The Welfare Effects of Climate Change for Outdoor Recreation

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October 2026

Abstract

Valuation of non-market climate amenities is a crucial component of climate policy. Due to individuals' direct exposure to ambient temperature, one ideal setting to study these values is outdoor recreation. In this paper, we combine millions of administrative campground reservation records with daily temperature data to study shifts in recreation value under climate change. By exploiting the timing of reservation and cancellation decisions, we estimate how individuals respond to both climate and weather. Preferences for realized temperature follow an inverse U-shape, with disutility from extreme cold outweighing disutility from extreme heat, while reservation decisions respond to the likelihood of cold conditions but not to the likelihood of heat. Climate projections in the western United States predict net welfare gains of $1 billion per year by century's end, but with substantial seasonal and regional heterogeneity in either gains or losses. Welfare gains depend on individuals' ability to accurately perceive climatic changes. These findings contribute to a growing set of climate damage estimates.

Keywords: Climate change, temperature, adaptation, recreation
JEL codes: Q26, Q51, Q54

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1 Introduction

Evaluations of policies to address climate change frequently rely on estimates of the social cost of carbon, a measure of the marginal damage to society caused by an additional ton of CO_2 emissions. However, the potential impacts of climate change are wide-ranging, and many are difficult to measure. Therefore, understanding of the impacts of climate change typically rests heavily on estimates of market damages and monetized health impacts. For example, Rennert et al. (2022), which provides a leading recent estimate of the social cost of carbon, bases its estimate on damages associated with sea-level rise, increased building energy expenditures, temperature-related mortality, and changes in agricultural productivity. Not included is the subjective amenity value of climate, likely because this value is not directly priced in markets and is therefore difficult to measure. Yet climate shapes the value people derive from time outdoors, both in the places they live (e.g. Albouy et al. 2016) and in the places they choose to visit.

These effects are perhaps most direct in outdoor recreation, where the value of a day spent hiking, fishing, or camping depends immediately on ambient conditions. As the climate changes, recreation values will shift, both because the climate people experience will change, and because people will adjust when and where they recreate in response. By one estimate, participation in outdoor recreation accounts for approximately 2.2 percent of the United States' Gross Domestic Product (BEA 2023), suggesting that effects of climate change on the value derived from recreation may be consequential.

Because climate amenity values are not directly priced by markets, they must be valued through either stated preference survey approaches, or inferred based on market behavior. An advantage of revealed preference methods is that they ground estimates of the subjective value individuals derive from environmental goods or services in real-world behavior and decisions, and thus naturally incorporate adaptive responses. Valuing climate effects on outdoor recreation presents a challenge though; people plan trips based on expectations of climate, but experience the weather that is realized. Yet few revealed preference estimates exist to provide insight into how individuals' expectations, beliefs, and adaptation behavior will shape the value that people ultimately derive from climate amenities.

In this paper, we estimate revealed preferences for extreme temperatures by combining millions of records of daily recreation behavior with exogenous shocks to climate and weather. By exploiting detailed microdata on the timing of planned reservations and last-minute cancellations, we estimate how individuals respond to both expected climate conditions and to realized weather. We use a structural model of visitation to obtain revealed preference estimates of the climate and weather damages of extreme temperatures. We then project how climate damages will evolve over the century under a high emissions scenario. Our framework explicitly models spatial and temporal substitution, allowing for estimation of adaptation value by varying the degree to which individuals update their expectations about climate.

We find an inverted U-shape for preferences over realized temperature, indicating disutility in both extreme hot and cold weather. Disutility from extreme cold weather exceeds that of extreme hot weather. Relative to a baseline of 22 to 24°C, we estimate a willingness to pay of $380 per person per trip to avoid a day above 42°C, and $700 to avoid a day below 0°C. We also find evidence that individuals adapt by substituting the timing and location of campground reservations away from colder climates.

To estimate the welfare effects of climate change over the coming century, we combine our revealed preference estimates with downscaled climate projections under the SSP3-7.0 emissions scenario. The two-stage nature of our empirical context allows us to distinguish ex ante adaptation, through reservation decisions made while conditions remain uncertain, from ex post responses to realized weather. Because reservations are made in advance based on expected conditions, the gains from ex ante adaptation depend on how individuals form expectations about a changing climate. We model expectations as updating only partially in response to observed climatic change: each year, individuals incorporate a fraction θ of the realized shift in climate into their perceived climate, with the remainder anchored on past conditions. By comparing welfare effects for different degrees of updating, we quantify the role of attention to climatic shifts in capturing gains from adaptation.

Under full updating, we project net welfare gains of roughly $1 billion per year by the end of the century. These aggregate effects mask substantial seasonal and regional heterogeneity. Gains are concentrated in spring and fall and at higher elevations, with net gains in the Pacific Northwest and Rocky Mountains, while summer trips and campgrounds in the Southwest

and Sierra Nevada see net losses. Almost all of the welfare gains are driven by changes in reservation behavior, highlighting the importance of attention to climatic shifts in capturing gains from adaptation.

This paper contributes to several literatures. First, it adds to a small set of revealed preference estimates of the non-market value of climate amenities (Albouy et al. 2016), and more broadly to the literature on sectoral climate damages, which includes estimates for temperature-related mortality (Deschênes and Greenstone 2011; Barreca et al. 2016; Carleton et al. 2022), agricultural productivity (Deschênes and Greenstone 2007; Schlenker and Roberts 2009), sea-level rise (Diaz 2016), mortality from wildfire smoke (Qiu et al. 2025), and energy expenditures (Clarke et al. 2018). Second, it draws on the climate econometrics literature that distinguishes responses to weather from responses to climate (Hsiang 2016; Kolstad and Moore 2020; Bento et al. 2023). Few studies observe both margins in the same setting; Earle (2025) is a notable exception in the recreation context. Our two-stage choice structure separates expected climate, which governs reservation decisions, from realized weather, which governs cancellations, within a single revealed preference framework. Third, the framework provides a new approach to measuring adaptation. Because the gains from adjusting reservation behavior depend on individuals recognizing the changing climate, we quantify how the welfare effects of climate change depend on the degree to which individuals update their expectations in response to climatic shifts.

In addition, it adds to the literature on climate and recreation. Our paper draws on the framework developed in Gellman, Walls, and Wibbenmeyer (2025) for estimating willingness-to-accept transient degradation of air quality due to wildfire smoke based on campground reservation and reservation cancellations. Apart from this, it is most similar to Dundas and von Haefen (2020), who estimated climate damages for recreational fishing, and Earle (2025), who estimated the welfare effects of temperature shocks for National Park visitation. Other related studies have estimated the influence of temperature on recreation visitation but did not directly derive welfare estimates, including Chan and Wichman (2020), Linsenmeier (2024), and Whitehead and Willard (2016).

Further, the study adds to literature that derives welfare estimates from recreation activity using aggregate data (Dundas and von Haefen 2020; Gellman, Walls, and Wibbenmeyer

2025; Newbold et al. 2022). This strand of literature builds on recreation studies that have used large datasets with novel methods (English et al. 2018; Kolstoe and Cameron 2017; Parthum and Christensen 2022; Wardle 2025). The two-stage choice structure that links preferences across decisions adds to existing work on sample selection correction in nonlinear models and in recreation contexts (Cameron and Kolstoe 2022; Gellman, Walls, and Wibbenmeyer 2025; Greene 2012; Terza 2009).

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 outlines our modeling approach. Section 4 presents estimates of climate and weather preferences. Section 5 presents projected welfare effects of climate change. Section 6 concludes.

2 Data

We combine data on recreation behavior and temperature records, producing several related datasets. First, we create a daily panel of federally managed campgrounds in the western United States for the years 2010 through 2017, which includes daily temperature and precipitation conditions as well as the distribution of daily maximum temperature over the previous ten years. Second, we compile records of trips to campgrounds, which include the ZIP code of origin, group size, reservation dates, and cancellation dates. We link these records to campground-level conditions from the daily panel. Lastly, we aggregate these records to a county by month level to estimate shares of reservations from origin counties to individual campgrounds.

2.1 Recreation

The recreation data is sourced from Recreation.gov,[1] the main web application to make reservations at federally managed campgrounds. This portal is used for campgrounds managed by the National Park Service, US Forest Service, Bureau of Land Management, US Army Corps of Engineers, and the Bureau of Reclamation. Users of this interface can access information about campground availability, pricing, amenities, and natural attractions in the area.

We restrict attention to campgrounds in the eleven western states over the years 2010 to

1. Recreation.gov. 2019. https://www.recreation.gov.

2017. These restrictions leave approximately 16 million transaction records from 2 million unique users at 999 campgrounds. The analysis focuses on overnight camping and thus excludes large-group and equestrian sites, which are also reservable through the interface.

Within a given order, we observe a user's full set of transactions, including the date of transaction, the time of reservation or cancellation, the ZIP code of origin, the group size, and other characteristics. The data distinguish between online, phone, and on-site transactions, meaning we can observe walk-ins and early checkouts. For the 999 campgrounds in the analysis, approximately 84 percent of transactions were made online, 9 percent by phone, and 7 percent on-site.

The version of the recreation data we obtain ends in 2017, owing to a change in the federal database contractor. Although Recreation.gov posts campground statistics at its Recreation Information Database (RIDB), the public data only report reservations to sites, and do not contain information on cancellations.[2] Therefore, with the current data it is not possible to observe whether individuals actually follow through on a reservation, a problem identified by Walls, Wichman, and Ankney (2018). In contrast, the database ending in 2017 contains full sets of transactions by individuals, which allows certainty regarding visitation.

2.2 Travel cost

We determine the travel cost from every origin ZIP code to every campground using GraphHopper, an open source routing engine that incorporates OpenStreetMap data.[3] The estimates represent the fastest route by car between each ZIP code and a given campground, where the user's ZIP code is linked to its corresponding ZIP code tabulation area (ZCTA) to measure a ZIP code centroid.[4] In total, we estimate driving times and distances between 5,031 origin ZCTAs and 999 campground destination campgrounds, representing approximately 5 million routes. These routes are generally consistent with those shown by Google Maps.

As in English et al. (2018), we calculate per-person round-trip travel costs between ZCTA

2. Recreation.gov. 2026. Recreation Information Database (RIDB). https://ridb.recreation.gov.

3. GraphHopper. 2019. https://www.graphhopper.com.

4. ZIP code to ZCTA crosswalks, including current and historical versions as early as 2010, are available by contacting website administrators at: Health Resources and Services Administration. Health Center Program GeoCare Navigator Resources. https://data.hrsa.gov/GeoCareNavigator/Resources#ToolsResources.

z and campground j as:

$$c_{zjt} = \frac{p^D_{zjt} D_{zj}}{n} + p^T_{zt} T_{zj}, \tag{1}$$

for round-trip travel distance D_{zj}, round-trip travel time T_{zj}, and group size n. The variable p^D_{zjt} measures the per-kilometer cost to travel between ZCTA z and campground j, incorporating gasoline costs, per-kilometer vehicle maintenance, and per-kilometer marginal vehicle depreciation. Gasoline costs are measured using state- and year-specific averages of per-kilometer gasoline costs, which we source from the Energy Information Administration and tie to nationwide average fuel economy from the Bureau of Transportation Statistics.[5,6] The per-kilometer vehicle maintenance costs and marginal depreciation data are sourced from AAA.[7,8] Finally, we estimate the hourly costs of travel time p^T_{zt} as one-third of the average household income in ZCTA z divided by 2,080 hours worked per year (English et al. 2018). All numbers are stated in 2020 US dollars.

2.3 Temperature, precipitation, and climate

We record the daily maximum temperature (°C) and precipitation (mm) for every campground. This information is sourced from 4 km gridded data produced by the PRISM Climate Group at Oregon State University.[9] Further, for each campground and calendar month, we calculate the share of days over the previous ten years with a daily maximum temperature in each 5°C bin. This distribution characterizes the climate an individual expects when reserving in advance. We also calculate the average monthly maximum temperature over the same window, which we use in a robustness check.

For each campground, we estimate future changes in climate using the NASA Earth

5. Energy Information Administration. 2026. Weekly Retail Gasoline and Diesel Prices. https://www.eia.gov/dnav/pet/pet_pri_gnd_a_epmr_pte_dpgal_m.htm.

6. Bureau of Transportation Statistics. 2026. Average Fuel Efficiency of US Light Duty Vehicles. https://www.bts.gov/content/average-fuel-efficiency-us-light-duty-vehicles.

7. For example: AAA. 2016. Your Driving Costs. https://web.archive.org/web/20221005214032/https://publicaffairsresources.aaa.biz/wp-content/uploads/2016/03/2016-YDC-Brochure.pdf.

8. 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. See English et al. (2018) and Hang et al. (2016) for further discussion on marginal depreciation in travel cost calculation.

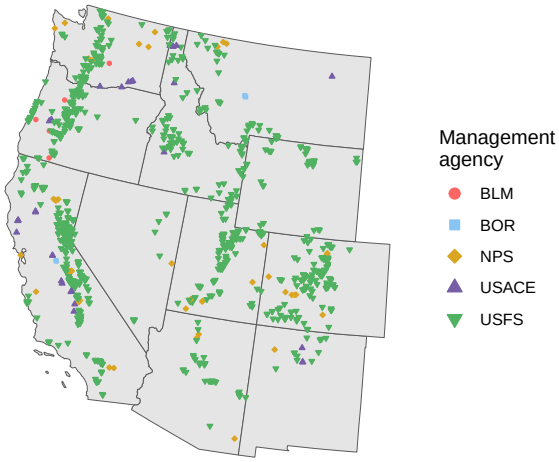
9. PRISM Group, Oregon State University. 2026. PRISM Climate Data. https://www.prism.oregonstate.edu.

Exchange Global Daily Downscaled Projections (CMIP6).[10] This gridded data product gives projections for daily maximum temperature, minimum temperature, and precipitation through 2100. We focus on SSP3-7.0, a high emissions scenario based on a pairing of a Shared Socioeconomic Pathway and a Representative Concentration Pathway. Following Burke et al. (2023) and Hausfather and Peters (2020), we treat SSP3-7.0 rather than RCP8.5 as the baseline high emissions scenario.

2.4 Descriptive features of the data

Several descriptive features of the data are germane for the analysis. The first is the geographic extent of campgrounds, which is mapped in Figure 1. Campgrounds represent a wide variety of regional climates, giving meaningful variation for the empirical estimation. Of the 999 campgrounds, 908 are managed by the US Forest Service, 50 by the National Park Service, 31 by the US Army Corps of Engineers, and 5 by the Bureau of Land Management and Bureau of Reclamation. The most-visited campgrounds tend to be in National Parks, though US Forest Service sites such as Big Bear and Lake Tahoe also rank among the most popular (Gellman, Walls, and Wibbenmeyer 2025).

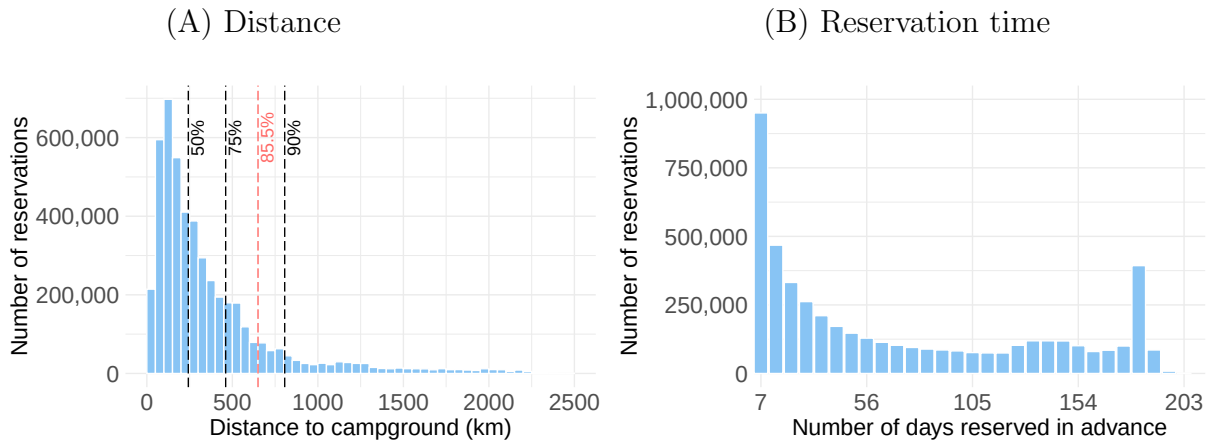
Figure 1: Map of campgrounds in dataset



In the estimating dataset we restrict attention to reservations coming from within driving

10. NASA. 2026. NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6). https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6.

Figure 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.

distance, which we designate as 650 km (about 400 miles). Panel A of Figure 2 shows that this threshold captures 85.5 percent of the reservations in the data. There are two reasons for this restriction. First, above 500 miles, visitors are likely to have flown to their destination, which complicates the calculation of travel cost (English et al. 2018). Second, limiting trips to those within driving distance reduces the possibility of chained, multi-destination trips. This restriction improves confidence that observed reservations represent primary purpose trips, a key issue identified by Lupi, Phaneuf, and von Haefen (2020).

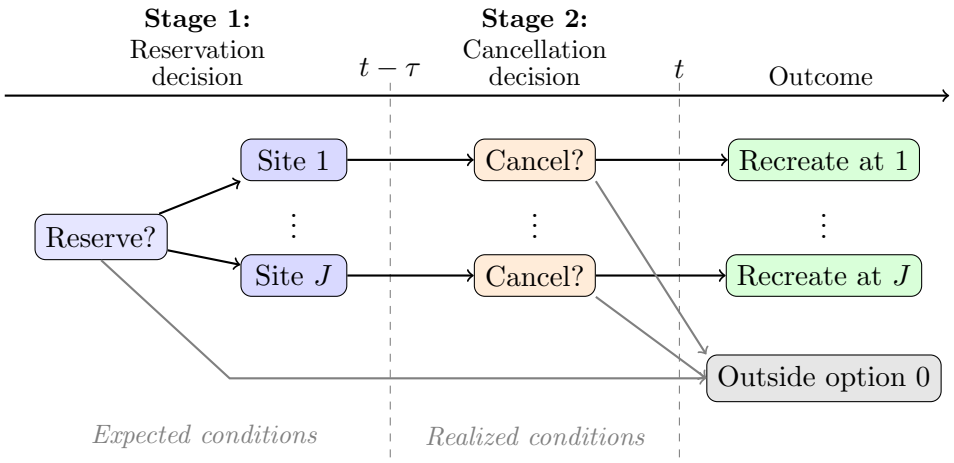
The timing of reservations is also relevant for this setting. Most campground reservations are made far in advance, before precise weather conditions can be known. Panel B of Figure 2 shows the timing of reservations. Although a plurality of trips are made within a week of arrival, the majority of reservations are made between two weeks and six months in advance.[11] This timing affects what reservers expect about their campground's weather conditions. More than six days before arrival, weather forecasts are likely to resemble a location's average climate (Shrader, Bakkensen, and Lemoine 2023).

11. Several popular locations become available six months in advance of arrival, giving a large mass to the distribution around 180 days in advance.

3 Modeling Approach

We model a two stage choice structure to capture how camping decisions respond to both climate and weather. In the first stage, an individual makes a reservation ahead of time based on expected climate conditions. In the second stage, once conditions are realized, an individual decides whether to cancel their reservation based on realized weather conditions. Because individuals may only cancel if they previously held a reservation, our framework links these choices using a control function. Figure 3 illustrates the timing of these decisions, where t gives the arrival date and τ denotes a bandwidth sufficiently close to the arrival date.

Figure 3: Timing of decisions



Because weather conditions are not known until close to the arrival date, one potential empirical strategy would be to estimate changes in new reservation rates within τ days of arrival as a function of weather variables. However, because many campgrounds approach full capacity shortly before an arrival date, this exercise would suppress identifying variation and attenuate estimates of demand parameters. Therefore, we consider the reservation decisions of individuals who reserve ahead of time, when the full choice set is available, as well as their cancellation decisions close to arrival, when their choice is unaffected by campground availability. An additional benefit of this choice structure is that it allows for study of preferences over both expected and realized conditions.

The preference parameters derived from these sequential choices inform a theory of wel-

fare change under alternative climate distributions. We present a framework to approximate changes to recreation value as the climate changes over the coming century. We also investigate the value of adaptation by varying the degree to which individuals update their expectations about climate, which determines how reservation decisions respond to climatic shifts.

3.1 Climate preferences using reservations

Let utility be defined as:

$$U_{ijt}^{R} = V_{ijt}^{R} + \varepsilon_{ijt}, \tag{2}$$

where V_{ijt}^{R} denotes the observable portion of utility to household i from visiting campground j on date t. The variable ε_{ijt} corresponds to fixed unobserved preferences to household i over site j at time t, which we assume are distributed iid type I extreme value.

When an individual reserves ahead of time, they are uncertain of what realized site conditions will be on the arrival date; therefore, they choose based on expected site conditions. Denoting the expectation of variable Y at the time of reservation as $\bar{Y}$, write the indirect utility at the time of reservation as:

$$V_{ijt}^{R} = \begin{cases} \delta^{R} c_{ijt} + \sum_{b \in B} \phi_{b}^{R} \, \overline{P}_{bjt} + \alpha^{R} \, \overline{\text{precip}}_{jt} + \psi_{j}^{R} + \lambda_{t}^{R} + \xi_{z(i),j,t}, & j \in \{1, 2, ..., J\}; \\ 0, & j = 0. \end{cases} \tag{3}$$

The variable c_{ijt} gives the travel cost for person i to site j at time t. Climate at site j is characterized by $\overline{P}_{bjt}$, the share of days over the previous ten years with a daily maximum temperature in bin $b \in B$ during the calendar month of date t, and by $\overline{\text{precip}}_{jt}$, expected precipitation. The vector of bin shares allows the effect of expected temperature on utility to be flexibly non-linear. Fixed effects ψ_{j}^{R} capture campground-specific, time-invariant unobservable quality, while λ_{t}^{R} consists of month and year fixed effects that capture time-specific shocks. Lastly, observable utility is a function of time-varying unobservable preferences at the level of an individual's home administrative zone z (which could be, for instance, a ZIP code or county), denoted $\xi_{z(i),j,t}$. Assume the term $\xi_{z(i),j,t}$ is normally distributed, is known

to the individual, and is unobserved by the econometrician.

While $\overline{P}_{bjt}$ and $\overline{\text{precip}}_{jt}$ represent an individual's expectation of site conditions, travel costs c_{ijt}, as well as the unobserved site and time characteristics ψ_j^R and λ_t^R, are assumed to be known to the individual ahead of time. The parameter of interest is the willingness to pay (WTP) for climate bin b, $\text{WTP}_b^R = \phi_b^R/\delta^R$, which gives the value of shifting a unit of probability mass from the reference bin to bin b.

Given the utility over the reservation decision in Equation 3, the probability an individual reserves at site j is:

$$\begin{aligned}\mathbb{P}(R_{ijt} = 1) &= \mathbb{P}(\varepsilon_{ikt} - \varepsilon_{ijt} \leq V_{ijt}^R - V_{ikt}^R \ \forall \ k \neq j) \\ &= \frac{\exp(V_{ijt}^R)}{\sum_{k=0}^{J} \exp(V_{ikt}^R)}. \end{aligned} \tag{4}$$

To estimate Equation 4, consider a market shares approach as in Berry, Levinsohn, and Pakes (1995). Group representative individuals i into their home zones, which will be operationalized as counties, indexed by z. A market is defined by a county, month, and year. The number of individuals in a market choosing campground j is the total group size of reservations from county z with arrival dates in month t, and the number choosing the outside option is the county's population less the total number of reservers. For every campground j, zone z, and visitation time t, the share of individuals choosing j is given by:

$$s_{zjt} = \frac{\exp(V_{zjt}^R)}{\sum_{k=0}^{J} \exp(V_{zkt}^R)}. \tag{5}$$

Taking logs and differencing relative to the outside option, for which $V_{z0t}^R = 0$, yields:

$$\begin{aligned}\log(s_{zjt}) - \log(s_{z0t}) &= V_{zjt}^R \\ &= \delta^R c_{zjt} + \sum_{b \in B} \phi_b^R \ \overline{P}_{bjt} + \alpha^R \ \overline{\text{precip}}_{jt} + \psi_j^R + \lambda_t^R + \xi_{z(i),j,t}. \end{aligned} \tag{6}$$

Estimation of Equation 6 proceeds with ordinary least squares (Berry, Levinsohn, and Pakes 1995).

3.2 Weather preferences using cancellations

For the second stage cancellation choice, write utility as:

$$U_{ijt}^{C} = V_{ijt}^{C} + \eta_{ijt}, \tag{7}$$

with η_{ijt} a fixed unobservable preference term, assumed to be distributed iid type I extreme value. Let V_{ijt}^{C} be constructed as:

$$V_{ijt}^{C} = \begin{cases} \delta^{C} c_{ijt} + g(\text{temp}_{jt}; \phi^{C}) + \alpha^{C} \text{ precip}_{jt} + \psi_{j}^{C} + \lambda_{t}^{C} + \xi_{z(i),j,t} + \rho \, \tilde{\varepsilon}_{ijt}, & j \in \{1, 2, ..., J\}; \\ 0, & j = 0, \end{cases} \tag{8}$$

where the variables temp_{jt} and precip_{jt} denote realized values of daily maximum temperature and daily precipitation for site j on day t. Fixed effects ψ_{j}^{C} are campground fixed effects, and λ_{t}^{C} consists of day-of-week, week-of-year, and year fixed effects. The term $\xi_{z(i),j,t}$ may be approximated using residuals from the estimation of Equation 6. In addition, since an individual may only cancel if they previously already held a reservation for site j and day t, the variable $\tilde{\varepsilon}_{ijt}$ accounts for unobserved preferences demonstrated by the choice of reservation. This term is defined in Section 3.3. Analogously to the reservation decision, when $g(\cdot)$ is estimated using bins $b \in B$, the parameter of interest is the willingness to pay for a given temperature bin, $\text{WTP}_{b}^{C} = \phi_{b}^{C} / \delta^{C}$.

The second stage probability that an individual does not cancel is:

$$\begin{aligned} \mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1) &= \mathbb{P}(\eta_{i0t} - \eta_{ijt} \leq V_{ijt}^{C}) \\ &= \frac{\exp(V_{ijt}^{C})}{1 + \exp(V_{ijt}^{C})}. \end{aligned} \tag{9}$$

Equation 9 implies a binary cancellation choice. In practice, individuals tend not to cancel and rebook, so a binary choice is a reasonable representation of a user's decision.[12]

12. In the estimating dataset, only 1.7 percent of all users who cancel a trip make a new reservation to a different campground for the same week of arrival as the original reservation. Intertemporal substitution after a cancellation is also low: 12.5 percent of cancelled trips result in a reservation for any new date within

3.3 Linking preferences across decisions using a control function

Equation 8 includes the term $\tilde{\varepsilon}_{ijt}$, which approximates an individual's preferences over the first stage reservation decision. Importantly, this term is unobserved. If unaccounted for, these preferences could bias parameter estimates since they are correlated with travel cost in the selected sample of reservers (Gellman, Walls, and Wibbenmeyer 2025).[13] However, a control function can approximate these preferences (Wooldridge 2015). Define $\tilde{\varepsilon}_{ijt} \equiv (\varepsilon_{i0t} - \varepsilon_{ijt})$. The conditional density of $\tilde{\varepsilon}_{ijt}$ is:

$$\begin{aligned} f(\ \tilde{\varepsilon}_{ijt} \mid R_{ijt} = 1) &= f(\ \tilde{\varepsilon}_{ijt} \mid \tilde{\varepsilon}_{ijt} \leq V^R_{ijt} - V^R_{ikt}\ \forall\ k \neq j) \\ &= \frac{f(\tilde{\varepsilon}_{ijt}) \cdot \mathbb{1}\{\tilde{\varepsilon}_{ijt} \leq V^R_{ijt} - V^R_{ikt}\ \forall\ k \neq j\}}{\mathbb{P}(R_{ijt} = 1)} \\ &= \frac{f(\tilde{\varepsilon}_{ijt}) \cdot \mathbb{1}\{\tilde{\varepsilon}_{ijt} \leq \min_{k \neq j}\{V^R_{ijt} - V^R_{ikt}\}\}}{\mathbb{P}(R_{ijt} = 1)}, \end{aligned} \tag{10}$$

which follows from the definition of a truncated density and from the definition of $\mathbb{P}(R_{ijt} = 1)$. Because the outside option is normalized to zero and campground shares are small relative to the outside option in every market, the observable utility of each campground is negative and the outside option has the highest observable utility, so that $\min_{k \neq j}\{V^R_{ijt} - V^R_{ikt}\} = V^R_{ijt}$.

the next six months. Therefore, since rebooking is uncommon, a binary decision is likely an appropriate model of a visitor's choice.

13. Individuals who reserved from a large distance are likely to have a stronger taste for the chosen site. Therefore, among the selected sample of individuals who held a reservation, the travel cost parameter is downward-biased if this selection is ignored.

An expression for $\tilde{\varepsilon}_{ijt}$ is:

$$\begin{aligned}
\mathbb{E}[\ \tilde{\varepsilon}_{ijt} \mid R_{ijt} = 1] &= \mathbb{E}[\ \tilde{\varepsilon}_{ijt} \mid \tilde{\varepsilon}_{ijt} \leq V^R_{ijt} - V^R_{ikt}\ \forall\ k \neq j] \\
&= \int_{-\infty}^{\infty} \tilde{\varepsilon}_{ijt}\ f(\tilde{\varepsilon}_{ijt} \mid \tilde{\varepsilon}_{ijt} \leq V^R_{ijt} - V^R_{ikt}\ \forall\ k \neq j)\ d\tilde{\varepsilon}_{ijt} \\
&= \frac{\int_{-\infty}^{\min_{k\neq j}\{V^R_{ijt} - V^R_{ikt}\}} \tilde{\varepsilon}_{ijt}\ f(\tilde{\varepsilon}_{ijt})\ d\tilde{\varepsilon}_{ijt}}{\mathbb{P}(R_{ijt} = 1)} \\
&= \frac{(\min_{k\neq j}\{V^R_{ijt} - V^R_{ikt}\}) \cdot \frac{\exp(\min_{k\neq j}\{V^R_{ijt} - V^R_{ikt}\})}{1+\exp(\min_{k\neq j}\{V^R_{ijt} - V^R_{ikt}\})} - \log(1 + \exp(\min_{k\neq j}\{V^R_{ijt} - V^R_{ikt}\}))}{P(R_{ijt} = 1)}.
\end{aligned} \tag{11}$$

Equation 11 defines the control function from the first stage reservation decision. First, we estimate the parameters of V^R_{ijt} in Equation 3 using the log shares model in Equation 6. These parameters are used to build the control function in Equation 11, which is included as a covariate in Equation 8.

3.4 Welfare effects of climate change

To estimate welfare effects under climate change, define distributions F_0 and F_t as the baseline climate and the counterfactual climate in year t.

The compensating variation of a representative agent i from zone z in a given month, where $R_{it} = j$ denotes a reservation at site j, follows from the change in expected utility and can be written as:

$$\begin{aligned}
CV_{zt} &= -\frac{1}{\delta^C}(\mathbb{E}[U_{it}|F_t] - \mathbb{E}[U_{it}|F_0]) \\
&= -\frac{1}{\delta^C}\sum_j \mathbb{P}(R_{it} = j|F_t)\mathbb{E}[U_{it}|F_t, R_{it} = j] - \mathbb{P}(R_{it} = j|F_0)\mathbb{E}[U_{it}|F_0, R_{it} = j] \\
&= -\frac{1}{\delta^C}\sum_{j\neq 0} \mathbb{P}(R_{it} = j|F_t)\mathbb{E}[\log(1 + \exp(V^C_{ijt}))|F_t] - \mathbb{P}(R_{it} = j|F_0)\mathbb{E}[\log(1 + \exp(V^C_{ijt}))|F_0].
\end{aligned} \tag{12}$$

The marginal utility of income δ^C from the cancellation stage converts utility into dollars. To obtain the aggregate welfare change in year y, we multiply each compensating variation CV_{zt} by the corresponding number of choice occasions CO_{zt}, which we measure as the population of zone z, and sum across origin zones $z \in Z$ and months $t \in T$, yielding:

$$\Delta W_y = \sum_{z \in Z} \sum_{t \in T} CV_{zt} \times CO_{zt}. \tag{13}$$

3.5 Climate perception and adaptation

Thus far, our welfare framework has assumed that individuals fully perceive the changing climate when making forward looking recreation decisions. This assumption may overstate individuals' ability to adapt when facing uncertainty about realized weather conditions. To capture imperfect attention to climatic shifts, we model perceived climate $\hat{F}_t$ as:

$$\begin{aligned} \hat{F}_0 &= F_0; \\ \hat{F}_{t+1} - \hat{F}_t &= \theta \left(F_{t+1} - F_t \right) \ \forall \ t \geq 0. \end{aligned} \tag{14}$$

Under this rule, individuals update their perceived climate by a fraction $\theta \in [0, 1]$ of each period's realized change, so that perceived climate in year t is $\hat{F}_t(\theta) = F_0 + \theta(F_t - F_0)$. An individual with $\theta = 1$ fully updates, and reservation behavior responds completely to the changing climate. An individual with $\theta < 1$ updates sluggishly, anchoring expectations partly on the baseline climate; in the limit $\theta = 0$, perceived climate never changes and reservation patterns remain fixed at the baseline.

Under this framework, compensating variation is:

$$CV_{zt}(\theta) = -\frac{1}{\delta^C} \sum_{j \neq 0} \mathbb{P}(R_{it} = j | \hat{F}_t(\theta)) \mathbb{E}[\log(1 + \exp(V_{ijt}^C)) | F_t] - \mathbb{P}(R_{it} = j | F_0) \mathbb{E}[\log(1 + \exp(V_{ijt}^C)) | F_0], \tag{15}$$

with aggregate welfare effects given by:

$$\Delta W_y(\theta) = \sum_{z \in Z} \sum_{t \in T} CV_{zt}(\theta) \times CO_{zt}. \tag{16}$$

4 Empirical Climate and Weather Preferences

For all analyses, we restrict a representative individual's choice set to locations within driving distance, which we assume to be within 400 miles of their origin ZCTA. English et al. (2018) show that, beyond this threshold, individuals are likely to have flown to their destination. Besides affecting the travel cost parameter, inclusion of visitors from farther distances creates the possibility of chained visits, which would overattribute the cost of a trip to a given choice. Within the two-stage choice framework, we are interested in individuals that reserved ahead of time based on the climate of the location, and then subsequently chose whether to cancel close to the arrival date based on realized weather. We therefore restrict the data to the set of visitors who reserved more than one week ahead of time, or $\tau = 7$ in Figure 3, and who faced the decision of whether to cancel within a week of the arrival time. We exclude reservations that were cancelled more than one week in advance. These restrictions result in a sample of 2,994,066 reservations for the cancellation model and 378,057 county-month-campground observations for the reservation model.

4.1 Responses to climate

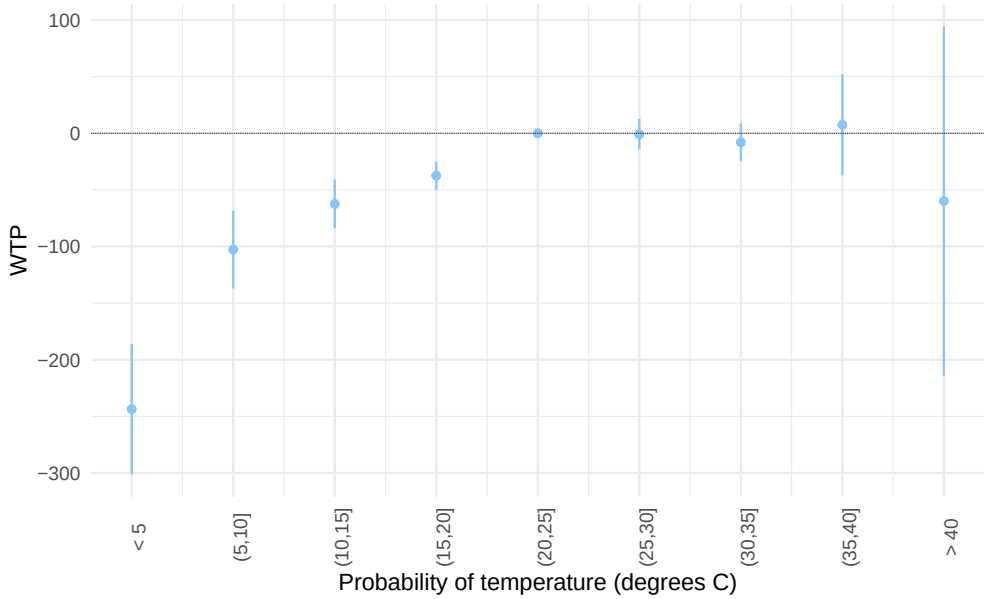
We measure responses to climate using reservations made at least one week in advance, estimating Equation 6. Log shares estimations carry several challenges. First, because log(0) is undefined, pairs of origin zones z and destinations j which see no activity for a given time t (i.e., $s_{zjt} = 0$) would drop out of the estimation. A second challenge is the dimensionality. The dataset features more than 5,000 origin ZIP codes and nearly 1,000 campgrounds, meaning that the choice set for most visitors is large. To overcome these challenges, we aggregate reservation behavior to a month by county level. This process reduces the frequency of observed zero shares and allows for feasible estimation. We characterize a campground's anticipated climate by $\overline{P}_{bjt}$, the share of days over the previous ten years with a daily maximum

temperature in each 5°C bin during the arrival month, with 20 to 25°C as the reference bin, and by expected precipitation $\overline{\text{precip}}_{jt}$. The estimation is weighted by county population, and standard errors are clustered at the campground level.

Figure 4 plots the estimates, which are reported in full in Table A1. Reservation decisions respond strongly to the likelihood of cold conditions. The coefficients on the bins below 20°C are negative, statistically significant, and increasing in magnitude as temperatures fall: a 10 percentage point increase in the share of days with highs below 5°C, relative to days with highs of 20 to 25°C, reduces the share of individuals reserving at a campground by about 28 percent, compared with reductions of about 13, 8, and 5 percent for the 5 to 10, 10 to 15, and 15 to 20°C bins.[14] In contrast, the coefficients on bins above 25°C are small and statistically indistinguishable from zero. Individuals thus avoid reserving at campgrounds and in months where cold conditions are likely, but do not systematically avoid those where hot conditions are likely.

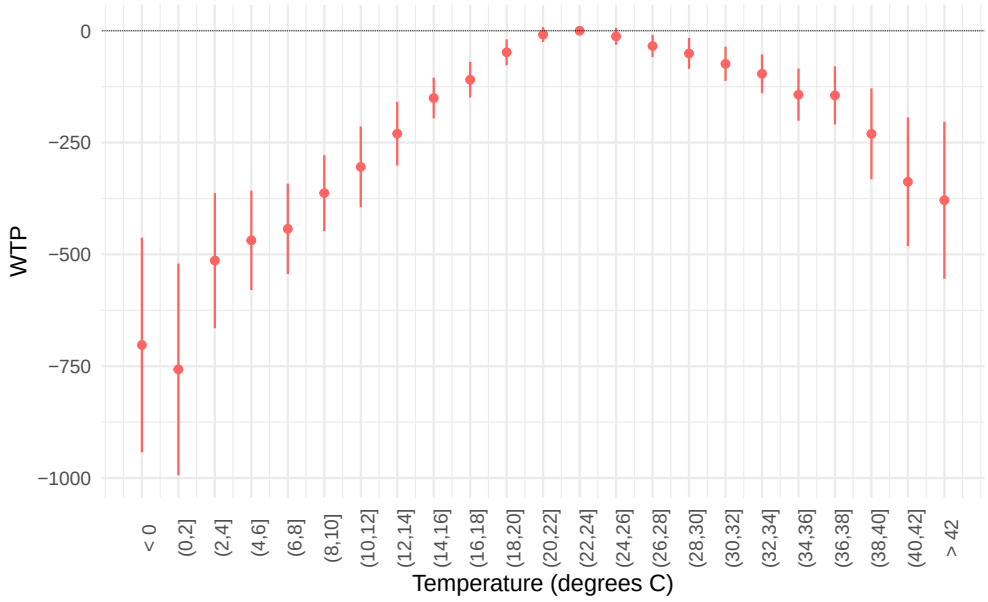
14. For a 10 percentage point shift in probability mass from the reference bin to bin b, the proportional change in the share of reservers is $\exp(0.1\,\phi_b^R) - 1$.

Figure 4: Responses to climate



Notes: Points show estimates from the reservation model in Table A1, expressed as ϕ_b^R/δ^R for each 5°C bin of daily maximum temperature, relative to the reference bin of 20 to 25°C. Each estimate corresponds to shifting all probability mass from the reference bin to bin b. Bars show 95 percent confidence intervals based on standard errors clustered at the campground level.

Figure 5: Willingness to pay for realized temperature



Notes: Points show the per-trip willingness to pay for a day with a maximum temperature in each 2°C bin, $\text{WTP}_b^C = \phi_b^C/\delta^C$, relative to the reference bin of 22 to 24°C, estimated from the cancellation model in Table A2. Negative values indicate a willingness to pay to avoid a day in the bin. Bars show 95 percent confidence intervals based on standard errors clustered at the campground level.

4.2 Responses to realized weather

We measure responses to weather using the cancellation decision close to the arrival date, estimating Equation 9 as a binary logit. The specification uses realized daily precipitation and maximum temperature on the arrival date, precip_{jt} and temp_{jt}, with 2°C temperature bins and a reference bin of 22 to 24°C, along with the control function terms $\tilde{\varepsilon}_{ijt}$ and $\xi_{z(i),j,t}$ from the reservation stage. The estimation is weighted by the group size of a party, and standard errors are clustered at the campground level. Full coefficient estimates are reported in Table A2.

Figure 5 reports the per-trip willingness to pay for each temperature bin, $\text{WTP}_b^C = \phi_b^C/\delta^C$. Preferences over realized temperature follow an inverted U-shape, an intuitive pattern consistent with evidence from other contexts (Deschênes and Greenstone 2011; Barreca et al. 2016; Linsenmeier 2024). Additionally, the monetized disutility of extreme cold largely exceeds that of extreme heat, with an estimated willingness to pay of $380 per person per trip to avoid a day above 42°C versus $700 to avoid a day below 0°C (relative to a baseline

of 22 to 24°C).

5 Welfare Effects of Climate Change

We simulate the welfare effects of climate change by combining the estimated reservation and cancellation models with projected daily maximum temperature and precipitation at each campground under SSP3-7.0 from NEX-GDDP-CMIP6. We define the baseline climate F_0 as the distribution of daily conditions over 2017 to 2026 and project welfare in each year from 2027 to 2100, with end-of-century values defined as the average over 2091 to 2100. For each campground, calendar month, and projection year, the projections provide the share of days with a daily maximum temperature in each 5°C bin, which enters the reservation stage, and in each 2°C bin, which enters the cancellation stage, along with mean precipitation. Perceived climate for the reservation stage follows Equation 14, with F_t measured as the ten-year trailing mean of the projected bin shares, so that an individual with $\theta = 1$ expects the climate of the preceding decade.

In each year, and for each origin county and month, we predict reservation probabilities for every campground in the choice set from Equation 4 under perceived climate, holding travel cost, county population, and the set of campgrounds fixed at their values in the estimation sample. Because campgrounds have limited capacity, predicted reservations are allocated subject to a monthly capacity for each campground, derived from its number of campsites, and individuals rationed from full campgrounds are reallocated across the remaining choice set.[15] Expected utility from a reservation at campground j is the inclusive value in Equation 12, integrated over the realized-year distribution of daily maximum temperature, with precipitation set to its mean conditional on each temperature bin. The control function term $\tilde{\varepsilon}_{ijt}$ is recomputed under each counterfactual allocation, so that the composition of visitors at each campground reflects counterfactual choice probabilities, while the unobserved quality term $\xi_{z(i),j,t}$ is held at its baseline value. Welfare changes are converted to dollars using the marginal utility of income from the cancellation stage, δ^C, and aggregated using

15. Monthly capacity is the campground's maximum number of campsites in that month during the sample period, multiplied by the median group size at the campground and by ten trips per campsite per month, which corresponds to an assumed three-night stay. Campground-months with no observed campsites are treated as closed.

county population as the number of choice occasions, as in Equation 13.[16]

5.1 Projected welfare effects

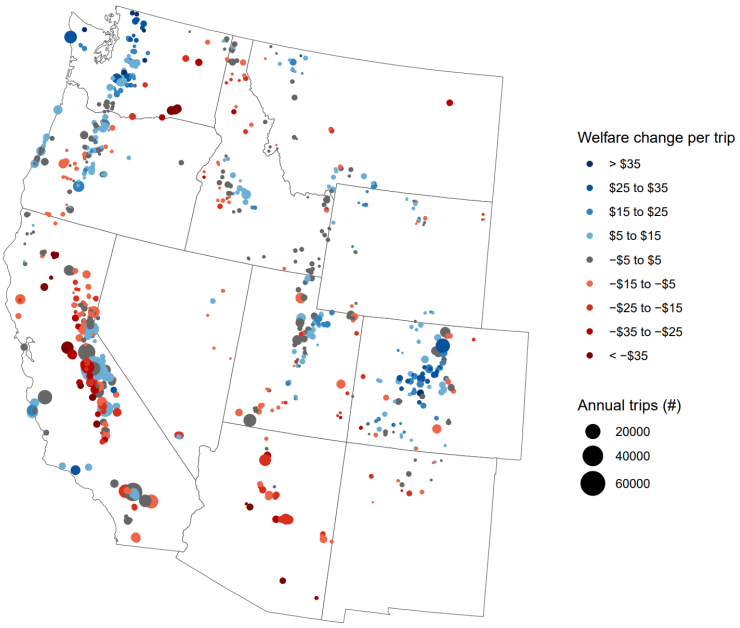
Figure 8 plots the projected annual change in aggregate welfare relative to the baseline climate under full updating ($\theta = 1$). Annual welfare changes are close to zero in the first years of the projection and rise steadily through mid-century, reaching roughly $500 million per year by 2060 and roughly $1 billion per year by 2075. The positive trend is consistent with the preference estimates in Section 4: because visitors are far more averse to cold than to heat, and reservation decisions respond to the likelihood of cold conditions, a warming climate reduces the number of trips exposed to the conditions visitors most dislike by more than it increases exposure to extreme heat.

In Figure 6 we plot the spatial distribution of end of century changes in welfare per trip, with each point being a campground in our dataset. The color of each point represents the welfare change per trip and the size of each point represents the annual number of trips for a given campground. We find relatively large amounts of spatial heterogeneity. Campgrounds in the Cascades of Washington and Oregon, the Colorado Rockies, and the mountains of central Idaho see per-trip gains that often exceed $25, while campgrounds in Arizona, southern Utah, and the Sierra Nevada of California, including several of the most visited campgrounds in the sample, see per-trip losses of similar magnitude. Within states, welfare gains are increasing in elevation (Appendix Figure A4), consistent with gains from fewer cold days at higher elevations and losses from more hot days at lower elevations. The aggregate gains in Figure 8 therefore mask losses for a substantial share of trips.

Welfare changes also vary across seasons. Figure 7 plots the distribution across campgrounds of the end-of-century welfare change per trip by season of arrival. Per-trip changes for summer trips, which account for the largest share of visitation, are centered near zero. Trips in the shoulder seasons gain: per-trip changes for spring trips are centered around $50, and fall trips see the largest gains, with changes between $50 and $150 per trip at

16. For the simulation, both stages are re-estimated with campground, month, and year fixed effects so that predictions can be formed at the campground-month level, and the reservation stage uses the pooled sample of early and late reservations (Table A3). Coefficient estimates are very similar to those in Tables A1 and A2.

Figure 6: Spatial distribution of welfare changes by end of century



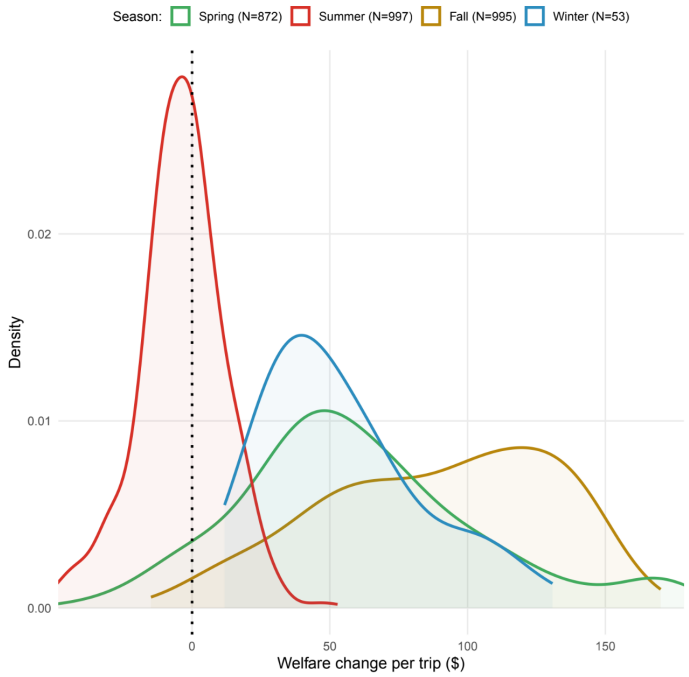
Notes: Each point is a campground. Color shows the change in welfare per trip, in 2020 dollars, between the baseline climate of 2017 to 2026 and the end-of-century climate of 2091 to 2100 under SSP3-7.0 and full updating ($\theta = 1$). Point size shows the campground's annual number of trips in the estimation sample.

most campgrounds. Winter trips also gain, though few campgrounds are open in winter. Appendix Figure A3 maps these seasonal changes and shows that summer losses are concentrated in California and the Southwest, while spring and fall gains are widespread. The seasonal pattern suggests that one margin of adaptation is a shift in the timing of trips toward the shoulder seasons, which our framework captures through reservation decisions that respond to expected climate.

6 Conclusion

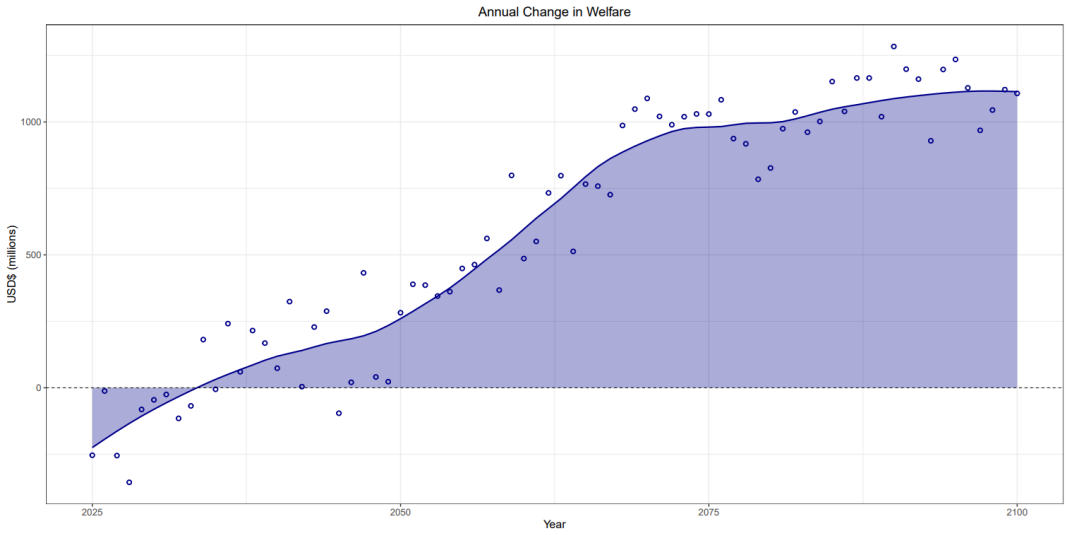
This paper uses administrative records of campground reservations and cancellations to estimate revealed preferences over climate and weather and to project the welfare effects of climate change for outdoor recreation in the western United States. The two-stage structure of the data separates reservation decisions, which are made in advance based on expected

Figure 7: Seasonality of welfare changes by end of century



Notes: Kernel densities across campgrounds of the end-of-century change in welfare per trip, in 2020 dollars, by season of arrival, under SSP3-7.0 and full updating ($\theta = 1$). N gives the number of campgrounds with trips in each season.

Figure 8: Projected annual change in welfare



Notes: Points show the projected change in aggregate annual welfare, in millions of 2020 dollars, relative to the baseline climate of 2017 to 2026, under SSP3-7.0 and full updating of expectations ($\theta = 1$). The line is a smoothed fit. Values are not discounted.

climate, from cancellation decisions, which are made close to the arrival date based on realized weather. Preferences over realized temperature follow an inverted U-shape, with a willingness to pay of $700 per person per trip to avoid a day below 0°C and $380 to avoid a day above 42°C, relative to a day with a high of 22 to 24°C. Reservation decisions respond to the likelihood of cold conditions but not to the likelihood of heat. Combining these estimates with downscaled climate projections under SSP3-7.0, we project net welfare gains of roughly $1 billion per year by the end of the century, with gains concentrated in the shoulder seasons and at higher elevations and losses for summer trips and for campgrounds in the Southwest and the Sierra Nevada.

Several limitations of the analysis deserve mention. First, our estimates are based on camping, which may not be representative of all forms of outdoor recreation. In particular, substitution within the day is not an available margin of adaptation for an overnight trip, as it is for the activities studied by Chan and Wichman (2020) and Dundas and von Haefen (2020). Second, we consider only the direct effect of temperature and precipitation on the value of a trip. We do not model ecosystem impacts of climate change, such as changes in species or land cover, impacts on natural amenities such as glaciers and water resources, or increases in the costs of natural disasters such as wildfire and smoke. Third, we assume that preferences over climate and weather remain constant over time. Finally, we hold the supply of campgrounds fixed. One implication of our results is that recreation value could increase by extending camping seasons in locations where spring and fall are becoming warmer, or by expanding capacity in cooler areas to accommodate substitution.

These findings add to a growing set of sectoral estimates of climate damages. For outdoor recreation, they indicate that the net effect of warming depends on the balance between fewer cold days and more hot days, that this balance varies substantially across regions and seasons, and that realizing the gains from a warming climate depends on the attention individuals pay to climatic shifts when planning their trips.

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Appendix to "The Welfare Effects of Climate Change for Outdoor Recreation"

Jacob Gellman, Zachari Pond, Matthew Wibbenmeyer

October 2026

Appendix A: Additional Tables and Figures A2

Appendix B: Bootstrapped $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$ A11

Appendix A: Additional Tables and Figures

Table A1: Climate preferences using reservations, $\mathbb{P}(R_{ijt} = 1)$

	(1)
Travel cost (dollars)	-0.013**
	(0.0003)
Expec. precip. (mm)	-0.060**
	(0.011)
Prob. high temp. (°C) < 5	-3.26**
	(0.377)
Prob. high temp. (°C) $\in$ (5,10]	-1.37**
	(0.236)
Prob. high temp. (°C) $\in$ (10,15]	-0.835**
	(0.143)
Prob. high temp. (°C) $\in$ (15,20]	-0.501**
	(0.084)
Prob. high temp. (°C) $\in$ (25,30]	-0.012
	(0.092)
Prob. high temp. (°C) $\in$ (30,35]	-0.106
	(0.112)
Prob. high temp. (°C) $\in$ (35,40]	0.101
	(0.304)
Prob. high temp. (°C) > 40	-0.800
	(1.05)
Campground FE	Yes
Month FE	Yes
Year FE	Yes
N	378,057

Notes: The dependent variable is the log share ratio $\log(s_{zjt}) - \log(s_{z0t})$ at the county by month by campground level (Equation 6), estimated on reservations made more than one week in advance of arrival. Temperature variables are the share of days over the previous ten years with a daily maximum temperature in each 5°C bin during the arrival month; the omitted bin is 20 to 25°C. Observations are weighted by county population. Standard errors are clustered at the campground level. * $p < 0.05$, ** $p < 0.01$.

Table A2: Weather preferences using cancellations, $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$

	(1)
Travel cost (dollars)	-0.002**
	(0.0003)
Precip. (mm)	-0.018**
	(0.002)
$\tilde{\varepsilon}_{ijt}$	-0.013
	(0.020)
$\xi_{z(i),j,t}$	0.081**
	(0.006)
High temp. (°C) < 0	-1.17**
	(0.087)
High temp. (°C) $\in$ (0,2]	-1.26**
	(0.156)
High temp. (°C) $\in$ (2,4]	-0.858**
	(0.120)
High temp. (°C) $\in$ (4,6]	-0.782**
	(0.097)
High temp. (°C) $\in$ (6,8]	-0.739**
	(0.096)
High temp. (°C) $\in$ (8,10]	-0.606**
	(0.067)
High temp. (°C) $\in$ (10,12]	-0.508**
	(0.036)
High temp. (°C) $\in$ (12,14]	-0.384**
	(0.028)
High temp. (°C) $\in$ (14,16]	-0.251**
	(0.026)
High temp. (°C) $\in$ (16,18]	-0.183**
	(0.022)
High temp. (°C) $\in$ (18,20]	-0.080**
	(0.020)
High temp. (°C) $\in$ (20,22]	-0.014
	(0.014)
High temp. (°C) $\in$ (24,26]	-0.021
	(0.016)
High temp. (°C) $\in$ (26,28]	-0.057**
	(0.018)
High temp. (°C) $\in$ (28,30]	-0.085**
	(0.023)
High temp. (°C) $\in$ (30,32]	-0.123**
	(0.025)
High temp. (°C) $\in$ (32,34]	-0.161**
	(0.029)
High temp. (°C) $\in$ (34,36]	-0.238**
	(0.036)
High temp. (°C) $\in$ (36,38]	-0.241**
	(0.043)
High temp. (°C) $\in$ (38,40]	-0.385**
	(0.064)
High temp. (°C) $\in$ (40,42]	-0.563**
	(0.089)
High temp. (°C) > 42	-0.632**
	(0.117)
Campground FE	Yes
Day-of-week FE	Yes
Week-of-year FE	Yes
Year FE	Yes
N	2,994,066

Notes: Binary logit for the probability that a reservation is not cancelled (Equation 9), estimated on reservations made more than one week in advance of arrival, excluding cancellations made more than one week in advance. Temperature bins refer to the realized daily maximum temperature on the arrival date; the omitted bin is 22 to 24°C. $\tilde{\varepsilon}_{ijt}$ and $\xi_{z(i),j,t}$ are the control function terms from the reservation stage. Observations are weighted by group size. Standard errors are clustered at the campground level. * $p < 0.05$, ** $p < 0.01$.

Table A3: Comparison of climate preferences using pooled late and early reservations versus early reservations only.

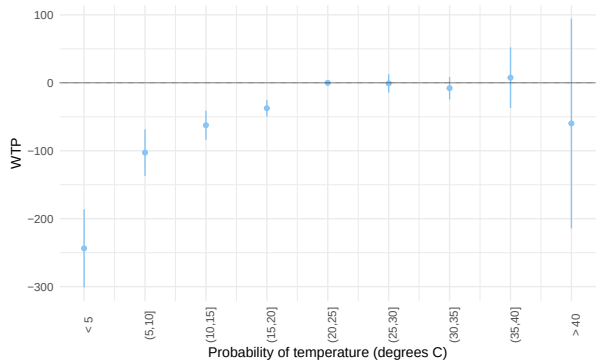
	(1)	(2)
Travel cost (dollars)	-0.013**	-0.013**
	(0.0003)	(0.0002)
Expec. precip. (mm)	-0.060**	-0.063**
	(0.011)	(0.011)
Prob. high temp. (degrees C) < 5	-3.26**	-3.06**
	(0.377)	(0.372)
Prob. high temp. (degrees C) $\in$ (5,10]	-1.37**	-1.32**
	(0.236)	(0.224)
Prob. high temp. (degrees C) $\in$ (10,15]	-0.835**	-0.783**
	(0.143)	(0.142)
Prob. high temp. (degrees C) $\in$ (15,20]	-0.501**	-0.517**
	(0.084)	(0.082)
Prob. high temp. (degrees C) $\in$ (25,30]	-0.012	-0.085
	(0.092)	(0.095)
Prob. high temp. (degrees C) $\in$ (30,35]	-0.106	-0.175
	(0.112)	(0.115)
Prob. high temp. (degrees C) $\in$ (35,40]	0.101	0.058
	(0.304)	(0.273)
Prob. high temp. (degrees C) > 40	-0.800	-0.836
	(1.05)	(0.912)
Campground FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Sample	Early	Pooled
N	378,058	448,583

Notes: Column (1) uses reservations made more than one week in advance of arrival, as in Table A1; column (2) pools reservations made at any time before arrival. The welfare simulation in Section 5 uses the pooled sample. Observations are weighted by county population. Standard errors are clustered at the campground level. * $p < 0.05$, ** $p < 0.01$.

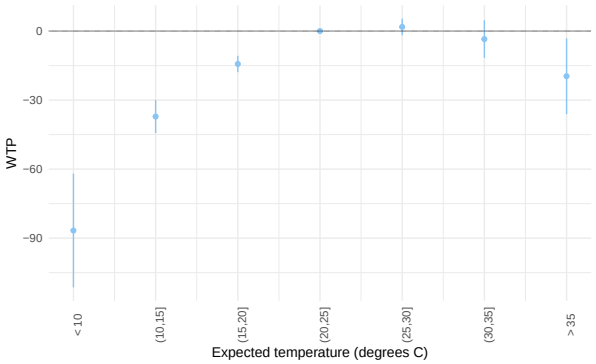
A1 Alternative empirical specifications

Figure A1: Responses to temperature probability versus temperature average.

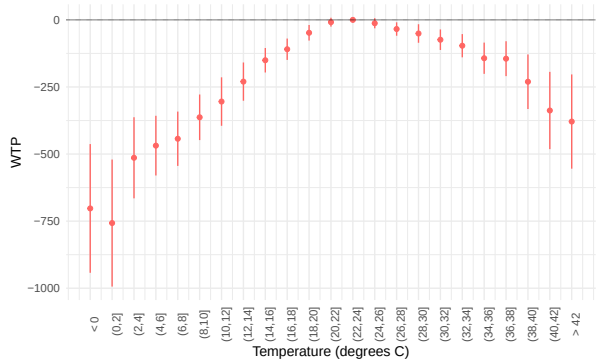
(A) Reservations, temperature probability



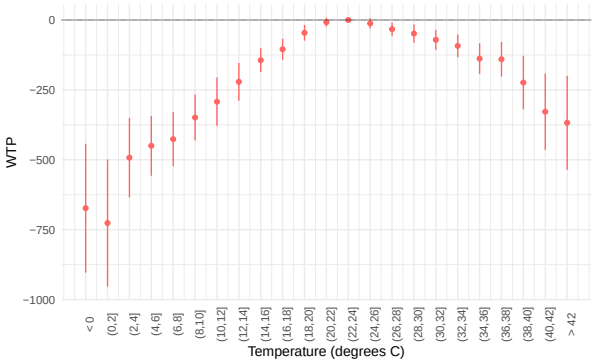
(B) Reservations, temperature average



(C) Cancellations, probability in first stage



(D) Cancellations, average in first stage



Notes: Panels (A) and (B) compare reservation-stage estimates when expected temperature is measured as the share of days in each 5°C bin over the previous ten years (the main specification) versus the ten-year average monthly maximum temperature in 5°C bins. Panels (C) and (D) show the corresponding cancellation-stage estimates, which differ only through the control function terms carried over from the first stage. Bars show 95 percent confidence intervals based on standard errors clustered at the campground level.

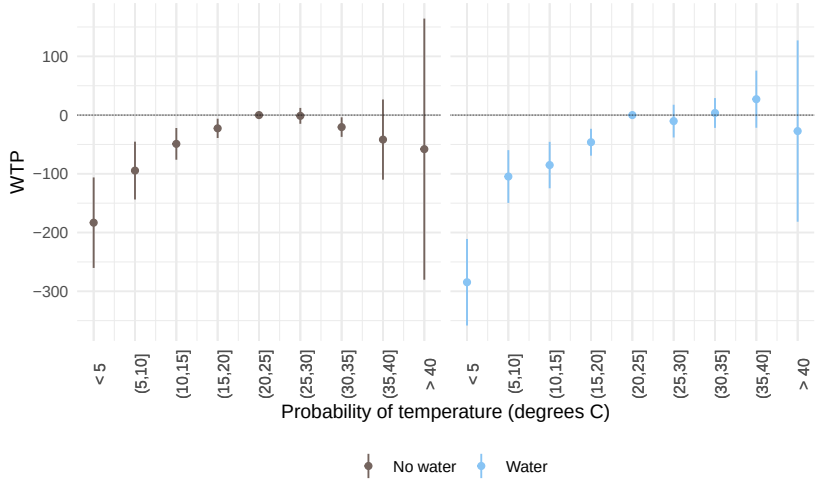
Table A4: Responses to temperature probability versus temperature average.

	(1)	(2)	(3)
Travel cost (dollars)	-0.013**	-0.013**	-0.013**
	(0.0003)	(0.0003)	(0.0003)
Expec. precip. (mm)	-0.075**	-0.060**	-0.062**
	(0.010)	(0.011)	(0.009)
Prob. high temp. (°C) < 5		-3.26**	
		(0.377)	
Prob. high temp. (°C) $\in$ (5,10]		-1.37**	
		(0.236)	
Prob. high temp. (°C) $\in$ (10,15]		-0.835**	
		(0.143)	
Prob. high temp. (°C) $\in$ (15,20]		-0.501**	
		(0.084)	
Prob. high temp. (°C) $\in$ (25,30]		-0.012	
		(0.092)	
Prob. high temp. (°C) $\in$ (30,35]		-0.106	
		(0.112)	
Prob. high temp. (°C) $\in$ (35,40]		0.101	
		(0.304)	
Prob. high temp. (°C) > 40		-0.800	
		(1.05)	
Expec. high temp. (°C) < 10			-1.16**
			(0.164)
Expec. high temp. (°C) $\in$ (10,15]			-0.497**
			(0.048)
Expec. high temp. (°C) $\in$ (15,20]			-0.191**
			(0.024)
Expec. high temp. (°C) $\in$ (25,30]			0.024
			(0.025)
Expec. high temp. (°C) $\in$ (30,35]			-0.047
			(0.056)
Expec. high temp. (°C) > 35			-0.263*
			(0.113)
Campground FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	378,057	378,057	378,057
Log-Likelihood	-590,679.196	-588,957.388	-589,531.579
AIC	1,183,394.393	1,179,966.776	1,181,111.158
BIC	1,194,432.364	1,191,091.489	1,192,214.185
Within R^2	0.310	0.316	0.314
RMSE	1.154	1.149	1.151

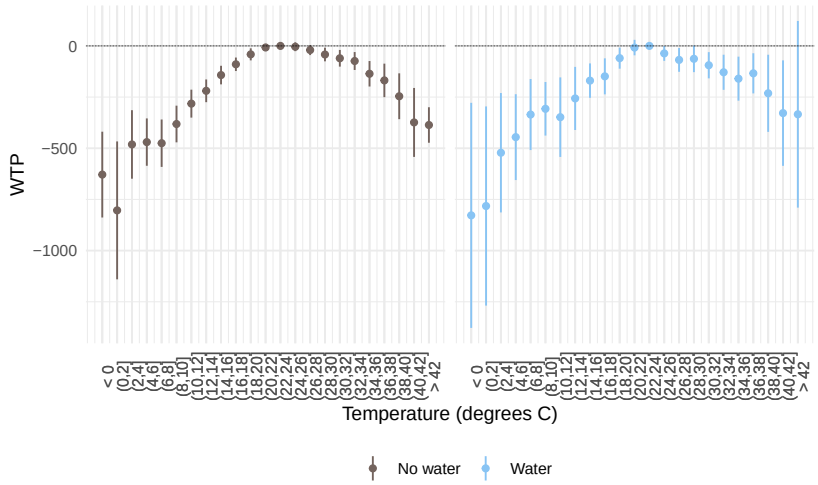
Notes: Reservation-stage estimates of Equation 6. Column (1) omits temperature; column (2) measures expected temperature as the share of days in each 5°C bin over the previous ten years (the main specification, as in Table A1); column (3) measures expected temperature as the ten-year average monthly maximum temperature in 5°C bins, with 20 to 25°C omitted. Observations are weighted by county population. Standard errors are clustered at the campground level. * $p < 0.05$, ** $p < 0.01$.

Figure A2: Heterogeneity by presence of water bodies near campground.

(a) Climate



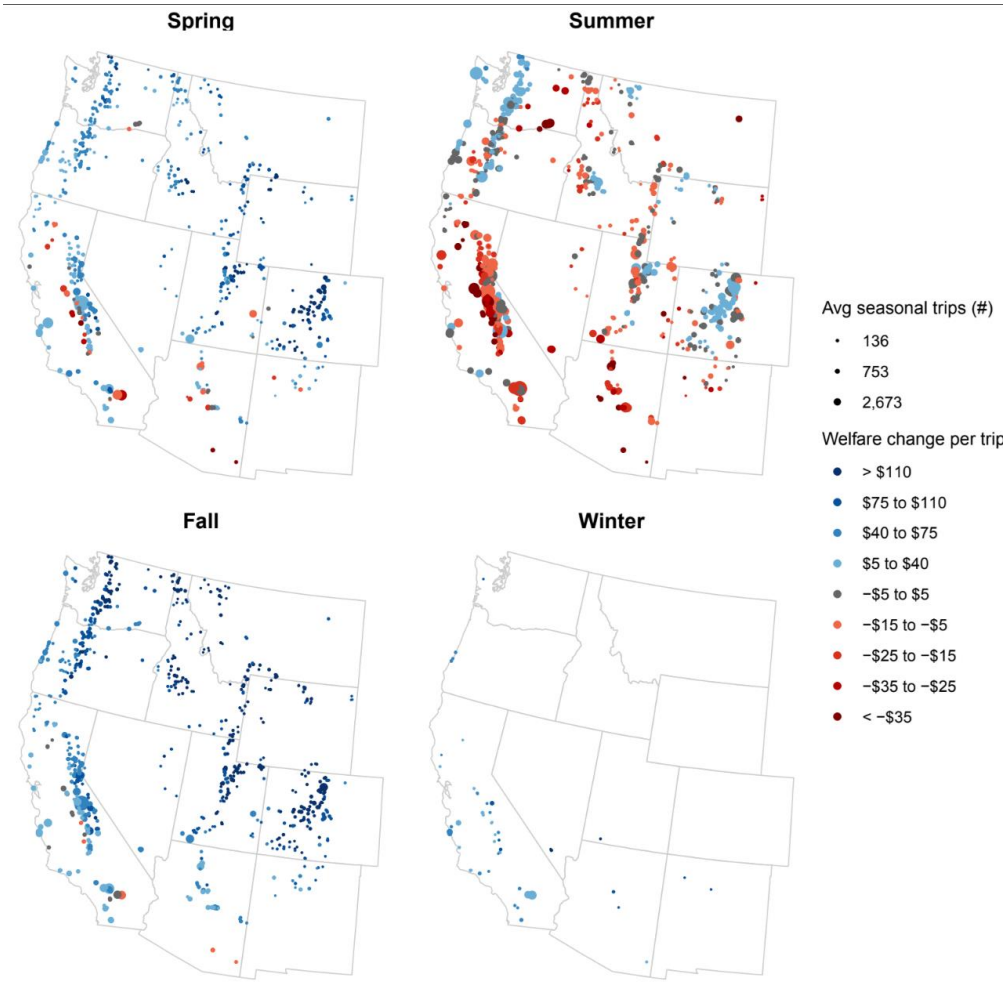
(b) Weather



Notes: Estimates from the reservation model (panel a) and the cancellation model (panel b) allowing temperature coefficients to differ between campgrounds with and without a water body nearby. In the reservation model, the estimate for the 35 to 40°C bin is positive only for campgrounds with water nearby, and aversion to the coldest bin is stronger with water nearby, though neither difference is statistically significant. In the cancellation model, visitors to campgrounds with water nearby appear less tolerant of cold (about 32 percent lower WTP for the below 0°C bin) and more tolerant of heat (6 to 21 percent higher WTP for the four hottest bins), though again the differences are not statistically significant. Bars show 95 percent confidence intervals based on standard errors clustered at the campground level.

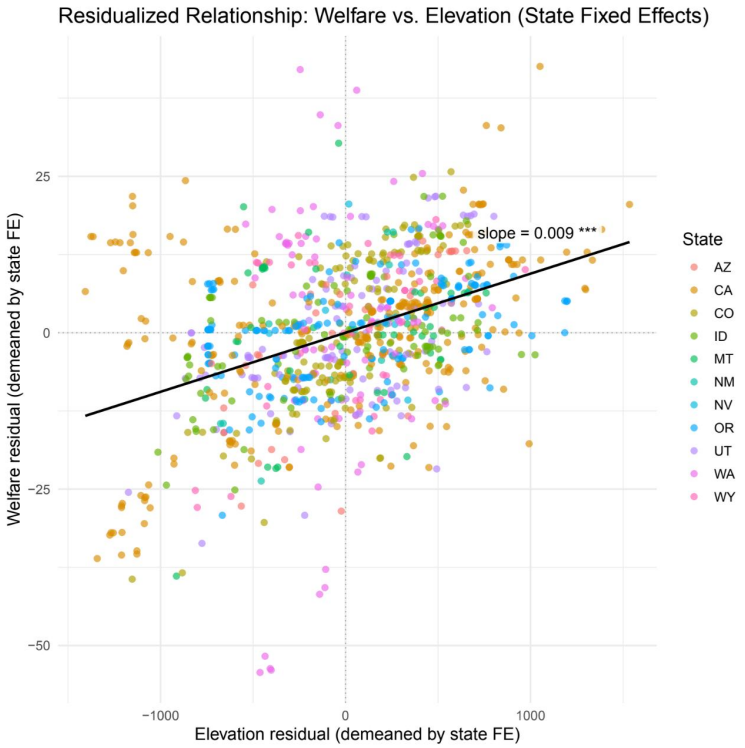
A2 Climate simulation

Figure A3: Mapping seasonality of welfare changes by end of century.



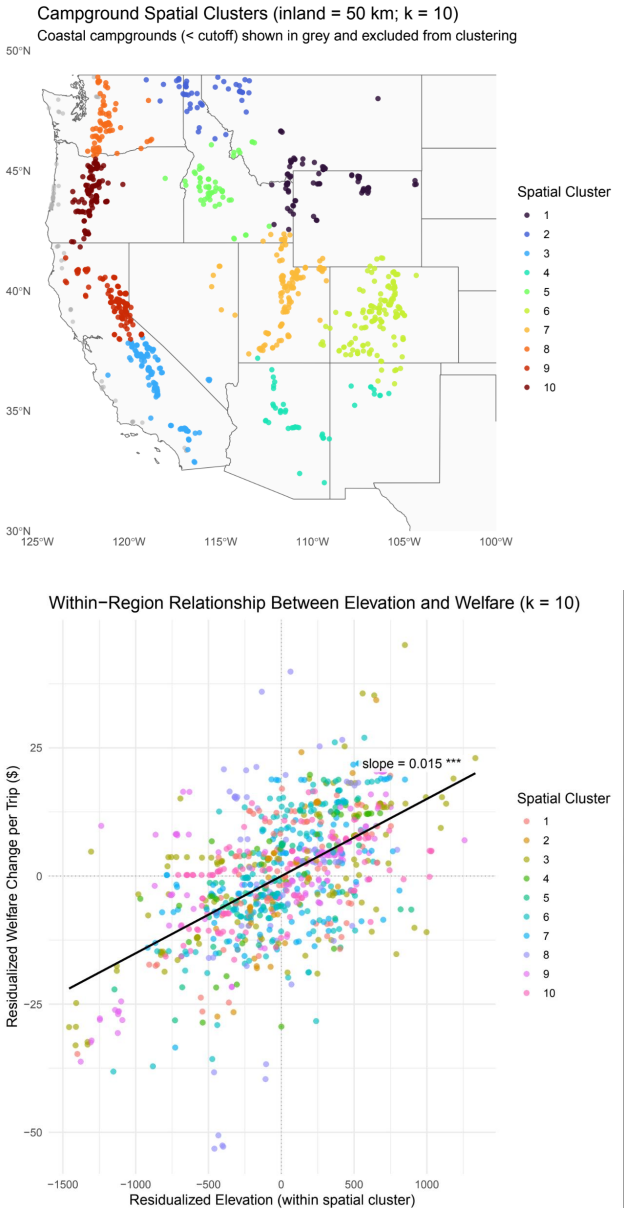
Notes: Each point is a campground. Color shows the end-of-century change in welfare per trip, in 2020 dollars, for trips arriving in each season, under SSP3-7.0 and full updating ($\theta = 1$). Point size shows the campground's average number of trips in the season.

Figure A4: Relationship of welfare gains to elevation, residualizing on state fixed effects.



Notes: Each point is a campground. Both axes are residuals from regressions on state fixed effects. Welfare is the end-of-century change per trip, in 2020 dollars, under SSP3-7.0 and full updating ($\theta = 1$); elevation is in meters.

Figure A5: Relationship of welfare gains to elevation, residualizing on k-means spatial clusters.

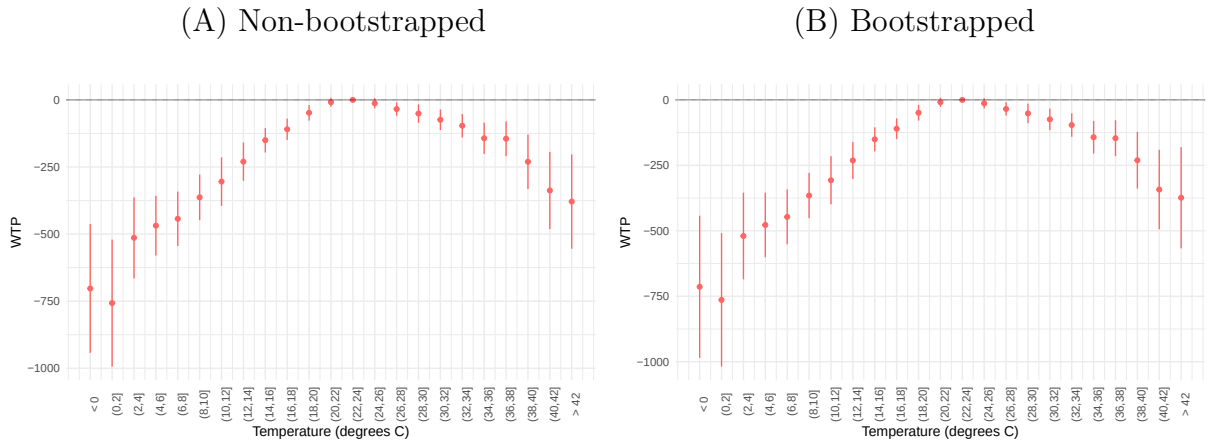


Notes: The top panel maps the spatial clusters obtained from k-means clustering of campground coordinates. The bottom panel repeats Appendix Figure A4 using cluster fixed effects in place of state fixed effects. Welfare is the end-of-century change per trip, in 2020 dollars, under SSP3-7.0 and full updating ($\theta = 1$); elevation is in meters.

Appendix B: Bootstrapped $\mathbb{P}(C_{ijt} = 0 | R_{ijt} = 1)$

The cancellation model in Equation 8 includes two generated regressors from the reservation stage, $\tilde{\varepsilon}_{ijt}$ and $\xi_{z(i),j,t}$. The standard errors reported in Table A2 treat these terms as known. This appendix reports results from a bootstrap that re-estimates both stages in each replication, so that uncertainty from the first stage is carried into the second. [XX Number of replications and resampling unit.] Figure B1 and Table B1 show that the point estimates are essentially unchanged and that bootstrapped standard errors are close to the clustered standard errors for most temperature bins, with modestly wider intervals for the coldest and hottest bins. Table B2 reports Shapiro-Wilk tests of normality for the bootstrap distribution of each coefficient, and Figure B2 plots the distributions. Normality is rejected only for the extreme temperature bins, where the distributions are skewed.

Figure B1: Comparison of non-bootstrapped to bootstrapped results.



Notes: Willingness to pay for realized temperature from the cancellation model, as in Figure 5, with 95 percent confidence intervals based on standard errors clustered at the campground level (panel A) and on the bootstrap (panel B).

Table B1: Comparison of non-bootstrapped to bootstrapped results, full coefficient set.

	(1)	(2)
Travel cost (dollars)	-0.002**	-0.002**
	(0.0003)	(0.0002)
Precip. (mm)	-0.018**	-0.018**
	(0.002)	(0.002)
$\tilde{\varepsilon}_{ijt}$	-0.013	-0.015
	(0.020)	(0.018)
$\xi_{z(i),j,t}$	0.081**	0.081**
	(0.006)	(0.007)
High temp. (°C) < 0	-1.17**	-1.18**
	(0.087)	(0.152)
High temp. (°C) $\in$ (0,2]	-1.26**	-1.27**
	(0.156)	(0.182)
High temp. (°C) $\in$ (2,4]	-0.858**	-0.866**
	(0.120)	(0.122)
High temp. (°C) $\in$ (4,6]	-0.782**	-0.797**
	(0.097)	(0.094)
High temp. (°C) $\in$ (6,8]	-0.739**	-0.747**
	(0.096)	(0.091)
High temp. (°C) $\in$ (8,10]	-0.606**	-0.610**
	(0.067)	(0.064)
High temp. (°C) $\in$ (10,12]	-0.508**	-0.509**
	(0.036)	(0.037)
High temp. (°C) $\in$ (12,14]	-0.384**	-0.383**
	(0.028)	(0.029)
High temp. (°C) $\in$ (14,16]	-0.251**	-0.250**
	(0.026)	(0.027)
High temp. (°C) $\in$ (16,18]	-0.183**	-0.182**
	(0.022)	(0.022)
High temp. (°C) $\in$ (18,20]	-0.080**	-0.081**
	(0.020)	(0.021)
High temp. (°C) $\in$ (20,22]	-0.014	-0.015
	(0.014)	(0.014)
High temp. (°C) $\in$ (24,26]	-0.021	-0.022
	(0.016)	(0.016)
High temp. (°C) $\in$ (26,28]	-0.057**	-0.057**
	(0.018)	(0.018)
High temp. (°C) $\in$ (28,30]	-0.085**	-0.084**
	(0.023)	(0.024)
High temp. (°C) $\in$ (30,32]	-0.123**	-0.122**
	(0.025)	(0.026)
High temp. (°C) $\in$ (32,34]	-0.161**	-0.159**
	(0.029)	(0.029)
High temp. (°C) $\in$ (34,36]	-0.238**	-0.236**
	(0.036)	(0.037)
High temp. (°C) $\in$ (36,38]	-0.241**	-0.242**
	(0.043)	(0.042)
High temp. (°C) $\in$ (38,40]	-0.385**	-0.381**
	(0.064)	(0.066)
High temp. (°C) $\in$ (40,42]	-0.563**	-0.565**
	(0.089)	(0.088)
High temp. (°C) > 42	-0.632**	-0.620**
	(0.117)	(0.142)
Campground FE	Yes	Yes
Day-of-week FE	Yes	Yes
Week-of-year FE	Yes	Yes
Year FE	Yes	Yes
Bootstrapped	No	Yes
N	2,994,066	2,994,066

Notes: Column (1) repeats Table A2 with standard errors clustered at the campground level; column (2) reports bootstrapped standard errors. * $p < 0.05$, ** $p < 0.01$.

Table B2: W statistics from Shapiro-Wilk test of normality for bootstrapped coefficients of $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$.

Coefficient	W statistic	p value
Travel cost	0.997	(0.3514)
Precip.	0.996	(0.1677)
$\tilde{\varepsilon}_{ijt}$	0.997	(0.4169)
$\xi_{z(i),j,t}$	0.997	(0.4492)
High temp. < 0	0.919	(0.0000)
High temp. in (0,2]	0.967	(0.0000)
High temp. in (2,4]	0.995	(0.0934)
High temp. in (4,6]	0.991	(0.0056)
High temp. in (6,8]	0.997	(0.4471)
High temp. in (8,10]	0.996	(0.1979)
High temp. in (10,12]	0.995	(0.1209)
High temp. in (12,14]	0.998	(0.7548)
High temp. in (14,16]	0.996	(0.3310)
High temp. in (16,18]	0.998	(0.8126)
High temp. in (18,20]	0.996	(0.1651)
High temp. in (20,22]	0.997	(0.4830)
High temp. in (24,26]	0.997	(0.6556)
High temp. in (26,28]	0.997	(0.3652)
High temp. in (28,30]	0.996	(0.1633)
High temp. in (30,32]	0.997	(0.5417)
High temp. in (32,34]	0.996	(0.1600)
High temp. in (34,36]	0.998	(0.9304)
High temp. in (36,38]	0.997	(0.4451)
High temp. in (38,40]	0.989	(0.0011)
High temp. in (40,42]	0.989	(0.0007)
High temp. > 42	0.969	(0.0000)

Notes: The null hypothesis is that the bootstrapped coefficients are normally distributed. p values in parentheses.

Figure B2: Distribution of estimated coefficients from bootstrapped estimation of $\mathbb{P}(C_{ijt} = 0|R_{ijt} = 1)$.

