl PM	Smoke x 97.5th pctl PM
Smoke in week of arrival	-0.062** (0.0120)	-0.211** (0.0180)	-0.261** (0.0210)	-0.310** (0.0250)
Travel cost (dollars)	-0.002** (0.0003)	-0.002** (0.0003)	-0.002** (0.0003)	-0.002** (0.0003)
Inv. distance to wildfire (km ⁻¹)	-8.646** (0.9250)	-7.907** (0.8400)	-7.819** (0.8240)	-7.720** (0.8160)
High temp. (degrees C)	0.033** (0.0020)	0.031** (0.0020)	0.031** (0.0020)	0.030** (0.0020)
Low temp. (degrees C)	-0.027** (0.0030)	-0.025** (0.0020)	-0.025** (0.0020)	-0.025** (0.0020)
Precip. in week of arrival (mm)	-0.006** (0.0010)	-0.006** (0.0010)	-0.006** (0.0010)	-0.006** (0.0010)
$\tilde{\varepsilon}_{ijt}$	-0.037** (0.0120)	-0.037** (0.0130)	-0.037** (0.0130)	-0.037** (0.0130)
N	2,518,859	2,688,739	2,688,739	2,688,739
WTP	25.45** (6.29)	87.13** (14.8)	107.95** (17.14)	127.84** (19.79)
Campground x week-of-year FE	Yes	Yes	Yes	Yes
Day-of-week 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.

Table F3: $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$, Binned PM_{2.5} Due to Smoke

	Weekly mean smoke PM _{2.5}	Weekly max smoke PM _{2.5}
Travel cost (dollars)	-0.002** (0.0003)	-0.002** (0.0003)
Inv. distance to wildfire (km ⁻¹)	-7.820** (0.8240)	-7.819** (0.8250)
High temp. (degrees C)	0.031** (0.0020)	0.031** (0.0020)
Low temp. (degrees C)	-0.025** (0.0020)	-0.025** (0.0020)
Precip. in week of arrival (mm)	-0.006** (0.0010)	-0.006** (0.0010)
ε_{ijt}	-0.037** (0.0130)	-0.037** (0.0130)
Solid line	-0.260** (0.0220)	-0.261** (0.0240)
Dashed line	-0.290** (0.0890)	-0.255** (0.0530)
Dotted line	-0.308 (0.1740)	-0.287** (0.0910)
WTP: Smoke PM _{2.5} $\leq 9 \mu\text{g}/\text{m}^3$	107.32** (17.27)	107.68** (16.56)
WTP: Smoke PM _{2.5} $\in (9, 35] \mu\text{g}/\text{m}^3$	119.95** (39.3)	105.3** (31.6)
WTP: Smoke PM _{2.5} $> 35 \mu\text{g}/\text{m}^3$	127.29 (67.91)	118.39** (40.2)
N	2,688,739	2,688,739
Campground x week-of-year FE	Yes	Yes
Day-of-week FE	Yes	Yes
Campground x year FE	Yes	Yes

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

Appendix G: Total welfare estimate data construction

In Section 5, we report estimates for the total annual number of recreation visits affected by smoke in the West; 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 National Association of State Park Directors. Each agency 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 report 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. Because we have visitors' exacts dates of arrival and length of stay, we can link this visitation to daily smoke conditions at each campground. We can therefore estimate, for example, the proportion of visitation that occurred under smoke conditions at a particular National Park in a given month, a proportion which accounts for temporal substitution within the month. We then multiply this proportion by the total visitation data from each relevant agency to predict the number of visits that took place under smoke conditions.³⁹ In this section, we detail this process for each data source.

For the National Park Service, we use the agency's Annual Summary Reports.⁴⁰ This dataset reports total monthly visitation at all national parks, national monuments, national recreation areas, and other lands that the agency manages. In the western states, 27 national parks are included in the Recreation.gov dataset, and 82 are not.⁴¹ For the 27 parks in the Recreation.gov dataset, we determine each park's monthly proportion of campers that were smoke-affected. We then multiply this proportion by each park's monthly visitation from the Annual Summary Reports to infer the total number of smoke-affected visits. 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.⁴² These data report visitation at all national forests at an annual level. In the West, 70 forests are included in the Recreation.gov dataset, and 8 are not.⁴³ 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

³⁹A smoke day is defined in Section 2.3.

⁴⁰National Park Service. Annual Summary Report. <https://irma.nps.gov/STATS>.

⁴¹For example, Yellowstone National Park is managed by an alternative reservation system.

⁴²US Forest Service. National Visitor Use Monitoring Program. <https://www.fs.usda.gov/about-agency/nvum>.

⁴³Campgrounds at some forests are only available on a first come, first serve basis. One example is the Umatilla National Forest in Oregon and Washington, which did not have reservable campsites until 2021.

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4 dataset, we use a statewide annual proportion of smoke-affected campers.
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6 The Bureau of Land Management records visitation statistics as part of its Recreation
7 Management Information System (RMIS).⁴⁴ We contacted the program administrator and
8 received data on site by year visitation for all BLM sites.⁴⁵ Most visitation is not reservable,
9 and a large portion is considered backcountry. Therefore, the Recreation.gov dataset contains
10 very few BLM campgrounds. We thus combine annual state level proportions of smoke-
11 affected campers from the Recreation.gov data with annual site visitation from the RMIS.
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14 For sites managed by the US Army Corps of Engineers, we use data from its Value to
15 the Nation (VTN) reports.⁴⁶ For the study period of 2008 to 2017, the agency only has one
16 year of recreation data, which is for the year 2016. We treat this year as representative of
17 typical annual visitation over the study period. For each site, we multiply the total number
18 of visitors by the state level average of smoke-affected campers from the Recreation.gov data
19 over all years.

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

25 Having approximated total visitation, we multiply each agency's annual smoke-affected
26 visits by the empirical estimate of losses due to wildfire smoke, valued at \$107 per trip. We
27 estimate that more than 21.5 million recreation visits per year are affected by smoke in the
28 West, with annual losses of \$2.3 billion. These damages apply to inframarginal visitors who
29 do not cancel their trip.

30 To generate estimates for lost visitation we follow Dundas and von Haefen (2020), who
31 calculate the welfare loss from reduced recreational fishing due to extreme temperatures.
32 They multiply the predicted number of lost trips by the value of a trip, which they note is

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⁴⁴Bureau of Land Management. Public Land Statistics. <https://www.blm.gov/about/data/public-land-statistics>.

⁴⁵Ridenhour, L. and Leitzinger, K. Bureau of Land Management. Personal correspondence.

⁴⁶US Army Corps of Engineers. Value to the Nation. <https://www.iwr.usace.army.mil/Missions/Value-to-the-Nation>.

one over the travel cost coefficient.⁴⁷ From Table 3 we can compute that the average value of a trip over the population, including those who do not visit, is $1/0.0244 = \$41$. To predict the number of lost trips, we can use the empirical estimates to calculate the cancellation rate due to smoke. This value is equal to:

$$\begin{aligned} & \hat{\mathbb{P}}(C_{ijt} = 0 | R_{ijt} = 1, s_{jt} = 1) - \hat{\mathbb{P}}(C_{ijt} = 0 | R_{ijt} = 1, s_{jt} = 0) \\ &= \frac{1}{1 + \exp(\hat{\delta}c_{ijt} + \hat{\phi} + X'_{jt}\hat{\gamma} + \hat{\psi}_{jt})^{-1}} - \frac{1}{1 + \exp(\hat{\delta}c_{ijt} + X'_{jt}\hat{\gamma} + \hat{\psi}_{jt})^{-1}} \\ &= 0.022, \end{aligned} \tag{13}$$

where the values for covariates are set to their predicted average and $\hat{\phi}$ is set to the coefficient of -0.2603 from Table 4. Notably, the cancellation rate of 0.022 is very close to the estimated cancellation rate of 0.023 from Gellman et al. (2022), which used a simpler linear probability model. As a back-of-the-envelope estimate, one can infer that lost visitation is approximately equal to $\frac{0.022}{1-0.022}$ times the number of smoke-affected visits. Table 6 reports these estimates of lost visitation. We find that welfare losses from lost visitation are much lower than from trips taken in spite of smoke, in line with earlier descriptive work from Gellman et al. (2022).

For further discussion, see Section 5.

⁴⁷The value of a cancelled trip will necessarily be lower than the welfare damage of smoke, or the individual would not have cancelled. For example, if an individual values a trip at \$57 without smoke, then they value the trip at $\$57 - \$107 = -\$50$ with smoke, so they would prefer to cancel the trip and take the $j = 0$ option of \$0, for a net loss of \$57, i.e. the value of the trip.