Valuing America's Best Idea: Demand for the U.S. National Park System

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Abstract

The U.S. National Park System contains some of the world's most spectacular natural resources and attracts more than 300 million visits each year. Combining individual-level surveys with fifteen years of park-level visitor counts, I estimate a recreation demand model for 140 national parks, nearly all those protected for their natural significance. Between 2005 and 2019, the annual recreational surplus generated by these parks grew 31 percent and peaked at $12 billion, almost five times the National Park Service's 2019 operating budget. The estimated model also produces a national park awesomeness index. Iconic parks like Yellowstone, Glacier, and Grand Canyon often rank highly, and parks with wide-ranging elevation, water resources, favorable temperatures, and charismatic wildlife, including bison, elk, and redwood forests, tend to be more awesome.

1 Introduction

The U.S. National Park System protects the country's most treasured sites, scenery, and wildlife, including world-famous destinations like Yellowstone and the Grand Canyon, seashores like Cape Hatteras and Point Reyes, historic points of interest, and much more. These sites attract 300 million visits each year, generating surplus for visitors and supporting local economies. Their significance is expressed most succinctly with their nickname, "America's Best Idea" (Burns & Dayton, 2009).

Despite the national parks' idyllic aura, the National Park Service (NPS) faces tradeoffs and political pressure like other government agencies. As a result, the NPS has long sought to quantify the benefits that

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the national parks provide. These efforts date back to at least the 1940s when A.E. Demaray, the Associate Director of the NPS, wrote to ten experts regarding how to "evaluate the benefits of the national parks" (U.S. NPS, 1949). The consultants' responses highlighted two categories of benefits: visitors' recreational enjoyment and the impact of visitor spending in communities surrounding the parks. Most consultants doubted the feasibility of valuing recreational enjoyment in dollar terms. Only one, Harold Hotelling, outlined a clear strategy, and while his response would eventually help spawn the recreation demand literature, it was overshadowed by the other consultants' skepticism. On the other hand, several experts were optimistic about valuing the local economic impacts of visitor spending.[1] Nearly 80 years after these correspondences, the NPS's approach to measuring the parks' economic benefits resembles these consultants' general sentiment. The NPS reports annual "Visitor Spending Effects" valuing the national parks' local economic impacts, but no consistent and systematic effort values the recreational benefits the parks provide visitors (Cullinane Thomas & Koontz, 2020).

Nonetheless, valuing the recreational surplus the parks provide remains important. For its entire existence, the NPS has sought to provide recreational access while simultaneously preserving resources for future generations ("U.S. Code Title 16 - Organic Act", 1916). This mission inherently involves tradeoffs between allowing visitors to enjoy park resources and restricting access to preserve them. Thus, measuring visitors' recreational surplus, and how this surplus changes over time, speaks directly to the NPS's founding mission. Additionally, recent global and national natural capital accounting initiatives seek to systematically track the value of environmental assets (Fenichel, 2024; United Nations, 2025). These initiatives make the national parks, some of the most famous natural resources in the world, an important line item on the federal balance sheet.

This paper values the recreational surplus generated by 140 U.S. national parks from 2005 through 2019 and explores which park attributes create (and erode) value. This sample of parks includes roughly all those in the contiguous United States protected for their natural, rather than historic, resources. To value the parks' recreational surplus, I construct a repeated Random Utility Model (RUM) of park visitation. Each month, individuals choose whether to visit a park, which park to visit, and whether to drive or fly on their trip. The utility of visiting a park depends on the travel costs required to access it and the park's attributes, including elevation, water resources, wildlife, infrastructure, and a measure of congestion—the average daily visitation to the park in the month. I embed all park attributes within park-by-month fixed effects, which I call "park effects". These parameters isolate the mean utility of visiting a park after controlling for the travel costs of accessing it. In plain terms, the park effects provide a national park *awesomeness* index.

I combine two main sources of visitation data to estimate the model: the 2008 and 2018 waves of a

[1] Banzhaf (2010) discusses these correspondences and the broader state of benefit-cost analysis at the time of their writing.

nationally representative telephone survey administered by the NPS and monthly, park-level visitor counts from the Visitor Use Statistics database. I first estimate the model during the two survey periods. Given these parameter estimates, I calibrate the model so that the predicted visitation for American Community Survey microdata exactly matches the monthly visitor counts from January 2005 through December 2019. In effect, I filter the monthly visitor counts through the structural model, transforming them into estimates of monthly park awesomeness. Finally, I regress the panel of park effects on park attributes to understand which attributes influence park awesomeness. Following Timmins and Murdock (2007), this park attribute regression accounts for the endogeneity of congestion using an instrumental variables strategy that exploits variation in the quality of substitute parks. With the estimated model, I value the recreational surplus provided by all 140 parks jointly, as well as the surplus provided by individual parks. Note that removing an individual park from the choice set decreases welfare through two channels. It eliminates a viable choice alternative, and it increases congestion at other parks in the system.

This analysis produces four sets of findings. The first set describes the national park awesomeness index. Iconic parks, like Yellowstone, Glacier, Grand Canyon, and Yosemite, often rank highly. Yet, the awesomeness index varies substantially month-to-month. Yellowstone and Glacier rank 2nd and 3rd in the July index but drop out of the top ten in the winter months. On the other hand, parks in warmer climates, including Grand Canyon, Joshua Tree, Arches, and Zion, rank more highly in cooler months.

The second set of findings explores how specific attributes influence parks' awesomeness. On average, visitors prefer parks with coastline and large waterbodies, iconic wildlife, like redwood forests and bison, wide-ranging elevation, lower congestion, and daily high temperatures between 65 and 80°F. While many attributes vary little over time, posing a challenge for causal inference, the month-to-month variation in my park effects makes a causal interpretation more plausible for congestion and weather variables.

The third set of findings describes the surplus generated by individual parks. The median national park yields $29 million of recreational surplus per year, nine times larger than the median park budget of $3.6 million. Both park awesomeness and travel costs determine which parks provide the most surplus. Parks relatively close to large population centers, which have low travel costs for many people, tend to be highly valuable. For example, Gateway National Recreation Area, near New York City, generates $492 million of surplus per year, the second-most of any park. Several of the most awesome parks are also among the most valuable; Grand Canyon generates $333 million of surplus per year, sixth-most of any park. However, remoteness and highly seasonal awesomeness limit the surplus produced by some of the most iconic parks, including Glacier and Yellowstone. Accounting for congestion spillovers meaningfully impacts these surplus estimates. Between 17 and 44 percent of each park's recreational surplus comes from decreasing congestion at other national parks.

The final set of findings presents the joint recreational surplus of the 140 parks in the sample and explores how and why this surplus changed over time. I estimate that these parks provided \$150 billion in recreational surplus across the 2005 to 2019 analysis period, about \$10 billion per year. This annual surplus is four times larger than the NPS's operating budget, which was \$2.5 billion in 2019. Tracking recreational surplus over time, I find that annual surplus grew 31 percent over the analysis period and 24 percent between 2013 and 2019 alone. Changes in unobserved factors—system-wide, month-of-sample fixed effects and residuals—account for roughly half the increase in surplus. This finding aligns with previous work documenting the importance of social media and marketing campaigns in driving increased visitation (Drugova et al., 2021; Wichman, 2024). Changes in demographics and travel costs have a smaller effect, accounting for a quarter of the increased surplus. Although I cannot pin down the exact reason for the increased interest in the national parks, I rule out changes in weather conditions, which explain almost none of the change in surplus.

It is worth noting that my surplus estimates do not reflect the full array of benefits the National Park System provides society. In particular, my estimates do not capture non-use, existence values. Furthermore, my recreational surplus estimates are likely conservative. Following standard practice in recreation demand literature, I drop visits that were not the primary purpose of a respondent's trip, because visitors did not trade off their full home-to-park travel cost to access the park alone (Lupi et al., 2020). Across my sample, roughly 46 percent of visits occur on non-primary purpose trips. Unfortunately, my survey data do not list every destination a respondent visited on their last trip, just the park they visited most recently. This feature precludes estimating a more sophisticated model that accounts for surplus generated by non-primary purpose trips.

This paper constitutes the most comprehensive analysis of demand for the U.S. National Park System to date. Previous nationwide studies of demand for the national parks tend to focus on visitation as the main outcome. Examples of these include Fisichelli et al. (2015), who predict that climate change will increase system-wide visitation by 8–23 percent, Keiser et al. (2018), who find a that air pollution decreases visitation, and Wichman (2024), who shows that social media has increased visitation. In a broader analysis of local economic impacts, Szabó and Ujhelyi (2024) find that receiving an official "National Park" designation increases visitation.[2] Other papers studying visitation at the national level include Bergstrom et al. (2020), Cai (2021), and Henrickson and Johnson (2013).

Another set of papers apply recreation demand models to value parks and their resources. These papers tend to be "narrow in scope, focusing on particular sites and/or activities" (Walls, 2022). Exceptions include Parsons et al. (2021) who value national parks across the Southwest using an innovative "site-portfolio" travel

[2]While all sites in the National Park System are typically called national parks, each site has an official designation on each site. These designations include National Park, National Seashore, National Recreation Area, etc.

cost RUM, and Gellman et al. (2025) who value the welfare impacts of wildfire smoke at federally-managed campsites in the western United States, many of which are located in or near national parks. In the closest study to mine, Neher et al. (2013) estimate willingness to pay to visit 58 national parks using park-specific on-site surveys conducted between 1994 and 2009. They estimate WTP for visiting each park separately, then regress WTP estimates on park attributes to predict the value of a trip to each national park. Multiplying a park's WTP estimate by its visitation, they estimate the total recreational surplus generated by the National Park System at $28.5 billion per year.

At least one previous study has estimated the combined use and non-use value of the National Park System with stated preference methods. Haefele et al. (2020) execute a choice experiment soliciting respondents' willingness to pay additional income taxes to prevent hypothetical cuts to park acreage and programming. They estimate the total value of the national parks and NPS programs at $92 billion per year.

My analysis fills a void at the intersection of these visitation and valuation studies. Unlike national visitation studies, I value the national parks' recreational surplus in dollar terms, which is critical for informing park management, damage assessments, and natural capital accounting initiatives. Unlike prior valuation studies, my analysis has a broad geographic and temporal scope. By covering 140 parks over fifteen years, I fill gaps in survey coverage and track how preferences for parks and their attributes change over time.

My model and estimation procedure also make methodological contributions to the recreation demand literature. Several recent papers call for more rigorous identification in recreation demand models (Ji et al., 2020; Lupi et al., 2020), and new applications make advances in this regard (Dundas & von Haefen, 2020; Earle & Kim, 2024; Kuwayama et al., 2022). Within this literature, my methods are most closely related to English et al. (2018) and Timmins and Murdock (2007). Like me, English et al. use a calibration procedure to combine individual-level surveys with site-level visitor counts. They exploit their visitor counts' longer time span to value the welfare impacts of the *Deepwater Horizon* oil spill, which occurred before their survey period. Like Timmins and Murdock, I linearize part of the travel cost RUM estimation problem to estimate preferences for congestion using instrumental variables.

I contribute to this literature by exploiting complementarities between these calibration and linearization techniques. Without calibration, a researcher can only analyze events within their survey period, which may be brief due to the costs of collecting data. On the other hand, the prevalence of site-level visitation data makes calibrating a model beyond the survey period feasible in many empirical settings (New York OPRHP, 2025; Utah DNR, 2025; Washington State Parks, 2025). Without linearization, the complexity of non-linear estimation encourages parsimonious model specifications and limits the set of feasible identification strategies. Indeed, these challenges have long made linearization a popular tool for identifying preferences in RUMs (Berry, 1994; Berry et al., 1995). Thus, combining calibration and linearization obtains the benefits of both techniques; researchers can leverage an array of identification strategies to value resource changes over extended time periods.

2 Model

In this section, I present a model of national park visitation. The model departs from the standard recreation travel cost model in two ways. First, individuals jointly choose which national park to visit and how to travel. By jointly modeling the park and travel mode choices, I combine elements of the recreation demand literature, which typically focuses on the park/site choice, and the transportation literature, which has long modeled travel mode choices (McFadden, 1974).[3] Second, congestion levels arise as an equilibrium outcome in my model. While congestion often influences recreation decisions, many papers abstract from congestion, because it complicates modeling, estimation, and welfare analysis. Following Timmins and Murdock (2007), I include congestion in the utility function and solve for equilibrium congestion levels when conducting welfare analyses. Public interest in overcrowding at national parks suggests that accounting for congestion is important in this empirical context.[4]

Suppose that individuals repeatedly choose whether to visit a national park, which national park to visit, and whether to drive or fly to the park. Denote the set of national parks $\mathcal{J} = \{1, 2, ...J\}$ and the set of travel modes $\mathcal{M} = \{R, F\}$, where R and F indicate driving and flying, respectively. Let j index the set of national parks and $j = 0$ denote the outside option: the best way of spending the month that does not involve visiting a national park. I group historic sites in the National Park System as a composite alternative denoted $j = J + 1$. Given this choice set, let U_{ijmt} denote the utility individual i receives from visiting park j using travel mode m during month t, where

$$U_{ijmt} = \begin{cases} \beta_D D_i + \epsilon_{i0t} & j = 0 \\ \delta_{jt} + \beta_{TC} TC_{ijRt} + \epsilon_{ijRt} & j \in \{1, ..., J\}, m = R \\ \delta_{jt} + \beta_F + \beta_{TC} TC_{ijFt} + \epsilon_{ijFt} & j \in \{1, ..., J\}, m = F \\ \delta_{J+1,t} + \epsilon_{i,J+1,t} & j = J + 1 \end{cases} \tag{1}$$

In equation 1, the β_{TC} coefficient represents the marginal disutility of travel costs; the β_F coefficient represents the preference for flying relative to driving after controlling for travel costs, TC; the vector D_i contains demographic variables, and ϵ is unobservable to the econometrician. For $j \in \{1, ..., J\}$, I call the

[3] An exception to much of the recreation demand literature, Hausman et al. (1995) develop a model of site and travel mode choices to value the recreational welfare impacts of the *Exxon Valdez* oil spill.

[4] Congressional subcommittee statement: https://www.doi.gov/ocl/overcrowding-parks
Media coverage: https://e360.yale.edu/features/greenlock-a-visitor-crush-is-overwhelming-americas-national-parks

park-by-month fixed effect, δ_{jt}, the “park effect”. It captures the mean utility provided by park j in month t after controlling for travel costs and the quality of other alternatives. Ranking the park effects produces a national park *awesomeness* index.

I assume that each error term vector, $\epsilon_{i..t}$, is independent and identically distributed following a Generalized Extreme Value (GEV) distribution. I specify a GEV distribution that implies a two-nest structure, where the no visit alternative, $j = 0$, is in its own nest. This distributional assumption allows error terms for “visit” alternatives to be correlated, partially relaxing the independence of irrelevant alternatives assumption. Under this nesting structure, the probability of choosing each alternative has a closed form:

$$P_{ijmt} = \begin{cases} \dfrac{\exp(V_{i0t})}{\exp(V_{i0t}) + (\sum_{k=1}^{J+1}\sum_{n\in\mathcal{M}}\exp(V_{iknt}/\lambda))^{\lambda}} & , \text{ if } j = 0 \\[2ex] \dfrac{(\sum_{k=1}^{J+1}\sum_{n\in\mathcal{M}}\exp(V_{iknt}/\lambda))^{\lambda}}{\exp(V_{i0t}) + (\sum_{k=1}^{J+1}\sum_{n\in\mathcal{M}}\exp(V_{iknt}/\lambda))^{\lambda}} \quad \dfrac{\exp(V_{ijmt}/\lambda)}{\sum_{k=1}^{J+1}\sum_{n\in\mathcal{M}}\exp(V_{iknt}/\lambda)}, & \text{ if } j \in \{1, ..., J\} \\[2ex] \dfrac{(\sum_{k=1}^{J+1}\sum_{n\in\mathcal{M}}\exp(V_{iknt}/\lambda))^{\lambda}}{\exp(V_{i0t}) + (\sum_{k=1}^{J+1}\sum_{n\in\mathcal{M}}\exp(V_{iknt}/\lambda))^{\lambda}} \quad \dfrac{\exp(V_{i,J+1,t}/\lambda)}{\sum_{k=1}^{J+1}\sum_{n\in\mathcal{M}}\exp(V_{iknt}/\lambda)}, & \text{ if } j = J+1 \end{cases} \tag{2}$$

where V_{ijmt} is the deterministic portion of utility from equation 1.

Two fractions comprise the choice probabilities for the visit alternatives, $j > 0$. The first fraction is the probability of choosing any of the visit alternatives. The second fraction is the probability of choosing a specific park and travel mode combination conditional on choosing a visit alternative. If an individual chooses the no visit alternative, then they do not select a specific park and travel mode. The parameter, λ, is the dissimilarity coefficient. The model is consistent with utility maximizing behavior when λ is between zero and one (Herriges & Kling, 1996). Values closer to one imply the visit alternatives are less similar. When λ equals one, the choice probabilities simplify to conditional logit choice probabilities.

To recover preferences for park attributes, I decompose the park effects for parks $j \in \{1, ..., J\}$ using a correlated random effects model. This model is similar to a model with park-by-season-of-the-year fixed effects. However, such fixed effects would subsume preferences for time-invariant attributes. This correlated random effects model replaces the park-by-season-of-the-year fixed effects with time-invariant park attributes and park-by-season-of-the-year means of time-varying attributes. For time-varying attributes, coefficient estimates are numerically equivalent to the fixed effects model, but I preserve cross-sectional variation to identify coefficients on time-invariant attributes (Mundlak, 1978; Wooldridge, 2019). Recovering coefficient estimates for time-invariant attributes is useful, because some park attributes do not vary meaningfully over the analysis period—e.g., elevation. Specifically, I decompose the park effects as

$$\delta_{jt} = \alpha_X X_{jt} + \alpha_Z Z_j + \phi_t + \bar{\alpha}_X \bar{X}_{js(t)} + \bar{\phi}_{j,1,s(t)} + ... + \bar{\phi}_{j,180,s(t)} + \nu_{jt} \tag{3}$$

where X_{jt} and Z_j contain time-variant and -invariant park attributes, and ϕ_t is a system-wide, month-of-sample fixed effect. $\bar{X}_{js(t)}$ represents the mean of the time-variant attributes at park j within the season-of-the-year of month t, and the $\bar{\phi}_{j,l,s(t)}$ terms are coefficients on the mean of the month-of-sample, l, indicator variable within the season-of-the-year of month-of-sample t, $s(t)$, at park j.[5] The α_X, α_Z, and $\bar{\alpha}_X$ terms are coefficient vectors, and the error-term, ν_{jt}, captures all unobservable park attributes.

The vector of time-variant park attributes, X_{jt}, includes the anticipated congestion at park j in month t, $\tilde{s}_{jt}$. In equilibrium, anticipated congestion levels equal model-predicted congestion levels at parks $j \in \{1, ..., J\}$.[6] The model-predicted congestion at park j in month-of-sample t can be calculated by summing choice probabilities across individuals and travel modes:

$$\widehat{s}_{jt} = \sum_i \sum_m P_{ijmt} \left(\tilde{s}_{jt} \right) \tag{4}$$

where the choice probability is explicitly written as a function of anticipated congestion, $\tilde{s}_{jt}$. For a class of random utility sorting models, Bayer and Timmins (2005) show that a congestion equilibrium exists and that, if congestion is a disamenity, the equilibrium is unique. My model differs from the class they examine, because parks can be visited either by driving or flying and congestion does not impact utility of the outside option or the historic site composite alternative. Appendix B adapts their proofs to confirm that their existence and uniqueness results extend to my model.

3 Data

My main data sources describe individual-level visitation, aggregate park-level visitation, and the physical and institutional attributes of the national parks. Here, I discuss each in turn.

3.1 Telephone surveys

The individual-level visitation data come from the NPS's Comprehensive Survey of the American Public, a telephone survey designed to learn about visitor experiences and gauge public sentiment towards the NPS

[5] It may seem strange that the park-by-season-of-the-year means of the month-of-sample indicators vary across parks. Note that I have an unbalanced panel, because some parks are inaccessible in winter months and one new park is added to the system during my analysis period. With an unbalanced panel, some parks have different denominators when I calculate the park-by-season-of-the-year means of the month-of-sample indicators.

[6] This congestion equilibrium does not require anticipated and model-predicted congestion levels to match for the outside option, $j = 0$, or the historic site composite alternative, $j = J + 1$. I assume that both these alternatives are unaffected by their congestion levels.

and its management practices. Each interview lasts approximately fifteen minutes and includes several questions regarding respondents' previous national park visits. I observe two key visitation variables: the national park each respondent visited most recently and the number of times they visited a national park in the past two years. For 23 percent of respondents, I also observe whether they drove or flew on their most recent visit.

Several characteristics of the Comprehensive Survey of the American Public make it useful for studying national park visitation. First, it is nationally representative. Phone numbers are selected using a regionally-stratified random sampling design, and individual respondents are randomly selected within each household. The data include weights to account for the regional stratification and match sample demographic statistics to Census statistics. I use these weights throughout my analysis. The sampling design includes both visitors and non-visitors, allowing me to model the extensive margin—the choice of whether or not to visit a national park.

Another useful feature is that the survey was conducted twice: once in 2008 and 2009 and again in 2018. The two waves contain identical visitation history questions and similar formats. The waves contain a few differences relevant for this analysis. The 2008 wave asked a random subset of 1,537 respondents whether they drove or flew on their most recent visit, but the 2018 wave did not collect travel mode information. The seasonal timing of interviews also varies between the two waves. The 2008 and 2009 interviews were split evenly between seasons to account for seasonal variation in visitation. The 2018 survey, citing a lack of seasonality in the 2008 and 2009 data, conducted interviews from June through November.

The survey also includes information on each respondent's home location, which is important for calculating travel costs. In the 2008 wave, I observe each respondent's telephone area code and state of residence. When the area code is within the state of residence, I take the largest city in the area code as the home city when calculating travel costs. For 1.6 percent of the 2008 wave, the area code and state of residence do not match. In these cases, I assign the largest city in the state of residence as the home city. In the 2018 wave, I only observe state of residence, and I assign a home county by randomly sampling from the state's population distribution. Once I assign each respondent a home city or county, I calculate the travel costs required to reach each national park in the choice set.

I calculate quarterly driving and flying travel costs following English et al. (2018). I describe these calculations briefly here and provide more detail in Appendix F. I use PC*Miler to compute driving times and mileages. I calculate the out-of-pocket, per-mile driving cost as the sum of per-mile maintenance, depreciation, and gas costs. I use maintenance and depreciation costs from AAA "'Your Driving Costs" reports, and I calculate per-mile gas costs using fuel prices from the Energy Information Administration and fuel efficiency statistics from the Bureau of Transportation Statistics (AAA, 2008; Bureau of Transportation

Statistics, 2023; U.S. Energy Information Administration, 2024). These calculations produce an average out-of-pocket driving cost of 26.4 cents per-mile. Driving travel costs also include the cost of travel time. I follow standard practice in the recreation demand literature and assume the cost of travel time is one third of each respondent's wage rate.

My flying travel costs include (1) the cost of driving from a respondent's home to the origin airport, (2) the cost of parking at the origin airport, (3) the cost of flying from the origin airport to the destination airport, (4) the cost of renting a car, and (5) the cost of driving from the destination airport to the national park. I take average airport parking and rental car costs from English et al. My airfare and route data come from Table 6 of the Consumer Airfare Report (Office of Aviation Analysis, 2015). I compute travel costs for sixteen origin-destination airport combinations for each respondent-park pair, and I take the minimum travel cost across these sixteen combinations as the flying travel cost for each respondent-park pair. I convert all driving and flying travel costs to 2018 dollars.

Table 1 shows how demographics from the pooled telephone survey sample compare to the general population. Before weighting, survey respondents tend to be wealthier, older, and more educated. After weighting, the sample demographic statistics match the general population along many dimensions, including age, income, race and ethnicity, region of residence, and parental status. The weighted sample remains more highly educated than the general population. Table 1 also shows basic visitation statistics for survey respondents. Respondents made five visits in the past two years, on average, and 62 percent visited at least once. Of the respondents who visited a park in the two years prior to their interview and answered the travel mode question, about 13 percent flew on their last visit.

The Comprehensive Survey of the American Public has a few weaknesses. It does not include any information on visit dates, only that the visits occurred within two years of the interview. Additionally, many less popular national parks are never a "most recent visit," which poses challenges for an estimation based on survey data alone. These weaknesses motivate my use of park-level visitor count data to complement the individual-level surveys.

3.2 Park-level visitor counts

I use monthly park visitor counts from the NPS Visitor Use Statistics database. The counts have a broad temporal and geographic scope, dating back to 1905 for the oldest parks and covering 383 national parks in recent years. Counting procedures vary by park and typically involve Park Rangers at entry booths and/or strategically placed vehicle counters. Many parks use person-per-vehicle multipliers to convert vehicle counts to person counts. Papers analyzing national park visitation commonly use these data (see, for example, Fisichelli et al., 2015; Henrickson & Johnson, 2013; Keiser et al., 2018; Wichman, 2024).

I restrict my analysis to use counts from January 2005 through December 2019, because this period overlaps closely with the individual-level survey data and the American Community Survey microdata I use to calibrate the model. To obtain a visitor count for the historic site composite alternative, $j = J + 1$, I aggregate counts at national parks that were not protected for their natural resources. When determining whether parks are protected for their natural resources, I use NPS designations. For all NPS units in the contiguous United States, the choice set explicitly includes National Parks, National Preserves, National Seashores, National Lakeshores, National Reserves, National Rivers, and National Recreation Areas, as well as all National Monuments over 150 acres. I group all other NPS units (e.g., National Monuments less than 150 acres, Historic Sites, Battlefields, and Memorials) in the historic site composite alternative.

I adjust the raw visitor counts to make them more suitable for recreation demand modeling and more compatible with the individual-level survey data. My adjustment addresses three specific factors: international visitation, non-primary purpose trips, and park re-entry. I drop international visitors, because the survey data include only U.S. residents. I drop non-primary purpose trips, following Lupi et al.'s (2020) recommendation in their best practices paper. I also correct for park re-entry, because visitors incur the full travel costs of reaching a park once per trip, not each time they enter a park. Accounting for these factors requires additional information on international visitation, trip purpose, and re-entry, which I obtain from 109 on-site surveys conducted by the NPS between 1995 and 2019. Appendix E describes this adjustment in more detail.

3.3 Park attribute data

To understand visitor preferences for park attributes, I compile several datasets describing the national parks themselves. My park attribute variables include natural features, such as the presence of coastline, large lakes or reservoirs, and wildlife, as well as parks' elevation and weather conditions. Some park attributes are administrative, such as whether a park charges an entrance fee or has an official "National Park" designation. I also collect information on park trail and road mileage and whether a boat or plane is required for access. Appendix table A1 provides summary statistics for these park attributes.

My congestion measure is the number of domestic, primary purpose trips per day. In other words, I divide the adjusted monthly visitor count described in section 3.2 by the number of days in the month. I opt against using a measure that reflects the density of visitors. Straightforward density-based measures can produce counterintuitive congestion levels, because park sizes vary dramatically. Gateway Arch NP covers only 90 acres, while Death Valley NP encompasses over 3 million. Furthermore, visitors do not distribute themselves uniformly throughout a park. Rather, they often congregate around major attractions—e.g., Old Faithful geyser in Yellowstone.

3.4 ACS microdata

When calibrating the model, I use one-year American Community Survey (ACS) microdata to capture changing demographics in the general population (Ruggles et al., 2021). The ACS includes many of the same demographics as the telephone survey data (see table 1) and reports the county of residence for about 60 percent of its respondents. If a respondent's county of residence is censored, I randomly assign a county of residence based on the population distribution within the Public-Use Microdata Area (PUMA) of residence using the Missouri Census Data Center's geographic correspondence tool (Geocorr). With demographics and counties of residence for all ACS respondents, I calculate travel costs just as I do for telephone survey respondents.

4 Estimation

This section describes an estimation and calibration procedure designed for the model and data described above. I present the procedure in three steps. In step 1, I estimate the parameters from equation 1 and the dissimilarity coefficient using maximum likelihood estimation. In step 2, I calibrate the monthly panel of park effects across the entire 2005 to 2019 analysis period. Finally, in step 3, I unpack the park effects and estimate the park attribute coefficients from equation 3.

4.1 Step 1: Maximum likelihood estimation

I begin by estimating the parameters in equation 1 using maximum likelihood. The goal is to find the parameter values that best explain the visitation information observed in the survey and visitor counts. I specify a three-part likelihood function that incorporates the two pieces of visitation information from the survey data: the location of respondents' most recent visit and the number of visits in the last two years. Because the individual-level survey data do not include the date of respondents' visits, I do not estimate the panel of mean utilities in this first step. Instead, I estimate two cross-sections of park effects, one for each survey period. Thus, I drop the t subscript from the model in the remainder of this subsection.

Using the choice probabilities from equation 2, the likelihood of observing individual i's visitation history is

$$L_i(\beta,\delta,\lambda) = \underbrace{\left(\Pi_{j=0}^{J}\Pi_{m\in\mathcal{M}}P_{ijm}^{y_{ijm}}\right)}_{(1)}\underbrace{(1-P_{i0})^{v_i}}_{(2)}\underbrace{(P_{i0})^{(24-1-v_i)}}_{(3)} \tag{5}$$

where v_i is the number of visits that respondent i takes in the two years preceding the interview, excluding the most recent visit, and y_{ijm} equals one if respondent i visits park j using travel mode m on their most recent visit and zero otherwise. The first term represents the likelihood of individual i's most recent visit. For this visit, I observe the park visited, and for a subset of respondents, I also observe the travel mode. The second term represents the likelihood of all other visits in the two years preceding the interview, and the third term represents the likelihood of all non-visits in the two years preceding the interview.

When maximizing the likelihood function, I constrain the visitation shares predicted by the model to match the visitation shares observed in the visitor count data for the 2008 and 2018 survey periods, separately. I impose these constraints by applying the contraction mapping introduced by Berry (1994) and adapted for the nested logit model by Grigolon and Verboven (2014): $\delta^{n+1} = \delta^n + \lambda\left[\ln(s) - \ln(\hat{s})\right]$. As the optimization routine iterates over values of β and λ, the contraction mapping solves for the unique vector of 2008 and 2018 park effects, δ, that matches the observed visitation shares (s) and the model predicted visitation shares ($\hat{s}$) in each survey period.

Using the contraction mapping has several benefits. First, it allows me to simultaneously combine information from the surveys and the visitor counts. Second, the contraction mapping solves for the park effects, so the optimization routine must search over smaller parameter space, reducing the computational burden. Third, the contraction mapping allows me to estimate park effects for parks that are never a "most recent visit" in the survey data.

By including two cross-sections of park effects, I control for all time-invariant attributes when estimating the other parameters in this step (Murdock, 2006). For example, parks with high travel costs may also exhibit an unobservable sense of remoteness. The cross-section of park effects control for this omitted variable to the extent that it is constant across time. Geographic sorting remains an identification concern (Parsons, 1991). Individuals who value national parks highly may choose to reside nearby in order to reduce their travel costs. If individuals with low travel costs value national parks more highly than those far away, such that they would visit more often even conditional on travel costs, then it will bias my travel cost coefficient estimate away from zero. The travel cost coefficient enters the denominator of all willingness to pay and welfare measures, suggesting that, in turn, these results would be biased towards zero. Bradt (2025) highlights that measurement error in the travel cost variable may also bias estimates. Classical measurement error would bias the travel cost coefficient towards zero and bias welfare measures upward. To gauge the magnitude of bias from geographic sorting and measurement error, Bradt replicates English et al. (2018) using a control function approach that corrects for sorting and classical measurement error. The control function decreases welfare estimates by about 12 percent. Ultimately, even this control function approach cannot reveal how geographic sorting and non-classical measurement error bias my estimates. However, I still view my main surplus estimates as conservative given my inability to capture the value of non-primary purpose trips and my conservative opportunity cost of travel time assumption.[7]

4.2 Step 2: Calibration

The maximum likelihood estimation yields estimates of the parameters from equation 1, including two cross-sections of park effects, one for the 2008 survey period and another for the 2018 period. In this calibration step, I toss out these park effect cross-sections and use the remaining parameter estimates, the annual American Community Survey (ACS) microdata, and the park-level visitor counts to calibrate a monthly panel of park effects from January 2005 through December 2019.

Calibration outside the survey period poses several challenges. First, population demographics may change meaningfully over the fifteen-year analysis period. I account for these demographic changes by calibrating the model using annual ACS microdata samples rather than the survey data. The calibration procedure also requires an assumption on the evolution of the travel cost, travel mode, demographic, and dissimilarity coefficients. I assume that these parameters are constant across the entire fifteen-year calibration period. While this is not necessary, early versions of the analysis allowed travel cost coefficient to vary between the 2008 and 2018 survey periods and recovered similar estimates. Further, Dundas and von Haefen (2020) allow travel cost coefficients to vary annually in their RUM of recreational marine fishing and obtain fairly stable estimates from 2004 through 2009.

Given these assumptions, the calibration procedure proceeds as follows. I begin by predicting choice probabilities for each individual in the ACS microdata.[8] Summing these choice probabilities across individuals generates predicted visitation shares for each park in each month, the same frequency as the observed visitor counts. Beginning with January 2005, I then apply the contraction mapping to obtain the unique vector of park effects that matches the predicted and observed visitation shares. Iteratively applying the contraction mapping month-by-month produces a full panel of park effects through December 2019. The key insight in this step is that I can predict ACS respondents' choice probabilities without observing their recreation choices. These predicted choice probabilities allow me to calibrate park effects outside the survey period.

[7]Section 6.6 tests the sensitivity of my estimates to other plausible opportunity cost of travel time assumptions.

[8]I use a random 1 precent sample of the ACS microdata to reduce the computational burden. In earlier tests, I recovered nearly identical park effects using a 5 percent subsample of the ACS microdata.

4.3 Step 3: Estimating preferences for park attributes

In this third step, I regress the panel of calibrated park effects on park attributes (equation 3). This regression has three important features. First, it is linear. Second, I exploit panel variation using a correlated random effects model. Third, congestion is endogenous, because any unobservable attribute that influences utility will also influence congestion levels. My discussion here focuses on the construction and validity of my instrumental variable. Joshi and Wooldridge (2019) describe the econometric properties of instrumental variables estimation of correlated random effects models in more detail.

I adopt the same congestion instrument as Bayer and Timmins (2007) and Timmins and Murdock (2007). Specifically, the instrument is the model-predicted visitation given only exogenous park attributes:

$$\hat{c}_{jt}^{IV} = \sum_i \sum_m P_{ijmt}(\alpha_{cong} = \nu_{jt} = 0)$$

where P_{ijmt} is defined as in equation 2 but the congestion coefficient, α_{cong}, and park-by-month error-term, ν_{jt}, are set to zero.

Note that the model conditions on a park's observable attributes, so the instrument exploits variation in the quality of each park's choice alternatives to isolate exogenous variation in its congestion levels. Put simply, a park with more appealing alternatives will be less congested, all else equal. Meanwhile, it is plausible to assume a park's mean utility does not depend on attributes at alternative parks except through congestion. For example, the presence of shoreline at Cape Hatteras should not influence the utility a visitor receives from visiting Yellowstone.

In fact, the instrument's identifying variation is more nuanced, because the correlated random effects model exploits within-park-season variation. Therefore, the instrument must predict within-park-season changes in congestion. Of the variables in my model, only weather conditions, travel costs, and demographics change within a season, meaning the instrument's identifying variation comes from changes in these variables. For example, a month with extreme heat at other parks in the southeast would increase predicted congestion at Great Smoky Mountains, conditional on its own attributes.

Generating the instrument requires values for parameters from the first step, β_F, β_{TC}, and λ, as well as α and $\phi_{j,s(t)}$. To obtain reasonable values of α, I estimate equation 3 with congestion omitted. Given these parameter values, I calculate the instrument and estimate equation 3 using instrumental variables.

5 Valuation

After estimating the model, I value the recreational surplus generated by national parks both individually and jointly. To estimate the surplus generated by all parks jointly, I calculate the compensating variation of removing all parks from the choice set. The distributional assumption on the error term leads to a closed-form equation for compensating variation:

$$CV_{it} = \frac{1}{\beta^{TC}} \left[\ln \left(\exp\left(V_{i0t}\right) + \exp\left(V_{i,J+1,t}/\lambda\right)^{\lambda} \right) - \ln \left(\exp\left(V_{i0t}\right) + \left(\sum_{j} \sum_{m} \exp\left(V_{ijmt}/\lambda\right) \right)^{\lambda} \right) \right]$$

Note that I do not remove the historic site composite alternative from the choice set. Therefore, my system-wide valuation estimates only reflect the recreational surplus provided by national parks in the contiguous United States protected for their natural resources.

Valuing an individual park is more complicated than valuing all parks jointly, because inter-site substitution impacts equilibrium congestion levels. My procedure for valuing individual parks follows Timmins and Murdock (2007). First, I solve for equilibrium congestion levels with the complete choice set. Then, I remove one park from the choice set and solve for the new equilibrium congestion levels. The surplus generated by park j for individual i at time t is the welfare loss of removing park j from the choice set:

$$CV_{it} = \frac{1}{\beta_{TC}} \left\{ \ln \left[\exp\left(V_{i0t}\right) + \left(\sum_{k \neq \{0,\ j\}} \sum_{m} \exp\left(V_{ikmt}(s^{*}_{t,1})/\lambda\right) \right)^{\lambda} \right] - \ln \left[\exp\left(V_{i0t}\right) + \left(\sum_{k=1}^{J+1} \sum_{m} \exp\left(V_{ikmt}(s^{*}_{t,0})/\lambda\right) \right)^{\lambda} \right] \right\}$$

where $s^{*}_{t,0}$ and $s^{*}_{t,1}$ represent equilibrium congestion levels before and after park j is removed from the choice set. Summing across individuals yields an estimate of the total recreational surplus generated by park j in month t.

6 Results

6.1 Travel preferences and demographic heterogeneity

Table 2 shows parameter estimates from the first estimation step. The travel cost coefficient is negative and significant, as expected. The "fly" parameter, which captures the preference for flying relative to driving, is also negative. Dividing it by the travel cost coefficient indicates that individuals would be willing to pay \$160 on average to drive rather than fly to their chosen site. The dissimilarity coefficient is between zero and one, implying the nested logit model is consistent with utility-maximizing behavior.

I interact several sociodemographic variables with the outside option. College graduates and individuals with higher household incomes are less likely to choose the outside option, and thus, more likely to visit a national park. Seniors and people with at least one child under 18 are less likely to visit. In terms of racial and ethnic diversity, non-Hispanic Whites are more likely to visit the parks than non-Hispanic Black individuals, Hispanics of any race, and non-Hispanics of other races. These race and ethnicity coefficient estimates align with prior research noting a lack of diversity among national park visitors (Mott, 2016; Xiao et al., 2022).

6.2 Park awesomeness

I now examine the calibrated the panel of park effects. Figure 1 shows how estimated park effects vary throughout the year for two parks, Glacier and Great Smoky Mountains. Glacier's park effects exhibit dramatic seasonal variation, peaking in the summer and collapsing in the winter. Converting the seasonal differences to dollar terms, potential visitors are willing to pay \$935 more on average to visit Glacier in July rather than January. Great Smoky Mountains displays more muted seasonality.

I find that park effects are negative for all parks and all months, which indicates that potential visitors, on average, prefer the no visit alternative to visiting a specific park.[9] In the context of the model, individuals will only choose to visit a park if it has a large, positive error term draw. This finding may be surprising, as many people incur large travel costs to visit the national parks. To interpret this result, note that survey respondents average five national park visits in the two years prior to their interview, meaning they choose the no visit alternative on nineteen of 24 choice occasions. Furthermore, the monthly visitor counts imply over 95 percent of individuals choose the no visit alternative each month. Given these visitation rates, negative park effects are reasonable.

[9]Note that one can easily change the interpretation of the park effects by taking the residual from a regression of the park effects on month-of-sample fixed effects. After this revision, park effects can be interpreted relative to the other parks, rather than the outside option.

By capturing the mean utility the parks provide after controlling for travel costs, the park effects provide a national park awesomeness index. To aid interpretation, I map the raw park effects to a 100-point scale where the maximum park effect over the 2005 to 2019 period scores 100 and the minimum scores a 0. Specifically, I calculate the index for park j in month t as $100 \times \frac{\delta_{jt} - \delta_{MIN}}{\delta_{MAX} - \delta_{MIN}}$, where δ_{MAX} and δ_{MIN} represent the maximum and minimum of all park effects. This ranking offers an attractive alternative to rankings from the popular media, which are typically based on anecdotal experiences or raw visitation counts. Unlike anecdotal rankings, my ranking systematically incorporates the visitation history of the entire U.S. population. Unlike rankings based on raw visitor counts, my ranking controls for travel costs and the availability of substitutes to isolate the appeal of the park itself.

Table 3 shows the ten most awesome parks in March, July, and October 2018. The top tens include many of the most famous national parks, such as Glacier, Grand Canyon, Yellowstone, and Yosemite. Surprisingly, Golden Gate National Recreation Area ranks first in all three months. Golden Gate provides views of the Golden Gate Bridge, beaches, redwood forests, and historic attractions like Alcatraz Island. It also receives 14.6 million visits per year, the most of any park in the sample. The second most highly visited park, Great Smoky Mountains, receives 10.1 million. Yet, Golden Gate may be overrated for several reasons. Although the model controls for the travel costs of accessing each park, it does not control for complementary destinations near a park. Visitors to Golden Gate likely visit other Bay Area attractions on the same trip, while Glacier, for example, has fewer complementary attractions in its vicinity. Furthermore, local residents may visit Golden Gate several times per month, or even several times per week. My modeling assumption that visitors take at most one trip per month may be appropriate for most people and most parks, but it is likely too coarse for local residents. If local residents visit frequently, the model will assume some of these visits come from people living farther away, biasing the park effect upward.

The seasonal variation in park awesomeness is also evident in the top ten rankings. March's top ten includes Grand Canyon, Joshua Tree, Arches, Zion, and Saguaro. These southwestern parks are pleasant in the spring, but they drop out of the top ten in the summer when their weather is hotter than ideal. Conversely, parks with cooler climates and limited peak seasons, like Acadia, Glacier, Mount Rainier, and Rocky Mountain, do not appear in the March top ten but rank highly in July. This seasonal variation also helps to explain why some of the National Recreation Areas and National Seashores rank highly. Glen Canyon, Lake Mead, and Lake Roosevelt are all centered around large reservoirs, making them popular boating destinations in warm months. Meanwhile, Gulf Islands offers warmer temperatures and beaches in March, when many other parks remain colder than ideal.

6.3 Preferences for park attributes

I now regress the panel of park effects on park attributes to determine what attributes attract (or deter) visitors and drive the park rankings. Recall that I address two challenges in this regression. First, I instrument for congestion, because unobservable park attributes influence both congestion levels and the park effects. Second, I recover preferences for both time-varying and time-invariant attributes using a correlated random effects model. For time-varying attributes, coefficient estimates are numerically equivalent to a model with park-by-season-of-the-year fixed effects, while coefficient estimates for time-invariant attributes are identified from cross-sectional variation.

Table 4 displays results from these park attribute regressions. Column 1 omits congestion and includes a parsimonious set of park attributes. Although omitting congestion biases these estimates, their direction is intuitive. Recreators tend to prefer larger parks, parks with wide-ranging elevation, coastal parks, and parks with large lakes or reservoirs. Water resources (coastline, large lakes, or reservoirs) are even more appealing when the temperature is warm, and precipitation reduces willingness to pay. I use these Column 1 estimates to calculate the congestion instrument for subsequent regressions.

Column 2 instruments for congestion. The estimated coefficient on congestion indicates that an increase of 100 visitors per day, 12 percent relative to the mean, decreases willingness to pay by about \$12. This impact is roughly equivalent to having four additional precipitation days, and it is one fifth the willingness to pay for warm weather at parks with water resources. The Anderson-Rubin 95 percent confidence interval, which is robust to weak instruments, indicates that the congestion coefficient estimate is statistically significant at the five percent level. To evaluate the relevance criteria, Appendix table A2 shows results from the first-stage instrumental variables regression. The coefficient estimate for the instrument is positive, as expected, and highly significant. Furthermore, the effective F-statistic from the first-stage regression is slightly greater than 10, the common rule of thumb for identifying weak instruments.

Accounting for congestion impacts other coefficient estimates, especially those on time-varying attributes. For example, failing to control for congestion leads me to underestimate the benefits of warm weather at parks with water resources, because the benefits of warm weather are partially negated by increased crowding. Controlling for the congestion disamenity, therefore, increases the estimate of willingness to pay for warm weather at parks with water resources.

Column 3 adds attributes describing park infrastructure, wildlife, and administrative details. Focusing on the infrastructure variables, visitors are willing to pay slightly more to visit parks with more roads and trails, but much less to visit a park that requires a ferry or sea plane to access. Coefficient estimates on wildlife attributes reveal that visitors prefer parks with bison, elk, and redwoods or sequoia trees, but prefer not to visit parks with grizzly or black bears.

Coefficient estimates for administrative attributes are less intuitive. First, consider preferences for sites with the official "National Park" designation. My estimates suggest that elevating a park from another designation to an official National Park designation actually decreases willingness to pay. This counterintuitive result conflicts with common wisdom and results from Szabó and Ujhelyi (2024), who show that redesignating parks as National Parks increases visitation. My finding can be partially explained by the fact that I observe only three redesignations in the 2005 to 2019 analysis period—Pinnacles, Gateway Arch, and Indiana Dunes. Szabó and Ujhelyi analyze a broader set of fourteen redesignations between 1970 and 2017. Adding this context, my results suggest that redesignations may have heterogeneous impacts and are likely not an all-powerful tool for increasing visitation.

Column 3 also includes an entrance fee indicator and an entrance fee size variable. I find that instituting an entrance fee decreases willingness to pay by about $7, on average. The entrance fee size coefficient estimate, while not statistically significant, is actually positive. This result is counterintuitive, as one would expect that increasing an entrance fee would decrease willingness to pay, all else equal. Two factors help to explain this positive coefficient estimate. First, many visitors purchase annual or lifetime system-wide passes that exempt them from paying park-specific entrance fees. For these visitors, park entrance fee changes do not impact the cost of entry, which pushes the entrance fee size coefficient towards zero. Second, national parks may use entrance fees as a management tool to reduce congestion and recoup costs associated with additional visitation. This behavior could lead to correlation between entrance fees and unobservable park attributes, resembling price endogeneity in an industrial organization setting. Thus, changes in unobservable attributes that increase visitation, induce fee increases, and are not captured by the month-of-sample fixed effects will bias the entrance fee size coefficient upward.

All four park attribute regression models include 5°F temperature bin indicator variables. Figure 2 plots the temperature bin coefficients for models 1 and 2. Both models identify preferences for temperature using within park-and-season-of-year variation. For example, the model explains variation in Yellowstone's June, July, and August park effects using variation in temperature during the same months of the year, after controlling for month-of-sample fixed effects and observed time-varying attributes. Exploiting within-park-season variation controls for omitted attributes constant within a park-season—e.g., some parks close their roads all winter. Omitted attributes that vary within a season and are correlated with temperature still pose threats to identification.

Visiting a park provides the most surplus at temperatures between 65°F and 80°F. Willingness to pay decreases sharply as temperatures become colder. Relative to the ideal temperature of 70°F, visiting when the temperature is 30°F reduces willingness to pay by nearly $400. Hot temperatures deter visitors less dramatically. Visiting when the temperature is 95°F reduces willingness to pay by around $120. Failing to control for congestion underestimates willingness to pay by 34 percent, on average. Once again, the direction of this bias is expected, because the disutility caused by cold or heat is partially offset by the appeal of lower congestion levels.

Before proceeding, note that park attribute coefficients have a limited impact on my valuation results. Only one park attribute coefficient, the congestion coefficient, influences the individual park surplus results, and none affect the joint surplus values. While it is possible that bias affecting the entrance fee size or National Park designation estimates spills over to the congestion coefficient, such bias appears minor given the stability of the congestion coefficient across models.

6.4 Valuing individual parks

Given the preference parameter estimates, I now calculate the recreational surplus produced by individual parks. Table 5 shows the ten parks that generated the most recreational surplus in 2018. I provide two recreational surplus estimates for each park. The preferred estimate accounts for congestion by solving for new equilibrium congestion levels after a park has been removed from the choice set. The second estimate ignores the impact of congestion spillovers by holding congestion levels fixed at the initial equilibrium. Thus, the difference between the "Accounting for congestion" column and the "Ignoring congestion" column reveals the portion of a park's recreational surplus that comes from decreasing congestion at other parks in the system. For example, Great Smoky Mountains generates $489 million of recreation surplus and $79 million of this total comes from decreasing congestion at other parks. Across the sample of parks, accounting for congestion spillovers increases surplus estimates by 17 to 44 percent.

This total surplus ranking differs from the awesomeness rankings for two reasons. First, I sum surplus across all months in the year, rather than examining surplus at each month separately. Second, the total surplus a park generates depends on its travel costs, whereas the awesomeness index controls for travel costs. All else equal, a park with low travel costs generates more surplus than a park with high travel costs. These two factors—annual aggregation and location—help explain the recreational surplus results in table 5. Golden Gate RA is conveniently located for Bay Area residents, and its climate remains favorable throughout the year. These features, along with Golden Gate's high awesomeness ranking, help to explain why it provides three times more surplus than the next most valuable park. Gateway RA, Great Smoky Mountains, and Delaware River Water Gap RA are also conveniently located, and they rank among the most valuable parks even though they do not appear in the awesomeness top 10. On the other hand, Yellowstone and Glacier, two parks with high travel costs and limited peak seasons, generate the 15th and 30th most annual surplus, despite ranking 2nd and 3rd in the July awesomeness ranking.

These park surplus values are typically much larger than park budgets. A park's recreational surplus exceeds its budget at all but three parks in my sample.[10] On average, parks generate \$80 million of recreational surplus annually, almost fifteen times the average budget of \$5.4 million. Arches has one of the highest surplus-to-budget ratios, generating \$143 million of surplus with a \$2 million budget. While simply comparing a park's recreational surplus to its budget should not be conflated with a comprehensive benefit-cost analysis, it is clear that the vast majority of parks provide recreational benefits far greater than their operating costs.

To gauge the plausibility of my surplus estimates, I compare my estimates for June 2005 to Parsons et al.'s (2021) surplus estimates for national parks in the Southwest in June 2002.[11] This comparison suggests that my estimates are relatively conservative. The largest discrepancies between our estimates come at Grand Canyon and Zion. I estimate the surplus generated by Grand Canyon in June 2005 to be \$19 million versus their \$52–\$73 million and by Zion to be \$7 million versus their \$28–\$41 million. These large differences are likely driven by non-primary purpose trips. In the summer, only 20 percent of Grand Canyon's visits and 17 percent of Zion's visits are primary purpose trips. These are among the lowest primary purpose trip rates of any park; the average primary purpose trip rate is 54 percent. Recall that I drop primary purpose trips, following standard practice in the recreation demand literature, essentially assigning them zero value. Parsons et al. account for non-primary purpose trips by allowing visitors to select multiple sites using an innovative portfolio model. Unfortunately, estimating a model like theirs is not feasible in my setting, as it requires observing every park a person visits on their trip. My estimates are more similar for parks with higher shares of primary purpose trips, including Bryce Canyon (\$8 million versus their \$10–\$15 million), Canyonlands (\$2 million versus their \$3–\$4 million), Mesa Verde (\$3 million versus their \$6–\$8 million), and Petrified Forest (\$5 million versus their \$5–\$8 million). These smaller differences could also be explained by differences in Parsons et al.'s and my travel cost calculations. Unlike my travel costs, Parsons et al.'s include lodging, food, and time costs incurred while at the park, in addition to the costs of traveling to the park.

6.5 Valuing the National Park System

Finally, I estimate the joint recreational surplus generated by all 140 parks in my sample. These parks produced \$150 billion of surplus between 2005 and 2019, roughly \$10 billion per year, with a maximum of \$11.7 billion in 2019. The magnitude of these annual surplus estimates is similar to other economic

[10]Several parks share budgets—e.g., Sequoia and King's Canyon. For these parks, I sum the surplus of all parks in the budget group and compare it to the total budget for the group. Surplus exceeds the budget at 133 of the 136 budget groups.

[11]I take estimates from Table 15 of Parsons et al. and multiply by 1.4 to convert 2002 dollars to 2018 dollars. This conversion allows for a direct comparison to my estimates, which are measured in 2018 dollars.

impacts monitored by the NPS. For 2019, the NPS estimates that visitors spent $13 billion in communities surrounding the parks in my sample. This spending supported $6 billion in labor income, added $10 billion to GDP, and supported $16 billion of total economic output (Cullinane Thomas & Koontz, 2020).[12] Adding recreational surplus to these other metrics increases estimated economic contributions by 26 percent.

Figure 3a tracks recreational surplus over time and reveals that annual surplus grew $2.8 billion, or 31 percent, between 2005 and 2019. Surplus grew slowly until 2013 but has surged since, increasing $2.3 billion between 2013 and 2019. Figure 3b shows which variables contribute to this increase in surplus. I focus on three sets of variables: (1) weather variables (temperature, precipitation, and the temperature-water resource interaction), (2) unobserved park attributes captured by the month-of-sample fixed effects and residuals from the park attribute regression, and (3) demographics and travel costs. For each set of variables individually, I predict the welfare change that would have occurred if the variables were held fixed at 2005 levels. The difference between the observed welfare and the welfare when the variables are fixed reveals how much changes in those variables contribute to the observed change in surplus. Figure 3b plots these differences. It shows that unobserved park attributes drive most of the increase in surplus. Allowing unobserved attributes to vary, rather than holding them fixed, increases surplus by over $1.5 billion in 2019. Mirroring the abrupt increase in total surplus from figure 3a, unobserved attributes become much more appealing starting in 2013. This timing corresponds with the rise of social media, which Wichman (2024) connects to increased park visitation, as well as the NPS Centennial (2016) and the "Find your Park" marketing campaign (2015-2016).

Changes in demographics and travel costs also contribute to the increase in surplus. Fixing these variables would reduce the increase in surplus by about $750 million. The importance of demographics and travel costs could be driven by rising incomes, population growth, or westward migration, which brings more people closer to the most awesome parks. Weather conditions contribute little to the increase in surplus. Yet, given the relatively strong preferences for temperature and the growing impact of climate change, it is possible that weather conditions will impact recreational surplus more meaningfully in the future.

6.6 Sensitivity checks

I execute several checks to gauge the sensitivity of the joint surplus estimate. The first set of sensitivity checks alter the opportunity cost of time assumption used to calculate travel costs. While my main results make a commonly-used assumption that the opportunity cost of travel time is one third of an individual's wage rate, recent work suggests the opportunity cost of travel time could be larger (Fezzi et al., 2014). Assuming the opportunity cost of time is one half the wage rate, I estimate the joint surplus generated

[12] Cullinane Thomas and Koontz's Appendix A provides economic contributions by park, which allows me to calculate the economic contributions from parks in my sample.

by the 140 parks in my sample at $14 billion in 2019, a 21 percent increase relative to my main estimate. Lloyd-Smith et al. (2019) find that the average opportunity cost of travel time is even greater, around 90 percent of an individual's wage rate. Under this assumption, I estimate joint surplus at $20.6 billion. Thus, my opportunity cost of travel time assumption yields conservative estimates relative to these alternatives.

The second set of sensitivity checks adopt different visitor count adjustments. Recall that my main results depend on a visitor count adjustment that converts the raw counts to estimates of primary purpose trips using park-specific re-entry rates and primary purpose trip rates from on-site survey data. As an alternative, I use a "simple visitor count adjustment" that adjusts all park visitor counts using the same re-entry and primary purpose trip rates—the average re-entry and primary purpose trip rates across all the on-site surveys. This simple adjustment decreases my joint surplus estimate by 16 percent. I also estimate surplus without adjusting the visitor counts. This check is unrealistic, because it treats all park entries as primary purpose home-to-park trips. However, it does help to bound my estimates and gauge the impact of the visitor count adjustment. Using the raw visitor counts produces a 2019 joint surplus estimate of $36 billion, 210 percent larger than my main estimate.

The final sensitivity check estimates the model using the 2008 survey and the visitor counts but not the 2018 survey. This check serves two purposes. First, it speaks to how measurement error in the travel cost variable might impact my estimates. Recall that I observe home locations less precisely in the 2018 survey. Second, it indicates whether changes in preferences over time might influence my estimates. These two factors have little combined impact on my joint surplus estimate. Estimating the model without the 2018 survey increases the joint surplus estimate by just 1.4 percent.

7 Conclusion

This paper values the recreational surplus generated by 140 national parks between 2005 and 2019. Jointly, these parks provide $10 billion of recreational surplus per year. Annual surplus grew 31 percent over the analysis period and peaked at almost $12 billion in 2019, more than four times the National Park Service's 2019 operating budget. In producing these valuation estimates, I also recover preferences for parks and their attributes. My model controls for travel costs to produce a national park *awesomeness* index and reveals that visitors tend to prefer parks with coastline and large waterbodies, wide-ranging elevation, bison, elk, redwood forests, favorable temperatures, and lower congestion.

These findings address a longstanding gap in the documented benefits of the U.S. National Park System. The National Park Service's current efforts to value the parks' economic contributions focus on visitor spending and local economic impacts. Attempts to value visitors' recreational surplus have focused on smaller sets of parks or specific points in time. By combining survey data with the National Park Service's monthly visitor counts, I create a unified framework to value recreational surplus across the system and across time. My analysis highlights that U.S. national parks provide substantial non-market benefits and underscores the National Park Service's continued success in preserving the country's most treasured resources for the enjoyment of present and future generations.

Table 1: Survey Respondent Demographics

Variable	Unweighted	Weighted	2010 ACS
Age			
18-29	11.8	21.3	20.4
30-39	13.5	16.3	17.4
40-49	16.7	16.7	18.9
50-59	24.1	20.8	18.1
60-69	18.5	14.3	12.8
70+	15.1	10.4	12.1
Household income			
Less than $10,000	4.5	6.0	5.5
$10,000 to $25,000	9.5	11.0	13.7
$25,000 to $50,000	20.3	23.2	23.9
$50,000 to $75,000	20.8	22.2	19.2
$75,000 to $100,000	17.3	15.9	13.6
$100,000 to $150,000	15.4	13.1	13.9
Greater than $150,000	12.0	8.3	9.9
Other socioeconomic variables			
College graduate	50.8	37.3	26.2
Has child	29.7	35.3	38.8
White, non-Hispanic	74.3	67.5	67.1
Black	8.5	10.8	11.6
Hispanic	7.3	13.3	14.1
NPS region of residence			
Alaska	14.1	0.2	0.2
DC only	11.6	0.2	0.2
Intermountain	14.9	14.9	14.6
Midwest	14.6	22.9	22.5
Northeast	15.1	22.9	23.7
Pacific	14.8	16.8	17.1
Southeast	14.7	21.8	21.4
Visitation statistics			
Visited in past 2 years	67.9	61.7	
Avg number of visits	9.2	4.7	
Flew (Subsample N = 1,537)	13.5	12.6	
Sample size	6,762	6,762	

Note: The table shows the share of respondents in various demographic groups for the pooled 2008-2009 and 2018 Comprehensive Survey of the American Public (CSAP) survey and the 2010 American Community Survey (ACS). Weights are included in the survey and match survey statistics to Census averages. Thus, the weighted variable means align closely with Census means.

Table 2: Step 1 maximum likelihood estimates

Variable	Estimate	Std. Error
Fly	-0.275	0.0041
Travel cost ($100)	-0.171	0.0006
Interacted with outside option		
$10k < income < $25k	0.065	0.0501
$25k < income < $50k	-0.311	0.0340
$50k < income < $75k	-0.465	0.0314
$75k < income < $100k	-0.543	0.0325
$100k < income < $150k	-0.758	0.0290
Income > $150k	-0.768	0.0306
Has kid(s)	0.048	0.0173
Senior	0.495	0.0371
White, non-Hispanic	-0.180	0.0273
Black, non-Hispanic	0.363	0.0336
Hispanic	0.072	0.0324
College graduate	-0.304	0.0108
Dissimilarity coefficient	0.346	0.0002

Note: The table reports estimates from the step 1 maximum likelihood estimation. For socioeconomic variables interacted with the outside option, positive estimates indicate that the group is more likely to select the outside option and less likely to visit a national park—e.g., conditional on travel costs and other demographics, seniors are more likely to select the outside option than other age groups. The Hispanic category contains Hispanic respondents of any race. "Other race, non-Hispanic" is the omitted race and ethnicity category.

Table 3: Park Awesomeness Index – Top 10

March		July		October	
Golden Gate RA	98.8	Golden Gate RA	96.2	Golden Gate RA	95.3
Lake Mead RA	90.6	Yellowstone	95.1	Grand Canyon	86.6
Grand Canyon	90.1	Glacier	94.8	Yosemite	86.4
Joshua Tree	87.6	Mount Rainier	94.7	Lake Mead RA	85.6
Arches	85.4	Lake Roosevelt RA	94.2	Mount Rainier	84.9
Gulf Islands SS	84.7	Olympic	92.2	Olympic	84.9
Yosemite	84.4	Glen Canyon RA	90.7	Bryce Canyon	84.2
Zion	84.4	Rocky Mountain	90.5	Acadia	83.9
Point Reyes SS	83.8	Acadia	89.3	Yellowstone	83.7
Saguaro	83.8	Lake Mead RA	89.0	Glen Canyon RA	83.6

Note: The table shows the top 10 most awesome parks for March, July, and October of 2018. The park rating rescales the raw park effects on a 100-point scale where the maximum park effect from January 2005 to December 2019 scores 100 and the minimum park effect scores 0.

Table 4: Preferences for park attributes

	(1)		(2)		(3)		(4)	
Variable	Estimate	WTP	Estimate	WTP	Estimate	WTP	Estimate	WTP
Visits per day (100s)			-0.020	-11.6	-0.020	-11.7	-0.020	-11.7
			(0.008)		(0.008)		(0.008)	
			[-0.0494, -0.0073]		[-0.0502, -0.0073]		[-0.0515, -0.0061]	
Size Q2	0.343	201.0	0.300	175.5	0.331	194.2		
	(0.124)		(0.170)		(0.147)			
Size Q3	0.442	258.9	0.469	274.6	0.524	307.1		
	(0.123)		(0.164)		(0.187)			
Size Q4	0.650	380.8	0.614	359.5	0.415	243.3		
	(0.136)		(0.191)		(0.197)			
Elevation range Q2	0.173	101.4	0.129	75.7	0.102	59.9		
	(0.138)		(0.173)		(0.163)			
Elevation range Q3	0.266	156.0	0.324	189.9	0.201	117.5		
	(0.127)		(0.182)		(0.167)			
Elevation range Q4	0.349	204.2	0.381	223.2	0.061	35.8		
	(0.127)		(0.169)		(0.190)			
Coastal	0.310	181.4	0.481	282.0	0.406	238.1		
	(0.147)		(0.274)		(0.241)			
Large lake or reservoir	0.281	164.7	0.318	186.5	0.245	143.8		
	(0.104)		(0.157)		(0.171)			
Water x warm (> 70F)	0.048	27.9	0.107	62.8	0.109	63.6	0.109	63.6
	(0.024)		(0.038)		(0.039)		(0.039)	
Precipitation days	-0.003	-1.9	-0.005	-2.8	-0.005	-2.8	-0.005	-2.8
	(0.001)		(0.002)		(0.002)		(0.002)	
Road miles (10 miles)					0.002	1.0		
					(0.002)			
Trail miles (10 miles)					0.002	1.3		
					(0.004)			
Requires ferry					-0.768	-450.0		
					(0.355)			
Bison					0.101	59.0		
					(0.215)			
Elk					0.082	48.0		
					(0.113)			
Bears					-0.250	-146.5		
					(0.125)			
Redwoods or sequoias					0.904	529.7		
					(0.407)			
National Park designation					-0.077	-45.0	-0.077	-45.0
					(0.022)		(0.022)	
Charges fee					-0.012	-7.1	-0.012	-7.1
					(0.028)		(0.028)	
Charges fee x fee					0.005	2.8	0.005	2.8
					(0.003)		(0.003)	
Mean visits per day (100s)			0.014	8.5	0.019	11.4		
			(0.010)		(0.010)			
Mean water x warm	-0.117	-68.3	-0.218	-127.5	-0.166	-97.3		
	(0.095)		(0.183)		(0.147)			
Mean precipitation days	-0.007	-4.1	-0.012	-7.2	0.007	4.2		
	(0.012)		(0.021)		(0.017)			
Mean NP designation					0.009	5.1		
					(0.184)			
Mean charges fee					0.017	10.2		
					(0.173)			
Mean charges fee x fee					0.027	16.0		
					(0.013)			
Observations	24,970		24,970		24,970		24,970	
Effective F-stat			12.0		12.1		10.0	
Month of sample FE	Yes		Yes		Yes		Yes	
Park-by-season-of-year FE							Yes	
Temperature Controls	Yes		Yes		Yes		Yes	

Note: The table presents estimates from a regression of park effects on park attributes. Standard errors clustered at the park-level are in parentheses. Columns 2, 3, and 4 instrument for congestion and report the Olea and Pflueger (2013) effective F-statistic and Anderson-Rubin 95% confidence intervals in brackets. Comparing columns 3 and 4 confirms that the correlated random effects model yields identical estimates to a model with park-by-season fixed effects. WTP is calculated by dividing each coefficient estimate by the travel cost coefficient from table 2 and rescaling to dollars. Table A1 contains variable definitions and descriptive statistics for the park attributes.

Table 5: Total surplus generated by the most valuable parks of 2018 (Millions of 2018$)

Park	Accounting for congestion	Ignoring congestion
Golden Gate RA	1,709.6	1,405.9
Gateway RA	491.7	419.1
Great Smoky Mtns	489.1	410.1
Lake Mead RA	467.1	352.8
Delaware River Water Gap RA	406.8	341.7
Grand Canyon	332.5	250.1
Gulf Islands SS	287.5	238.8
Yosemite	264.7	188.1
Rocky Mountain	258.6	204.5
Mount Rainier	213.0	160.6

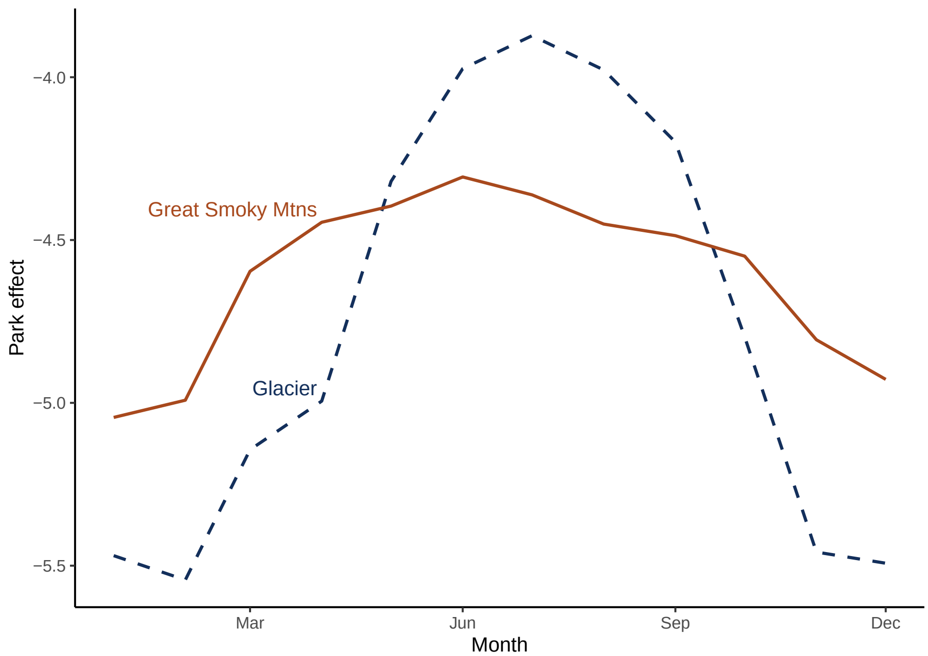
Note: The table shows the ten parks that generated the most total recreational surplus in 2018. The main estimates account for congestion by finding a new congestion equilibrium after a park is removed from the choice set. The "ignoring congestion" column removes parks from the choice set but assumes congestion remains unchanged at substitute sites.

Table 6: Joint recreational surplus sensitivity checks

Sensitivity check	Surplus (billion)	Percent difference
Main result	\$11.7	
Opportunity cost of time = 50% wage rate	\$14.2	20.8%
Opportunity cost of time = 90% wage rate	\$20.6	75.9%
No visitor count adjustment	\$36.3	209.6%
Simple visitor count adjustment	\$ 9.9	-15.8%
Drop 2018 survey	\$11.9	1.4%

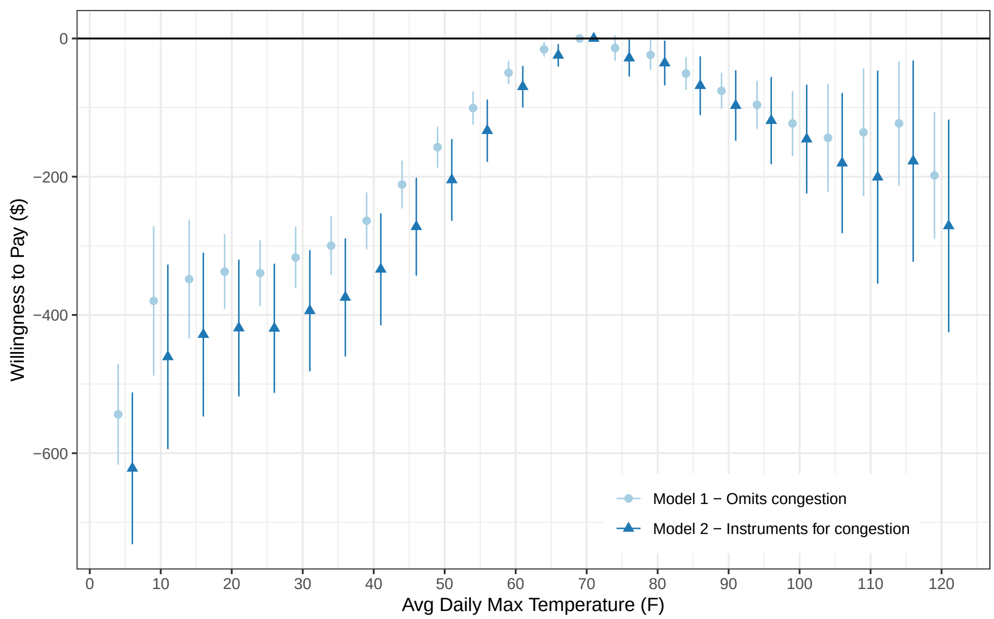
Note: The table shows the joint recreational surplus generated by the 140 parks in my sample during 2019 under alternative assumptions. The main results assumes the opportunity cost of time is one third a respondent's wage rate and adjusts the visitor count data using park-specific data and predictions for primary purpose trip rates and re-entry rates. The "Simple visitor count adjustment" assumption adjusts each park's visitor counts using the average primary purpose trip rate and re-entry rate across all parks. The "Percent difference" column shows the difference between the sensitivity check estimate and the main estimate.

Figure 1: Park effects vary month-to-month



Note: The figure plots the park effects for Great Smoky Mountains NP (solid) and Glacier NP (dashed) in 2018.

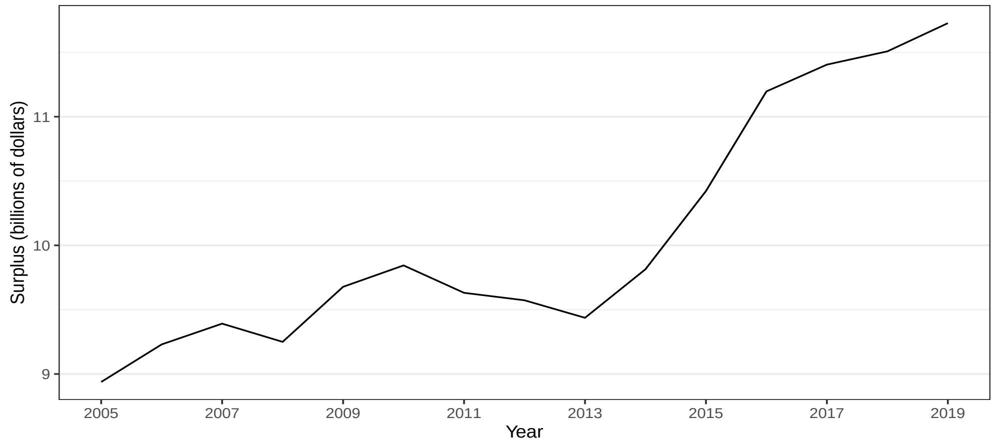
Figure 2: Cold decreases WTP more than heat



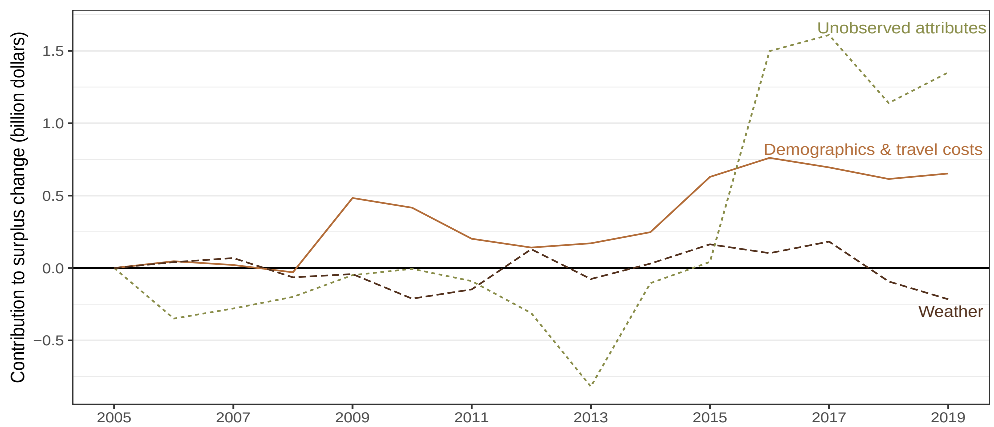
Note: The figure plots coefficient estimates for each 5°F temperature bin. Light blue circles represent point estimates from model 1 of table 4, which omits congestion. Dark blue triangles circles represent point estimates from model 2 of table 4, which is identical except that it instruments for congestion. Vertical lines indicate 95% confidence intervals. The y-axis converts point estimates into willingness to pay terms by dividing by the travel cost coefficient.

Figure 3: Recreational surplus produced by the National Park System

(a) Surplus increased 31 percent between 2005 and 2019



(b) Unobserved attributes drive the increase in surplus



Note: Panel (a) shows the annual recreational surplus generated by the 140 national parks in my sample, roughly all national parks protected for their natural significance. Panel (b) plots the difference between the observed increase in surplus and the change in surplus that would have occurred if a set of variables were held fixed at 2005 levels. For example, in 2019, welfare given observed demographics and travel costs is about $750 million larger than welfare given 2005 demographics and travel costs.

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A Supplementary Tables and Figures

Table A1: Descriptive statistics for park attributes

Variable	Description	Mean	SD	Min	Max
Elevation range (ft)	Elevation range (ft)	2,569.1	2,926.9	10.5	13,606.4
Road miles	Miles of road	155.8	279.1	0.0	2,106.0
Trail miles	Miles of hiking trails	107.1	191.9	0.0	1,133.2
Coastal	Coastal – Atlantic, Pacific, Gulf, or Great Lakes	0.21	0.41	0.0	1.0
Large lake or reservoir	Contains inland lake or reservoir larger than 40 acres (and not coastal)	0.26	0.44	0.0	1.0
Requires ferry	Requires ferry or seaplane to access	0.04	0.20	0.0	1.0
Bison	Bison present	0.06	0.23	0.0	1.0
Elk	Elk present	0.25	0.43	0.0	1.0
Bears	Grizzly or black bears present	0.35	0.48	0.0	1.0
Redwoods or sequoias	Contains redwoods or giant sequoias	0.05	0.22	0.0	1.0
Visits per day	Visits per day	3,003.4	6,036.8	0.0	52,036.5
Average daily high temperature (F)	Average daily high temperature (F)	66.6	18.7	7.6	121.3
Precipitation days	Number of days with precipitation	4.6	3.8	0.0	28.0
Park size (thousands of acres)	Park acreage (thousands)	204.6	444.8	0.1	3,408.4
National Park designation	Officially designated as a National Park	0.34	0.47	0.0	1.0
Water x warm (> 70F)	Coastal or contains reservoir/lake and average daily high temperature > 70F	0.16	0.36	0.0	1.0
Charges fee	Charges entrance fee	0.50	0.50	0.0	1.0
Charges fee x fee ($)	Entrance fee (conditional on charging fee)	12.8	8.4	3.0	35.0

Table A1 presents descriptive statistics for the park attributes included in the park attribute regressions. Elevation range varies substantially across parks. Dry Tortugas National Park has an elevation range of only 10 feet, while Mount Rainier National Park has an elevation range of over 13,000 feet. The park attribute regressions include each park's elevation range quartile. Shenandoah National Park has the largest elevation range in the third quartile (3,476 feet). Devil's Tower National Monument has the largest elevation range in the second quartile (1,277 feet), and Missouri National Recreational River has the largest elevation range in the first quartile (471 feet). Several attributes are very uncommon, which makes identifying preferences for these attributes challenging. Only six of the 140 parks in the sample require a ferry or seaplane to access (Apostle Islands National Lakeshore, Channel Islands National Park, Cumberland Island National Seashore, Dry Tortugas National Park, Gulf Island National Seashore, and Isle Royale National Park). Seven parks in the sample contain redwoods or giant sequoias (Golden Gate National Recreation Area, Kings Canyon National Park, Muir Woods National Monument, Point Reyes National Seashore, Redwood National Park, Sequoia National Park, and Yosemite National Park), and eight parks contain bison (Badlands National Park, Chickasaw National Recreation Area, Grand Canyon National Park, Grand Teton National Park, Tallgrass Prairie National Preserve, Theodore Roosevelt National Park, Wind Cave National Park, and Yellowstone National Park).

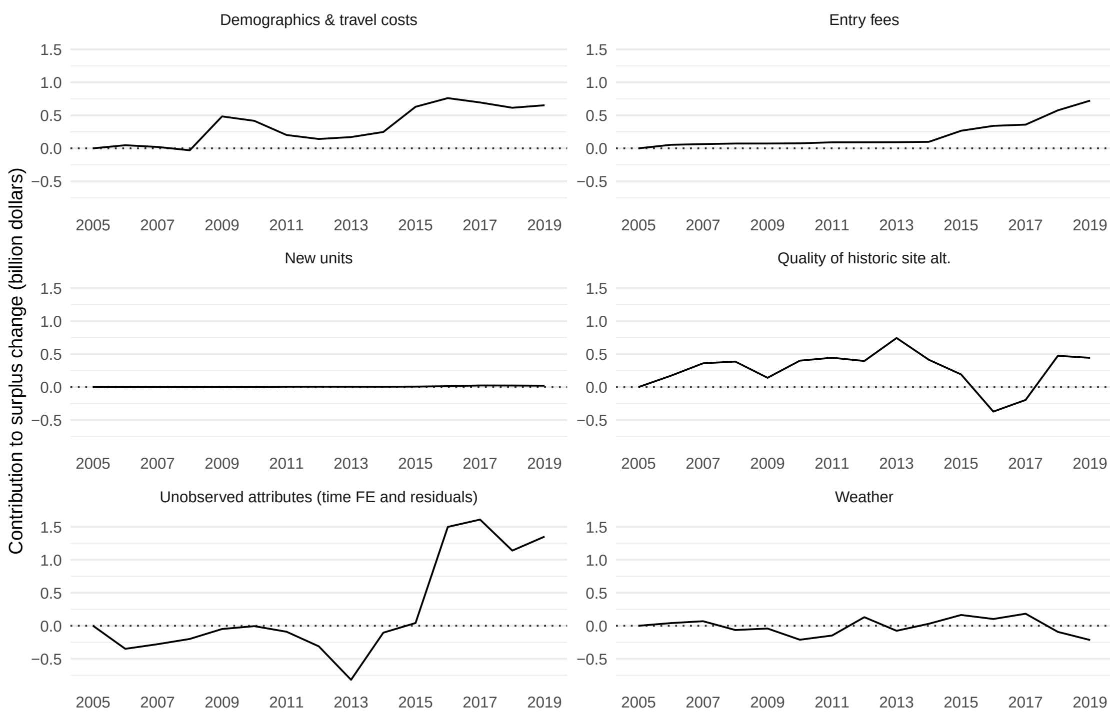
Table A2: Instrumental variables regression first stage estimates

Dependent Variable:	Congestion (hundreds of visitors per day)		
Model:	(1)	(2)	(3)
Variables			
Congestion IV	0.3237*** (0.0933)	0.3224*** (0.0926)	0.3224*** (0.0925)
Size Q2	-2.486 (3.534)	-0.8279 (2.674)	
Size Q3	0.9140 (2.701)	3.427 (3.652)	
Size Q4	-3.002 (3.675)	-3.304 (3.360)	
Elevation range Q2	-2.380 (2.390)	-3.098 (2.483)	
Elevation range Q3	2.627 (4.266)	0.3731 (4.057)	
Elevation range Q4	1.475 (3.072)	-1.924 (3.655)	
Coastal	8.254 (8.558)	4.005 (6.840)	
Contains large lake or reservoir	1.390 (3.658)	-1.979 (3.542)	
Contains water x warm (> 70F)	2.073*** (0.6205)	2.105*** (0.6292)	2.105*** (0.6283)
Precipitation days	-0.0591 (0.0495)	-0.0564 (0.0494)	-0.0564 (0.0493)
Road miles (10 miles)		0.0156 (0.0472)	
Trail miles (10 miles)		0.0805 (0.1006)	
Requires ferry		-5.077 (5.629)	
Bison		4.672 (3.912)	
Elk		-2.210 (2.697)	
Bears		-4.295 (3.446)	
Redwoods or Sequoias		22.01 (14.85)	
National Park designation		-1.594*** (0.4863)	-1.594*** (0.4856)
Charges fee		-0.5399 (0.6037)	-0.5399 (0.6029)
Charges fee x fee		0.1568*** (0.0453)	0.1568*** (0.0452)
Mean IV	0.5043** (0.1941)	0.5217*** (0.1724)	
Mean contains water x warm	-4.440 (5.472)	-3.362 (4.737)	
Mean precipitation days	-0.3519 (0.5824)	-0.0996 (0.4434)	
Mean NP designation		-4.049 (4.516)	
Mean charges fee		-4.078 (3.385)	
Mean charges fee x fee		0.4956** (0.2374)	
Fixed-effects			
Time	Yes	Yes	Yes
Unit-season-of-the-year			Yes
Fit statistics			
Observations	24,970	24,970	24,970

Clustered (Unit) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table contains estimates from the instrumental variables first stage regression corresponding to columns (2), (3), and (4) of table 4. All models include temperature controls and their unit-by-season-of-the-year means.

Figure A1: A more-detailed surplus change decomposition



This figure decomposes the change in recreational surplus provided by the National Park System using a wider variety of variables than figure 3b. The entry fee panel should be interpreted with caution. It suggests that the rising entrance fees over the analysis period have increased the recreational surplus, but this result is driven by my counterintuitive positive coefficient on entrance fee size. The "Quality of historic site alt." panel has a slightly complicated interpretation. Because I value only naturally significant parks, a higher quality historic site alternative actually decreases the surplus provided by naturally significant parks. Thus, positive values in the "Quality of historic site alt." panel actually indicate that the mean utility provided by the outside option had decreased relative to 2005 levels.

B Proving a unique congestion equilibrium exists

Proposition 1 *If congestion negatively impacts utility, then for each choice occasion t, there exists a unique vector of congestion levels, $\mathbf{cong_{\cdot t}}^* = (cong^*_{1t}, ..., cong^*_{Jt})$ such that:*

$$\mathbf{cong_{\cdot t}}^* = \sum_i \sum_{m \in \mathcal{M}} P_{ijmt}(\mathbf{cong_{\cdot t}}^*)$$

where P_{ijmt} is defined as in Section 2. Thus, $\mathbf{cong_{\cdot t}}^*$ represents the unique congestion equilibrium.

B.1 Set up

For a class of RUMs, Bayer and Timmins (2005) prove that a unique equilibrium exists when congestion is a disamenity. The proof presented below closely resembles theirs. However, my model differs from their class of models in two ways. First, the utility provided by two alternatives—the outside option, $j = 0$, and the historic site composite alternative, $j = J + 1$—does not depend on congestion levels. Thus, my definition of equilibrium only specifies congestion levels at parks explicitly included in the choice set. Second, congestion at one park influences the utility provided by two choice alternatives, because visitors can visit a park either by driving or flying.

Before proceeding, define several functions. Define a function $\widetilde{P}_{ijmt}(s_{\cdot t}) = P_{ijmt}(\mathbf{cong_{\cdot t}})$ where $s_{\cdot t} = \frac{1}{N}\mathbf{cong_{\cdot t}}$. This function, $\widetilde{P}_{ijmt}$, writes the choice probabilities as functions of visitation shares, $s_{\cdot t}$, rather than congestion levels. Define model-predicted congestion levels as $g_j(\mathbf{cong_{\cdot t}}) = \sum_i P_{ij\cdot t}(\mathbf{cong_{\cdot t}})$ where $P_{ij\cdot t} = \sum_{m \in \mathcal{M}} P_{ijmt}$ and a vector equivalent describing model-predicted congestion at parks $j \in \{1, ..., J\}$ as $g(\mathbf{cong_{\cdot t}})$. Define the difference in observed and model-predicted congestion as $\Psi(\mathbf{cong_t}) = \mathbf{cong_t} - g(\mathbf{cong_t})$. Finally, define $\Psi^{(1)}$ to be the matrix of partial derivatives of Ψ. For any j, $\Psi^{(1)}_{jj} = 1 - \frac{\partial g_j}{\partial \mathbf{c}ong_j}$ and for any j and $k \neq j$, $\Psi^{(1)}_{jk} = -\frac{\partial g_j}{\partial \mathbf{c}ong_k}$.

It is also helpful to note that the partial derivatives of choice probabilities with respect to congestion at the same park j and at another park k are given by:

- $\frac{\partial P_{ijm}}{\partial c_j} = \frac{\alpha}{\lambda} P_{ijm}[1 - (1-\lambda)P_{ij\cdot|trip} - \lambda P_{ij\cdot}]$ where $P_{ij\cdot|trip}$ denotes the probability that individual i selects park j conditional on taking a trip
- $\frac{\partial P_{ijm}}{\partial c_k} = -\frac{\alpha}{\lambda} P_{ik\cdot}[\lambda P_{ijm} + (1-\lambda)P_{ijm|trip}]$

B.2 Existence

The function defining model-predicted visitation shares, $\frac{1}{N}\sum_i \sum_{m \in \mathcal{M}} \widetilde{P}_{ijmt}(s_{\cdot t})$, is continuous and maps from the closed and bounded interval $[0, 1]^J$ to itself. Therefore, Brouwer's Fixed Point Theorem implies there exist visitation shares, $s^*_{\cdot t}$ such that $s^*_{\cdot t} = \frac{1}{N}\sum_i \sum_{m\in\mathcal{M}} \widetilde{P}_{ijmt}\left(s^*_{\cdot t}\right)$. Multiplying both sides by N and substituting P_{ijmt} for $\widetilde{P}_{ijmt}$, the existence of $s^*_{\cdot t}$ implies the existence of $\mathbf{cong_{\cdot t}}^*$.

B.3 Uniqueness

There is a unique congestion equilibrium if the matrix of partial derivatives, $\Psi^{(1)}$, has a positive dominant diagonal. Thus, it suffices to show that for any j, $\Psi^{(1)}_{jj} > \sum_{k\neq j} |\Psi^{(1)}_{jk}|$.

Using the partial derivatives to expand $\Psi^{(1)}_{jj}$ and $\Psi^{(1)}_{jk}$, it suffices to show:

$$1 - \frac{\alpha}{\lambda}\sum_i P_{ij\cdot}[1-(1-\lambda)P_{ij\cdot|trip} - \lambda P_{ij\cdot}] > \sum_{k\notin\{0,\ j,\ J+1\}} \sum_i |-\frac{\alpha}{\lambda}P_{ik\cdot}[\lambda P_{ij\cdot} + (1-\lambda)P_{ij\cdot|trip}]\ |$$

Note that we can remove the absolute value from the right-hand side, because $\alpha < 0$ when congestion decreases utility and the dissimilarity coefficient, λ, lies in the unit interval. This sign is intuitive, because increased congestion at one park increases the probability of choosing the other parks.

Re-arranging terms, the right-hand side can be written as:

$$-\frac{\alpha}{\lambda}\sum_i [\lambda P_{ij\cdot} + (1-\lambda)P_{ij\cdot|trip}] \sum_{k\notin\{0,\ j,\ J+1\}} P_{ik\cdot}$$

Using the fact that $\sum_{k\notin\{0,\ j,\ J+1\}} P_{ik\cdot} \leq 1 - P_{ij\cdot} - (1-P_{i,trip})$, it suffices to show that:

$$1 - \frac{\alpha}{\lambda}\sum_i P_{ij\cdot}[1-(1-\lambda)P_{ij\cdot|trip} - \lambda P_{ij\cdot}] > -\frac{\alpha}{\lambda}\sum_i \left(P_{i,trip} - P_{ij\cdot}\right)[\lambda P_{ij\cdot} + (1-\lambda)P_{ij\cdot|trip}]$$

where $P_{i,trip}$ denotes the probability that individual i takes a trip (i.e., selects $j > 0$).

Thus, Ψ has a positive dominant diagonal if $\forall i, j$:

$$P_{ij\cdot}[1-(1-\lambda)P_{ij\cdot|trip} - \lambda P_{ij\cdot}] \geq \left(P_{i,trip} - P_{ij\cdot}\right)[\lambda P_{ij\cdot} + (1-\lambda)P_{ij\cdot|trip}]$$

This inequality simplifies to $1 \geq P_{i,trip}$. Thus, Ψ has a positive dominant diagonal and the congestion equilibrium is unique.

C Valuation Estimates

Table C1: Monthly aggregate surplus estimates (millions of 2018 dollars)

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Acadia	1.13	1.06	1.89	5.50	16.73	29.82	39.93	43.26	35.24	29.07	2.73	0.99
Agate Fossil Beds M	0.01	0.01	0.03	0.03	0.11	0.16	0.18	0.11	0.11	0.05	0.01	0.00
Alibates Flint Quarries M	0.02	0.02	0.06	0.05	0.05	0.04	0.03	0.04	0.04	0.04	0.02	0.01
Amistad RA	5.09	5.07	8.59	7.92	7.17	5.34	5.31	4.50	3.74	3.43	3.32	4.05
Apostle Islands LS	0.31	0.37	0.24	0.27	0.89	1.60	2.64	2.97	1.65	0.69	0.18	0.32
Arches	5.27	5.42	15.28	16.07	17.51	14.93	11.83	12.91	17.13	13.79	7.85	5.45
Assateague Island SS	3.65	3.88	5.12	8.89	12.21	17.86	25.28	24.71	13.25	7.94	4.71	2.64
Aztec Ruins M	0.16	0.15	0.29	0.34	0.32	0.37	0.34	0.26	0.29	0.27	0.19	0.16
Badlands	0.88	0.71	1.16	1.38	4.76	10.28	11.04	10.01	5.77	1.68	0.92	0.65
Bandelier M	0.59	0.59	1.54	1.39	1.38	0.94	0.90	0.87	1.02	1.27	0.67	0.20
Big Bend	2.81	3.30	5.44	3.19	2.04	1.00	0.80	0.77	1.06	1.79	2.66	2.93
Big Cypress Preserve	0.95	1.66	1.40	1.13	0.68	0.48	0.50	0.36	0.45	0.48	0.90	1.11
Big South Fork River and Recreation Area	3.18	5.03	6.37	6.12	6.67	7.03	5.90	3.76	5.02	6.07	3.36	4.23
Big Thicket Preserve	1.12	0.68	1.37	1.20	1.54	1.38	1.28	1.41	1.05	1.24	1.32	1.02
Bighorn Canyon RA	0.61	0.59	0.92	1.07	1.83	2.49	2.89	2.56	1.16	0.68	0.31	0.47
Biscayne	10.07	8.04	8.47	6.65	2.68	6.15	6.30	5.68	4.85	3.93	5.15	8.59
Black Canyon of Gunnison	0.66	0.41	0.56	0.79	2.83	2.15	1.92	2.20	2.39	1.14	1.26	0.26
Bluestone SR	0.00	0.01	0.01	0.01	0.02	0.31	0.35	0.29	0.22	0.20	0.01	0.01
Booker T Washington M	0.06	0.09	0.13	0.18	0.13	0.16	0.18	0.14	0.09	0.16	0.11	0.06
Bryce Canyon	3.97	3.85	8.58	14.53	22.82	23.70	20.79	23.09	28.23	17.47	6.23	4.46
Cabrillo M	7.98	7.39	7.79	6.55	5.20	5.11	5.15	4.83	3.99	4.34	5.09	2.63
Canaveral Seashore	10.60	17.31	10.18	13.64	15.17	10.49	9.75	8.01	5.14	4.16	5.04	5.01
Canyon de Chelly M	1.77	1.45	2.03	1.71	1.98	1.64	1.24	1.62	1.13	1.15	1.07	1.14
Canyonlands	0.85	1.16	4.99	6.11	6.33	4.42	2.94	3.59	4.99	4.30	2.08	0.85
Cape Cod SS	2.91	2.88	3.57	3.69	5.40	8.33	10.16	13.46	9.68	5.84	3.30	3.41
Cape Hatteras SS	4.84	5.66	12.11	11.15	13.80	18.75	16.65	17.51	12.08	10.02	7.59	5.28
Cape Lookout SS	0.54	0.46	0.98	1.24	1.70	2.25	3.66	3.17	1.96	1.88	2.46	0.07
Capitol Reef	1.62	1.89	6.68	9.57	11.62	7.83	6.16	6.45	10.33	9.51	3.18	1.49
Capulin Volcano M	0.16	0.13	0.53	0.20	0.40	0.64	0.68	0.51	0.45	0.34	0.25	0.11
Carlsbad Caverns	1.62	1.63	4.66	2.19	2.26	3.11	3.17	1.70	1.53	2.24	1.56	0.61
Casa Grande Ruins M	0.91	1.21	1.23	0.49	0.22	0.14	0.11	0.10	0.16	0.26	0.36	0.22
Cedar Breaks M	2.04	1.05	1.17	1.43	2.27	3.01	7.15	6.66	4.30	2.62	1.48	1.41
Channel Islands	1.56	2.18	2.45	2.73	2.07	2.06	2.17	1.96	1.67	1.49	1.37	1.19
Chattahoochee River RA	17.38	16.86	16.39	17.42	19.02	14.74	19.63	14.05	18.61	11.64	11.76	16.01
Chickasaw RA	6.19	6.72	8.30	8.02	14.50	19.24	19.48	18.89	12.37	5.58	4.43	4.89
Chiricahua M	0.61	0.81	1.10	0.65	0.28	0.16	0.13	0.14	0.20	0.34	0.40	0.20
City of Rocks R	0.06	0.03	0.14	0.37	2.08	1.82	1.44	1.51	1.42	1.41	0.58	0.55
Colorado M	1.80	1.46	2.16	1.66	2.39	1.79	1.66	1.85	2.50	1.89	1.49	1.57

Table C1: Monthly aggregate surplus estimates (millions of 2018 dollars) *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Congaree	1.38	1.79	2.86	1.65	2.33	1.21	0.86	1.16	0.60	1.03	1.27	1.48
Crater Lake	2.37	1.55	1.70	2.46	5.41	9.66	12.87	12.03	11.70	7.03	3.04	0.86
Craters of the Moon M	1.16	1.16	1.44	2.24	4.73	5.44	5.32	4.27	5.70	2.08	0.58	0.63
Cumberland Island SS	0.20	0.35	0.64	0.47	0.39	0.33	0.29	0.26	0.20	0.25	0.27	0.13
Curecanti RA	1.44	1.16	1.18	1.65	3.14	3.47	3.12	3.40	3.24	2.13	1.31	0.81
Cuyahoga Valley	8.27	7.45	8.41	10.86	16.40	13.56	15.60	13.93	11.19	12.30	9.02	8.59
Death Valley	7.51	11.01	12.76	10.00	9.63	5.75	6.23	8.93	7.89	9.63	7.82	8.74
Delaware River Water Gap RA	29.57	28.40	8.36	31.25	38.63	37.74	49.92	45.57	36.68	36.71	35.33	28.70
Devil's Postpile M	0.00	0.00	0.00	0.00	0.00	1.27	2.87	2.41	2.64	0.93	0.00	0.00
Devils Tower M	0.20	0.17	0.53	0.85	2.83	6.01	6.44	5.92	3.84	1.19	0.37	0.21
Dinosaur M	1.59	0.83	1.74	2.58	5.50	6.94	6.78	6.06	4.60	2.35	1.13	0.82
Dry Tortugas	0.40	0.57	0.45	0.37	0.36	0.34	0.31	0.35	0.28	0.04	0.32	0.10
Effigy Mounds M	0.13	0.14	0.15	0.18	0.14	0.18	0.21	0.17	0.13	0.16	0.06	0.07
El Malpais M	0.59	0.60	1.08	1.00	1.03	0.80	0.77	0.69	0.77	0.74	0.55	0.37
El Morro M	0.23	0.23	0.38	0.48	0.47	0.36	0.32	0.41	0.27	0.25	0.23	0.16
Everglades	2.33	4.62	3.07	2.44	1.77	1.46	1.44	1.25	2.03	3.55	4.59	7.80
Fire Island SS	0.49	0.86	0.94	0.94	1.08	1.57	2.72	2.66	1.71	1.15	0.80	0.42
Florissant Fossil Beds M	0.22	0.19	0.31	0.27	0.51	0.83	0.82	0.80	0.70	0.35	0.05	0.02
Fossil Butte M	0.04	0.04	0.10	0.12	0.32	0.47	0.53	0.44	0.43	0.17	0.06	0.01
Gateway RA	38.71	31.59	36.05	40.03	44.83	52.69	47.92	50.45	41.33	35.77	37.32	35.03
Gauley River RA	0.04	0.14	0.26	0.16	0.29	0.52	0.37	0.36	1.70	0.76	0.17	0.09
George Washington Carver M	0.10	0.24	0.39	0.37	0.36	0.24	0.27	0.17	0.25	0.30	0.19	0.07
Gila Cliff Dwellings M	0.39	0.53	1.16	0.72	0.60	0.46	0.44	0.35	0.37	0.41	0.31	0.11
Glacier	0.73	0.61	0.96	1.09	6.96	18.74	28.05	22.90	15.96	3.46	0.87	0.94
Glen Canyon RA	7.74	3.68	10.97	17.85	21.98	38.71	29.86	25.16	19.59	15.99	9.75	5.13
Golden Gate RA	274.69	182.93	166.19	132.51	115.26	97.63	95.59	120.63	113.87	127.94	115.47	166.85
Grand Canyon	30.93	24.07	34.96	29.20	28.00	24.52	23.16	26.69	26.30	27.00	25.77	31.93
Grand Portage M	0.08	0.09	0.17	0.11	0.33	0.69	0.85	1.19	0.59	0.30	0.08	0.06
Grand Teton	2.68	1.89	1.85	1.57	6.54	11.68	11.81	12.75	12.22	5.05	1.34	1.88
Great Basin	0.19	0.23	1.45	0.62	0.92	1.24	1.49	1.09	2.18	0.72	0.18	0.21
Great Sand Dunes	0.45	0.53	1.91	1.16	2.95	2.99	2.46	2.72	2.25	1.47	0.68	0.40
Great Smoky Mtns	20.59	22.54	33.87	35.49	40.10	53.75	52.96	45.96	55.55	52.40	40.68	35.18
Guadalupe Mountains	0.71	1.05	0.89	1.31	0.95	0.81	0.48	0.64	0.61	0.98	1.23	0.48
Gulf Islands SS	21.31	26.97	35.59	26.27	34.63	28.34	26.45	24.88	20.93	10.44	10.46	21.18
Hagerman Fossil Beds M	0.08	0.08	0.13	0.10	0.13	0.13	0.10	0.09	0.10	0.07	0.06	0.04
Hot Springs	7.04	8.58	10.91	9.05	8.77	8.63	9.28	9.74	8.08	8.37	6.85	5.91
Hovenweep M	0.07	0.07	0.21	0.37	0.35	0.26	0.20	0.19	0.26	0.21	0.08	0.03
Indiana Dunes LS	6.65	6.12	10.34	7.01	9.54	14.18	21.92	11.28	9.65	7.74	3.45	2.33
Isle Royale	0.00	0.00	0.00	0.00	0.05	0.23	0.30	0.40	0.15	0.02	0.00	0.00

Table C1: Monthly aggregate surplus estimates (millions of 2018 dollars) *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jefferson National Expansion ML	3.44	3.85	8.72	6.42	7.01	9.26	24.42	9.69	6.38	5.77	4.53	3.42
Jewel Cave M	0.03	0.02	0.18	0.13	0.40	1.49	1.70	1.57	0.98	0.26	0.07	0.01
John Day Fossil Beds M	0.32	0.36	1.11	1.38	1.78	1.98	2.42	1.58	1.65	0.91	0.43	0.19
Joshua Tree	31.75	25.58	30.43	20.81	13.82	7.50	5.39	6.47	7.32	11.42	19.21	23.48
Kings Canyon	4.88	2.96	3.13	4.92	8.36	9.51	11.10	11.83	9.81	6.53	4.26	5.62
Lake Chelan RA	0.07	0.08	0.09	0.12	0.22	0.27	0.33	0.31	0.30	0.19	0.08	0.07
Lake Mead RA	42.12	39.85	53.03	47.43	42.11	44.43	34.86	33.21	32.41	32.14	32.85	32.63
Lake Meredith RA	4.62	7.74	5.50	6.17	7.03	7.18	7.86	5.12	2.79	2.40	3.05	2.82
Lake Roosevelt RA	8.11	7.24	7.54	7.98	12.91	17.70	30.41	22.72	11.36	4.59	2.63	2.88
Lassen Volcanic	1.92	1.06	0.91	1.95	2.75	5.35	7.03	6.60	6.12	4.00	1.03	1.08
Lava Beds M	0.46	0.47	0.43	0.65	0.80	1.47	1.47	1.12	0.91	0.62	0.46	0.22
Little River Canyon Preserve	0.73	0.87	1.77	1.85	2.50	4.14	3.11	2.67	1.77	1.64	0.80	0.72
Mammoth Cave	1.03	1.23	4.51	4.00	3.93	4.78	5.88	3.96	3.14	3.32	1.84	0.82
Mesa Verde	1.40	0.85	1.73	2.04	3.01	3.65	2.88	2.99	3.16	2.37	0.97	0.91
Mississippi River & RA	2.12	2.06	2.07	1.54	3.10	2.48	1.92	1.87	1.74	1.50	1.31	1.14
Missouri Recreational River	0.48	0.47	0.55	0.47	0.72	0.78	0.72	0.67	1.68	0.63	0.49	0.75
Mojave Preserve	6.03	5.37	4.74	5.87	4.53	3.47	2.40	2.59	4.08	4.34	6.51	6.14
Montezuma Castle M	2.63	2.98	5.06	4.10	2.92	1.95	1.58	1.36	1.94	2.36	2.21	0.98
Mount Rainier	6.13	3.89	5.12	4.33	14.73	28.73	42.76	44.04	27.35	15.92	14.33	5.70
Muir Woods M	7.37	4.71	6.34	5.69	5.18	5.24	5.63	5.36	4.35	3.89	2.62	6.54
Natural Bridges M	0.16	0.17	0.64	1.02	1.05	0.55	0.39	0.33	0.75	0.66	0.23	0.07
New River Gorge R	4.10	3.78	5.02	8.21	9.93	9.52	9.18	8.27	5.41	6.76	2.99	2.11
Niobrara SR	0.20	0.08	0.16	0.20	0.69	1.16	2.00	1.59	0.91	0.21	0.09	0.06
North Cascades	0.00	0.00	0.00	0.01	0.10	0.17	0.46	0.36	0.31	0.09	0.00	0.00
Obed Wild and Scenic River	0.92	0.89	1.39	1.03	1.14	1.04	0.95	1.10	0.75	0.79	0.96	1.12
Olympic	11.63	7.84	8.22	10.42	17.87	24.70	23.45	36.43	21.26	12.74	6.37	5.11
Oregon Caves Monument and Preserve	0.33	0.25	0.57	0.55	1.14	1.14	1.07	0.95	1.13	0.62	0.25	0.18
Organ Pipe Cactus M	3.38	3.41	4.03	1.45	1.44	1.06	0.90	0.53	0.89	1.16	1.54	1.78
Ozark Scenic River	1.74	1.80	4.20	4.99	6.81	10.78	14.04	13.76	8.48	4.45	4.22	2.27
Padre Island Seashore	3.00	5.61	4.34	4.37	4.79	4.02	4.80	4.14	1.70	1.86	1.57	1.85
Petrified Forest	2.71	2.66	4.94	4.11	5.34	6.70	4.50	3.86	3.57	3.32	2.13	2.14
Petroglyph M	1.51	1.49	2.07	2.01	1.23	1.06	0.90	0.91	0.97	1.69	1.34	1.02
Pictured Rocks LS	1.19	1.62	0.90	0.59	1.57	2.81	5.00	5.50	3.62	1.98	0.19	0.48
Pinnacles	3.83	3.70	3.67	3.56	3.05	3.04	1.29	1.71	1.63	1.82	2.42	3.12
Pipestone M	0.02	0.02	0.05	0.08	0.31	0.25	0.28	0.27	0.23	0.15	0.06	0.03
Point Reyes SS	15.95	16.15	14.74	15.26	13.49	12.87	12.11	16.38	8.24	8.76	10.92	13.40
Rainbow Bridge M	0.00	0.00	0.24	0.28	1.03	1.06	1.01	0.85	0.81	0.41	0.09	0.00
Redwood	2.28	1.46	1.91	2.34	3.18	3.78	3.28	2.91	2.81	1.97	1.42	1.83
Rio Grande Wild and Scenic River	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table C1: Monthly aggregate surplus estimates (millions of 2018 dollars) *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rocky Mountain	11.43	7.28	11.72	9.92	17.37	35.95	39.95	40.46	46.11	20.34	9.01	9.06
Ross Lake RA	0.47	0.55	0.60	0.65	5.87	6.92	10.24	5.85	7.04	6.76	1.12	0.45
Russell Cave M	0.06	0.10	0.15	0.16	0.09	0.14	0.09	0.06	0.11	0.11	0.08	0.04
Saguaro	11.32	12.95	13.91	8.21	4.50	2.73	2.74	2.94	2.73	4.00	6.93	5.48
Saint Croix SR	0.05	0.01	0.01	1.25	5.78	7.79	6.67	6.97	4.23	1.09	0.20	0.03
Salinas Pueblo Missions M	0.17	0.19	0.23	0.24	0.31	0.23	0.20	0.18	0.20	0.25	0.16	0.07
Santa Monica Mountains RA	6.46	7.29	6.73	5.89	5.76	3.84	3.16	3.85	4.14	4.56	2.07	3.39
Scotts Bluff M	0.11	0.17	0.52	0.47	0.92	1.11	1.21	1.01	0.98	0.42	0.14	0.32
Sequoia	9.87	8.07	10.38	10.72	14.84	15.86	17.55	18.92	15.29	10.11	7.96	11.14
Shenandoah	2.08	1.47	3.03	4.79	6.79	6.84	7.28	7.47	4.76	8.74	6.32	1.54
Sleeping Bear Dunes LS	1.24	1.22	1.78	1.69	6.34	15.60	25.81	24.92	8.60	5.87	1.18	1.02
Sunset Crater Volcano M	0.41	0.41	1.11	0.94	0.80	0.82	0.66	0.61	0.63	0.52	0.50	0.19
Tallgrass Prairie Preserve	0.03	0.04	0.15	0.15	0.26	0.23	0.19	0.17	0.23	0.18	0.10	0.03
Theodore Roosevelt	0.29	0.20	0.77	1.32	5.80	8.21	9.55	8.06	6.30	3.78	1.10	0.34
Timpanogos Cave M	0.06	0.07	0.32	0.37	0.65	1.93	1.89	1.73	0.63	0.36	0.09	0.08
Tonto M	0.46	0.59	0.77	0.34	0.17	0.11	0.09	0.08	0.12	0.17	0.29	0.13
Upper Delaware S & R River	0.31	0.28	0.21	0.36	1.23	1.32	2.09	2.42	1.59	0.36	0.31	0.20
Voyageurs	0.42	0.62	0.43	0.02	1.94	2.93	2.79	2.96	1.56	0.65	0.16	0.01
Whiskeytown- Shasta-Trinity RA	3.07	3.36	4.51	4.54	8.06	8.39	6.77	0.00	1.88	1.99	0.37	1.98
White Sands M	8.35	6.26	11.88	5.79	5.31	4.26	4.11	3.39	3.76	4.14	4.88	2.86
Wind Cave	1.00	1.19	1.77	2.49	2.63	5.82	5.78	6.01	3.96	1.58	0.89	0.76
Yellowstone	2.82	2.63	1.42	1.94	20.98	35.38	37.34	35.83	34.59	10.88	0.81	1.66
Yosemite	13.55	13.15	13.87	20.01	23.93	29.26	22.97	24.38	33.33	25.62	16.69	27.90
Zion	7.03	6.67	15.76	16.25	13.93	12.32	8.70	10.62	13.73	12.45	8.72	7.53

Note: The table shows the recreational surplus generated by each park and each month of 2018. All surplus estimates in this table account for congestion.

Table C2: Recreational surplus per raw visitor count (2018 dollars)

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Acadia	95	87	80	76	67	60	53	56	59	60	67	78
Agate Fossil Beds M	84	77	71	66	57	50	42	47	50	51	57	68
Alibates Flint Quarries M	83	76	71	65	56	49	41	45	49	50	56	67
Amistad RA	82	76	70	65	56	48	41	45	48	49	56	67
Apostle Islands LS	80	73	68	63	55	48	41	45	48	49	55	65
Arches	166	134	113	96	81	70	58	70	83	93	106	130
Assateague Island SS	94	87	80	75	67	60	52	56	58	59	67	78
Aztec Ruins M	88	80	74	68	58	51	43	47	51	52	58	71
Badlands	83	76	70	65	56	49	42	46	49	50	56	67
Bandelier M	86	79	73	67	58	50	42	47	50	51	58	69
Big Bend	84	77	72	66	57	49	41	46	49	50	57	68
Big Cypress Preserve	16	15	13	12	11	11	11	11	11	11	12	14
Big South Fork River and Recreation Area	127	113	100	89	82	76	70	70	70	67	80	100
Big Thicket Preserve	96	89	82	76	67	59	51	55	58	58	65	78
Bighorn Canyon RA	104	95	87	80	71	64	55	60	62	62	69	84
Biscayne	364	247	173	125	120	117	115	123	131	135	174	244
Black Canyon of Gunnison	87	79	73	67	58	51	43	47	51	52	58	70
Bluestone SR	79	73	67	63	55	48	41	45	48	49	55	65
Booker T Washington M	94	87	80	76	67	60	52	56	58	59	66	78
Bryce Canyon	123	104	90	78	67	58	48	59	69	77	85	101
Cabrillo M	115	104	95	86	74	65	56	61	64	66	75	92
Canaveral Seashore	95	88	81	75	67	59	52	55	58	58	66	78
Canyon de Chelly M	77	64	54	45	38	33	27	30	32	33	42	56
Canyonlands	89	81	75	69	59	52	43	48	52	53	59	72
Cape Cod SS	26	24	21	19	18	17	16	17	19	19	21	23
Cape Hatteras SS	79	74	68	64	55	48	41	45	48	50	56	66
Cape Lookout SS	79	74	68	63	55	48	41	45	48	50	56	66
Capitol Reef	104	90	79	70	60	52	44	53	62	69	75	88
Capulin Volcano M	101	92	85	79	69	62	54	58	60	60	68	81
Carlsbad Caverns	85	78	72	66	57	49	42	46	49	51	57	69
Casa Grande Ruins M	109	99	91	83	72	64	55	60	63	64	72	88
Cedar Breaks M	91	83	76	70	60	52	43	48	52	54	60	73
Channel Islands	97	88	80	73	62	53	44	49	53	56	63	78
Chattahoochee River RA	95	88	81	76	67	59	52	55	58	59	66	78
Chickasaw RA	117	105	95	85	83	82	81	84	86	85	91	103
Chiricahua M	112	98	87	77	68	60	52	61	69	76	83	96
City of Rocks R	158	128	107	89	81	74	67	75	81	85	100	124
Colorado M	126	97	77	61	52	45	38	45	52	57	70	93

Table C2: Recreational surplus per raw visitor count (2018 dollars) *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Congaree	192	160	135	116	103	92	82	94	106	116	131	157
Crater Lake	257	193	153	124	103	87	72	89	105	121	143	185
Craters of the Moon M	354	256	199	160	135	116	97	117	137	153	183	244
Cumberland Island SS	94	88	81	76	67	59	52	55	58	58	66	78
Curecanti RA	71	55	44	34	28	23	18	23	28	31	40	53
Cuyahoga Valley	94	87	80	75	67	59	52	56	58	59	66	78
Death Valley	93	85	78	71	61	52	44	49	53	55	62	75
Delaware River Water Gap RA	214	176	146	126	115	106	98	108	116	123	142	172
Devil's Postpile M						72	59	73	86	98		
Devils Tower M	101	92	85	79	70	62	54	58	61	61	68	82
Dinosaur M	281	221	181	150	135	124	111	124	135	142	167	212
Dry Tortugas	94	88	81	75	66	58	51	54	57	58	65	78
Effigy Mounds M	62	52	44	36	31	26	21	24	26	27	34	46
El Malpais M	87	80	74	68	58	50	42	47	51	52	58	70
El Morro M	88	80	74	68	59	51	43	47	51	52	59	71
Everglades	69	69	68	68	57	47	39	47	54	60	62	65
Fire Island SS	78	72	66	63	55	48	41	45	48	49	56	65
Florissant Fossil Beds M	101	92	85	79	69	62	54	58	61	61	68	81
Fossil Butte M	382	271	209	167	139	119	99	119	140	158	191	258
Gateway RA	77	72	65	62	54	47	40	44	47	49	55	64
Gauley River RA	79	73	67	63	55	48	41	45	48	49	55	65
George Washington Carver M	96	89	82	76	67	60	52	56	58	59	66	78
Gila Cliff Dwellings M	105	96	89	81	71	63	54	59	62	62	70	85
Glacier	60	51	44	38	36	34	31	34	37	38	42	50
Glen Canyon RA	94	75	60	49	46	44	41	46	50	52	61	76
Golden Gate RA	229	171	131	101	87	75	64	75	86	94	120	164
Grand Canyon	120	91	69	53	44	36	29	36	43	49	63	87
Grand Portage M	81	74	68	64	55	48	41	45	48	49	55	66
Grand Teton	49	40	32	26	22	19	15	18	22	24	30	39
Great Basin	110	100	92	84	74	65	56	61	64	65	73	89
Great Sand Dunes	126	94	72	55	46	39	31	38	45	51	66	90
Great Smoky Mtns	64	56	49	43	41	38	36	38	41	41	47	55
Guadalupe Mountains	85	78	72	66	57	49	42	46	49	51	57	69
Gulf Islands SS	96	89	82	76	67	59	52	55	58	59	66	79
Hagerman Fossil Beds M	159	106	74	52	40	30	21	29	37	46	65	100
Hot Springs	96	89	83	76	67	60	52	56	58	59	66	79
Hovenweep M	88	80	74	68	59	51	43	48	51	52	59	71
Indiana Dunes LS	94	87	80	75	66	59	52	55	58	58	65	77
Isle Royale	80	73	68	63	55	48	41	45	48	49	55	65

Table C2: Recreational surplus per raw visitor count (2018 dollars) *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jefferson National Expansion ML	86	74	64	55	49	44	38	40	41	41	50	65
Jewel Cave M	84	77	71	65	57	50	42	47	50	51	57	68
John Day Fossil Beds M	111	100	91	83	73	66	58	63	65	65	73	88
Joshua Tree	107	89	75	64	56	49	41	46	49	52	64	83
Kings Canyon	248	195	157	127	113	102	91	103	113	121	146	189
Lake Chelan RA	90	81	74	68	59	52	44	50	52	53	59	72
Lake Mead RA	92	83	76	70	60	52	43	48	52	54	61	74
Lake Meredith RA	83	76	71	65	56	49	41	45	49	50	56	67
Lake Roosevelt RA	149	134	122	111	107	106	102	101	95	87	98	118
Lassen Volcanic	187	147	117	92	80	71	61	72	81	88	109	142
Lava Beds M	116	104	95	86	75	67	58	63	66	67	75	92
Little River Canyon Preserve	79	74	68	63	55	48	41	44	48	49	55	65
Mammoth Cave	133	110	92	77	70	64	58	64	70	74	87	107
Mesa Verde	168	115	82	59	47	37	27	36	45	52	73	108
Mississippi River & RA	79	73	68	63	55	48	41	45	48	49	54	65
Missouri Recreational River	97	89	82	76	67	60	53	56	59	59	66	79
Mojave Preserve	107	92	80	70	60	52	43	53	61	69	76	90
Montezuma Castle M	109	99	91	83	73	64	55	60	63	64	72	88
Mount Rainier	256	207	173	147	138	131	122	135	143	147	166	202
Muir Woods M	100	90	82	74	63	54	45	51	55	57	65	80
Natural Bridges M	90	82	75	69	60	52	43	48	52	53	60	72
New River Gorge R	102	90	78	69	62	57	52	53	53	52	63	79
Niobrara SR	272	211	170	139	125	115	104	115	126	132	158	204
North Cascades	90	81	74	67	59	52	44	50	52	53	59	
Obed Wild and Scenic River	79	73	68	63	55	48	41	45	48	49	55	65
Olympic	94	82	72	65	58	53	48	56	62	66	71	80
Oregon Caves Monument and Preserve	365	253	190	149	122	101	82	103	123	142	174	239
Organ Pipe Cactus M	110	100	92	84	73	64	55	60	63	64	73	89
Ozark Scenic River	96	89	82	76	67	60	52	56	59	59	66	79
Padre Island Seashore	97	90	83	77	68	60	52	55	58	58	66	79
Petrified Forest	107	98	90	83	72	64	55	60	63	63	71	87
Petroglyph M	86	79	73	67	58	50	42	47	50	51	58	69
Pictured Rocks LS	60	50	42	36	32	28	25	29	32	34	40	49
Pinnacles	241	197	164	137	123	112	101	113	123	132	152	190
Pipestone M	59	49	41	33	28	23	18	21	23	24	31	43
Point Reyes SS	100	91	82	75	63	54	45	51	55	58	65	80
Rainbow Bridge M			75	69	60	52	43	48	52	53	60	72
Redwood	97	87	79	72	62	54	45	51	54	56	63	77
Rio Grande Wild and Scenic River	84	77	71	66		49		46	49	50	56	68

Table C2: Recreational surplus per raw visitor count (2018 dollars) *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rocky Mountain	103	86	75	65	57	50	43	51	59	65	72	85
Ross Lake RA	90	81	74	68	59	52	45	50	53	53	60	72
Russell Cave M	79	74	68	63	55	48	41	44	48	49	55	65
Saguaro	108	99	91	83	72	64	55	60	63	64	72	87
Saint Croix SR	79	73	68	63	55	48	41	45	48	49	54	65
Salinas Pueblo Missions M	103	94	87	80	70	62	54	58	61	61	69	83
Santa Monica Mountains RA	97	88	80	73	62	53	44	49	53	56	63	78
Scotts Bluff M	84	76	71	65	57	50	42	46	50	51	56	68
Sequoia	249	196	157	127	113	102	91	103	113	121	146	189
Shenandoah	87	76	65	57	51	46	41	42	43	43	53	67
Sleeping Bear Dunes LS	95	87	81	75	67	60	53	56	58	59	66	78
Sunset Crater Volcano M	109	99	91	83	73	64	55	60	63	64	72	87
Tallgrass Prairie Preserve	97	89	82	76	67	60	52	56	59	59	66	79
Theodore Roosevelt	100	91	84	78	69	62	54	58	61	60	67	81
Timpanogos Cave M	127	109	96	83	75	69	62	63	64	62	74	96
Tonto M	108	99	91	83	72	64	55	60	63	64	72	87
Upper Delaware S & R River	78	72	66	63	55	48	41	45	48	49	55	65
Voyageurs	97	89	82	76	67	60	53	56	59	59	66	79
Whiskeytown- Shasta-Trinity RA	118	107	97	88	77	67	58		66	68	77	94
White Sands M	251	178	132	100	84	72	61	71	82	91	119	168
Wind Cave	84	77	71	66	57	50	42	47	50	51	57	68
Yellowstone	97	77	62	51	47	44	40	44	48	50	59	74
Yosemite	105	92	81	72	62	54	46	55	64	71	77	90
Zion	65	52	42	34	28	23	17	23	29	33	40	51

Note: The table shows the recreational surplus per VUS visit for each park and each month of 2018. I calculate surplus per visit by dividing the estimated aggregate recreational surplus by the Visitor Use Statistics (VUS) visitor count. These values may be useful for administrative purposes, because VUS visitor counts are commonly cited by the National Park Service. However, these estimates are not consistent with my model's definition of a trip, because the VUS does not account for re-entry and non-primary purpose visitation. Park-months missing an estimate received zero visits during that month.

D Full park awesomeness index

Table D1: Park awesomeness ratings

Park	Spring	Summer	Fall	Winter
Golden Gate RA	99.2 (1)	97.3 (1)	95.3 (1)	98.8 (1)
Yellowstone	92.4 (2)	95.7 (2)	92.3 (2)	72.9 (29)
Glacier	86.8 (14)	94.8 (3)	88.9 (6)	66.0 (60)
Mount Rainier	88.6 (11)	94.7 (4)	89.5 (3)	76.2 (15)
Olympic	91.2 (4)	94.4 (5)	89.2 (4)	81.6 (6)
Lake Roosevelt RA	89.5 (9)	94.2 (6)	85.6 (13)	79.5 (8)
Glen Canyon RA	89.8 (8)	93.3 (7)	85.8 (12)	76.8 (13)
Lake Mead RA	91.8 (3)	91.5 (8)	86.4 (10)	85.1 (3)
Yosemite	90.0 (7)	91.1 (9)	88.9 (7)	83.4 (5)
Grand Canyon	91.0 (5)	90.0 (12)	87.3 (9)	85.2 (2)
Rocky Mountain	86.2 (18)	90.7 (10)	89.0 (5)	76.2 (16)
Bryce Canyon	90.1 (6)	90.2 (11)	88.2 (8)	72.6 (32)
Acadia	84.9 (21)	89.3 (13)	85.9 (11)	60.4 (82)
Arches	88.8 (10)	87.7 (16)	85.4 (14)	74.5 (23)
Grand Teton	84.5 (22)	88.1 (14)	85.1 (15)	72.0 (37)
Crater Lake	83.2 (28)	87.8 (15)	85.0 (16)	71.8 (38)
Joshua Tree	87.6 (12)	80.8 (44)	79.8 (27)	84.1 (4)
Great Smoky Mtns	85.4 (20)	87.0 (17)	83.8 (17)	75.8 (19)
Gulf Islands SS	86.8 (13)	85.3 (20)	79.8 (28)	78.4 (10)
Capitol Reef	86.6 (15)	84.0 (29)	82.7 (19)	68.4 (49)
Zion	86.6 (16)	85.1 (23)	82.6 (20)	75.2 (20)
Sequoia	86.3 (17)	86.5 (18)	83.3 (18)	78.1 (11)
Point Reyes SS	86.0 (19)	85.0 (24)	79.2 (31)	81.0 (7)
Ross Lake RA	83.1 (29)	85.9 (19)	81.2 (21)	61.2 (79)
Gateway RA	84.5 (23)	85.3 (21)	80.2 (23)	76.0 (17)
Theodore Roosevelt	83.0 (30)	85.2 (22)	80.2 (24)	57.1 (97)
Badlands	80.0 (44)	84.8 (25)	77.7 (34)	61.9 (77)
Sleeping Bear Dunes LS	76.9 (62)	84.6 (26)	75.1 (43)	59.3 (90)
Delaware River Water Gap RA	83.9 (25)	84.4 (27)	79.8 (26)	74.7 (22)
Whiskeytown- Shasta-Trinity RA	84.2 (24)	84.3 (28)	71.9 (65)	72.4 (33)
Saguaro	83.8 (26)	75.6 (73)	74.4 (49)	79.0 (9)
Death Valley	83.6 (27)	81.4 (41)	79.5 (29)	78.0 (12)
Cape Hatteras SS	81.9 (37)	83.6 (30)	77.3 (36)	69.0 (48)
Chickasaw RA	82.0 (36)	83.5 (31)	77.3 (35)	70.0 (44)
Dinosaur M	82.1 (35)	83.5 (32)	77.7 (33)	67.4 (52)
Kings Canyon	82.7 (32)	83.3 (33)	80.6 (22)	73.7 (25)
White Sands M	83.0 (31)	78.8 (52)	74.8 (45)	76.3 (14)
Craters of the Moon M	82.1 (34)	83.0 (34)	80.1 (25)	66.6 (56)
Canyonlands	82.4 (33)	80.1 (45)	77.8 (32)	64.9 (63)
Devils Tower M	77.7 (56)	82.4 (35)	76.3 (39)	53.9 (107)
Lassen Volcanic	77.5 (58)	82.4 (36)	79.4 (30)	69.5 (45)
Petrified Forest	80.3 (42)	81.6 (37)	74.5 (48)	69.5 (46)
Jefferson National Expansion ML	74.8 (77)	81.5 (38)	70.5 (74)	63.8 (66)
Wind Cave	76.6 (68)	81.5 (39)	75.8 (40)	64.3 (65)
Redwood	80.4 (41)	81.5 (40)	76.6 (38)	72.3 (34)
Amistad RA	81.2 (38)	78.7 (53)	73.0 (57)	71.7 (39)
Assateague Island SS	77.8 (55)	81.2 (42)	74.6 (47)	63.4 (69)
Cedar Breaks M	75.0 (76)	81.0 (43)	75.7 (41)	67.8 (50)
Chattahoochee River RA	80.7 (39)	79.8 (48)	76.8 (37)	72.9 (30)
Canaveral Seashore	80.4 (40)	77.9 (60)	69.9 (79)	74.4 (24)
Lake Meredith RA	80.1 (43)	80.1 (47)	70.8 (70)	73.7 (26)
Indiana Dunes LS	76.0 (72)	80.1 (46)	72.4 (64)	66.1 (58)

Table D1: Park awesomeness ratings *(continued)*

Park	Spring	Summer	Fall	Winter
Mesa Verde	78.5 (49)	79.6 (49)	75.6 (42)	66.8 (54)
Muir Woods M	79.5 (45)	79.1 (51)	74.9 (44)	76.0 (18)
Cabrillo M	79.5 (46)	77.9 (59)	73.3 (55)	75.1 (21)
Ozark Scenic River	76.0 (73)	79.4 (50)	73.7 (53)	60.5 (81)
Big Bend	79.2 (47)	70.9 (94)	70.0 (78)	71.6 (40)
Cuyahoga Valley	78.9 (48)	77.5 (63)	72.7 (60)	67.0 (53)
Bighorn Canyon RA	76.7 (65)	78.6 (54)	70.6 (73)	62.6 (73)
Cape Cod SS	74.8 (78)	78.6 (55)	74.6 (46)	63.5 (68)
Hot Springs	78.4 (50)	78.1 (57)	74.2 (50)	71.1 (42)
Santa Monica Mountains RA	78.3 (51)	75.6 (74)	73.1 (56)	73.6 (27)
Saint Croix SR	76.6 (67)	78.3 (56)	71.0 (68)	39.2 (130)
Biscayne	78.2 (52)	77.5 (62)	72.4 (63)	73.5 (28)
Mojave Preserve	78.2 (53)	75.0 (76)	72.9 (59)	72.7 (31)
John Day Fossil Beds M	76.8 (63)	78.0 (58)	73.4 (54)	59.8 (86)
Padre Island Seashore	78.0 (54)	76.7 (65)	67.7 (89)	72.0 (35)
Curecanti RA	77.2 (59)	77.7 (61)	74.1 (51)	65.1 (62)
Montezuma Castle M	77.7 (57)	73.2 (84)	70.4 (75)	69.5 (47)
Black Canyon of Gunnison	77.2 (60)	75.4 (75)	72.9 (58)	61.0 (80)
Carlsbad Caverns	77.0 (61)	76.7 (64)	70.3 (76)	66.0 (59)
Pinnacles	76.7 (64)	75.8 (71)	68.9 (82)	72.0 (36)
City of Rocks R	76.7 (66)	75.8 (70)	71.2 (67)	59.8 (85)
Organ Pipe Cactus M	76.6 (69)	70.2 (96)	66.8 (94)	71.4 (41)
New River Gorge R	76.5 (70)	76.0 (69)	69.6 (80)	63.4 (70)
Great Sand Dunes	76.4 (71)	76.4 (66)	71.4 (66)	58.5 (95)
Devil's Postpile M		76.2 (67)	73.7 (52)	
Voyageurs	73.6 (82)	76.1 (68)	68.7 (84)	59.2 (92)
Colorado M	75.6 (74)	73.8 (82)	72.7 (61)	66.8 (55)
Pictured Rocks LS	69.4 (95)	75.6 (72)	71.0 (69)	62.3 (76)
Canyon de Chelly M	75.1 (75)	73.8 (81)	68.4 (85)	67.6 (51)
Lava Beds M	71.0 (92)	74.8 (77)	68.8 (83)	61.5 (78)
Big South Fork River and Recreation Area	74.4 (79)	74.5 (78)	69.3 (81)	65.5 (61)
Timpanogos Cave M	67.4 (105)	74.1 (79)	63.9 (103)	46.6 (123)
Channel Islands	74.0 (80)	72.2 (91)	67.9 (86)	66.6 (57)
Oregon Caves Monument and Preserve	73.8 (81)	73.8 (80)	70.8 (71)	60.0 (83)
Shenandoah	73.6 (83)	73.4 (83)	70.7 (72)	58.5 (94)
Jewel Cave M	64.9 (111)	73.0 (85)	67.1 (92)	40.5 (128)
Petroglyph M	72.9 (84)	69.1 (99)	67.8 (88)	64.5 (64)
Natural Bridges M	72.8 (85)	68.6 (102)	67.5 (90)	54.5 (103)
Rainbow Bridge M	72.6 (86)	72.7 (86)	67.9 (87)	28.7 (136)
Apostle Islands LS	66.9 (107)	72.6 (87)	67.1 (91)	54.0 (105)
Great Basin	70.7 (93)	72.3 (89)	72.5 (62)	54.9 (101)
Mammoth Cave	71.0 (91)	72.4 (88)	65.9 (96)	56.5 (98)
Mississippi River & RA	72.3 (87)	70.7 (95)	65.0 (100)	62.5 (75)
Niobrara SR	66.6 (108)	72.3 (90)	64.9 (101)	51.3 (114)
Everglades	72.2 (88)	68.8 (101)	70.2 (77)	71.0 (43)
Bandelier M	72.0 (89)	69.4 (98)	67.0 (93)	59.6 (88)
Cape Lookout SS	68.4 (101)	71.9 (92)	65.5 (98)	53.6 (108)
Guadalupe Mountains	71.3 (90)	68.3 (103)	65.3 (99)	63.4 (71)
Little River Canyon Preserve	68.3 (103)	71.2 (93)	62.4 (109)	54.6 (102)
Scotts Bluff M	68.7 (99)	69.8 (97)	65.8 (97)	53.2 (110)
El Malpais M	69.5 (94)	67.7 (105)	64.4 (102)	59.2 (91)
Gila Cliff Dwellings M	69.2 (96)	65.5 (112)	61.0 (114)	59.8 (84)
Grand Portage M	62.8 (120)	69.1 (100)	62.8 (105)	47.5 (121)
Chiricahua M	68.9 (97)	59.1 (126)	59.6 (119)	62.7 (72)
Sunset Crater Volcano M	68.7 (98)	68.0 (104)	63.3 (104)	57.4 (96)

Table D1: Park awesomeness ratings *(continued)*

Park	Spring	Summer	Fall	Winter
Big Thicket Preserve	68.4 (100)	67.5 (106)	62.5 (108)	59.1 (93)
Congaree	68.4 (102)	64.0 (117)	58.7 (120)	59.5 (89)
Casa Grande Ruins M	68.2 (104)	56.8 (131)	56.6 (124)	63.8 (67)
Big Cypress Preserve	67.2 (106)	61.6 (121)	58.4 (122)	62.6 (74)
Florissant Fossil Beds M	64.1 (115)	67.0 (107)	62.6 (107)	51.5 (113)
Fire Island SS	62.0 (123)	66.6 (108)	61.1 (113)	53.3 (109)
North Cascades	57.5 (129)	66.5 (109)	61.6 (111)	28.3 (137)
Fossil Butte M	64.1 (114)	66.5 (110)	62.7 (106)	44.8 (124)
Missouri Recreational River	64.7 (113)	65.1 (114)	66.5 (95)	55.9 (100)
Capulin Volcano M	62.9 (119)	65.7 (111)	60.1 (116)	49.8 (116)
Tonto M	65.6 (109)	55.4 (133)	54.5 (127)	59.7 (87)
Upper Delaware Scenic and Recreational River	63.0 (118)	65.3 (113)	60.8 (115)	46.6 (122)
El Morro M	65.3 (110)	63.5 (118)	58.5 (121)	54.0 (106)
Hovenweep M	64.8 (112)	62.9 (119)	59.6 (118)	48.0 (120)
Lake Chelan RA	62.6 (121)	64.5 (115)	61.5 (112)	49.6 (118)
Aztec Ruins M	63.5 (116)	64.4 (116)	59.8 (117)	52.1 (111)
Obed Wild and Scenic River	63.2 (117)	62.4 (120)	56.8 (123)	54.4 (104)
Salinas Pueblo Missions M	62.1 (122)	60.1 (123)	56.2 (125)	51.9 (112)
Gauley River RA	54.5 (132)	58.0 (129)	61.9 (110)	42.9 (126)
Dry Tortugas	60.4 (124)	59.7 (124)	54.8 (126)	56.2 (99)
Isle Royale	49.3 (136)	60.2 (122)	52.3 (132)	27.1 (138)
Pipestone M	59.6 (125)	58.2 (128)	54.3 (129)	35.8 (132)
Cumberland Island SS	59.6 (126)	57.0 (130)	51.1 (134)	50.7 (115)
Hagerman Fossil Beds M	59.0 (127)	59.3 (125)	54.4 (128)	49.6 (117)
Agate Fossil Beds M	56.1 (131)	58.5 (127)	53.1 (130)	32.0 (135)
George Washington Carver M	58.1 (128)	55.3 (134)	52.4 (131)	48.4 (119)
Tallgrass Prairie Preserve	56.8 (130)	55.8 (132)	52.3 (133)	38.4 (131)
Bluestone SR	37.5 (138)	54.7 (135)	49.1 (135)	23.4 (139)
Effigy Mounds M	53.5 (133)	53.5 (136)	48.3 (136)	44.6 (125)
Booker T Washington M	51.3 (134)	50.6 (137)	46.1 (137)	40.1 (129)
Russell Cave M	51.1 (135)	50.3 (138)	44.9 (138)	41.3 (127)
Alibates Flint Quarries M	48.9 (137)	47.6 (139)	43.9 (139)	35.4 (133)
Rio Grande Wild and Scenic River	36.8 (139)	24.9 (140)	26.6 (140)	33.0 (134)

Note: The table shows each park's maximum rating by season for 2018. I rank these maximum ratings by season, in parentheses. The table's rows are ordered by the maximum park effect across the entire year.

E Data appendix

E.1 Weather Data

To construct a park-month panel of weather variables, I obtain monthly temperature and precipitation summaries for weather stations from the National Center for Environmental Information's Global Summary of the Month database. I use two variables from these monthly summaries: (1) the average daily high temperature and (2) the number of days with great than one-tenth of an inch of precipitation (I call these days "precipitation days"). Not all parks have weather stations within their boundaries, and some weather stations are missing data. Thus, constructing a balanced panel of weather observations at the park-level is a nontrivial exercise. Auffhammer and Kellogg (2011) face a similar problem, and I follow their approach to selecting weather stations and imputing missing observations.

For each park, I select the nearest station with more than 50 percent complete data as the "primary station" for the park. If two stations are within the park's boundaries, then I break the tie by selecting the station with more complete data. Of the 140 parks in my sample, 82 have a primary station within their boundaries, and on average, the primary stations are 2 miles from their park. These primary stations are missing 18 percent of their monthly observations.

To impute the missing primary station data, I use gridded PRISM weather observations.[13] For each primary station, I regress non-missing primary station observations on the nearest PRISM observations. I use the coefficient estimates from this simple regression to impute the missing primary station data.

I assess the performance of this imputation by dropping 20 percent of the observed primary station data, imputing the observations as if they were missing, and comparing the imputed observations to the true observations. The mean absolute error is 0.85°F when imputing the average high temperature variable and 0.78 days when imputing the number of precipitation days. The average R-squared for the imputation regressions is 0.99 when imputing temperature and 0.82 when imputing the number of precipitation days. The predictive power of the imputation regressions and the relatively small mean absolute error suggest the imputation provides reasonable estimates for the missing primary station observations.

E.2 Park attribute data sources

- Elevation: U.S. Geological Survey (2022b)
- Road miles: U.S. Census Bureau (2019)

[13]The PRISM weather data are available at a 4km grid across the contiguous United States and do not contain any missing observations.

- Trail miles: U.S. Geological Survey (2022a). I compare the USGS trails data to administrative trail data from the NPS. Park-level trail mileages from these two datasets are similar (R-squared 0.99). These datasets show that eleven parks do not have trails. For these eleven parks, I inspect park websites and sum the mileage of advertised trails.
- Coastal: Curdts (2011)
- Large lakes and reservoirs: U.S. Geological Survey (2019)
- Ferry: Park websites contain "Direction & Transportation" or "Getting here" pages.
- Wildlife: U.S. National Park Service (2019)
- Visits per day: Visitors Use Statistics, U.S. Department of the Interior (n.d.)
- Temperature and precipitation: PRISM Climate Group, Oregon State University (2014)
- Size: U.S. National Park Service Land Resources Division (2024)
- Designation: U.S. National Park Service (2024)
- Entrance fees: Provided by NPS Social Sciences Division upon request

Several of these datasets are not measured at the park level: elevation, roads, trails, large lakes and reservoirs, temperature and precipitation. Thus, I also make use of park boundary shapefiles from National Park Service - Land Resources Division (2022).

E.3 NPS Visitor Services Project On-Site Surveys

To augment my visitor count data, I obtain five statistics from on-site surveys conducted by the NPS Visitor Services Project and the NPS Socioeconomic Monitoring Program. These statistics vary by park and the season of the year. I use three statistics, (1) the re-entry rate, (2) the proportion of domestic visitors, and (3) the proportion of primary purpose trips, to convert raw visitor counts into the number of domestic, primary purpose trips. I use the last two statistics, (4) average stay length and (5) average group size, when calculating travel costs.

The NPS conducted 312 on-site surveys for the Visitor Services Project and 14 (as of December 2023) for the Socioeconomic Monitoring Program. I obtained summary statistics for Visitor Services Project surveys from Washington State University's online database (**VSP**) and Socioeconomic Monitoring survey responses from the NPS Social Sciences Division upon request. Of the 326 total surveys, 109 were conducted at parks in my sample more recently than 1995, and 70 of the 140 parks in my sample conducted at least one survey since 1995 (some parks conducted multiple surveys). For the 70 parks without an on-site survey, I impute the five statistics required for my analysis.

Most surveys do not include every question needed to calculate these five statistics. I observe 62 re-entry questions, 108 domestic visitor questions, 50 primary purpose questions, 103 stay length questions, and 70 group size questions. The questions are standardized for all parks. Here are the questions from the Yellowstone NP Winter 2012 survey:

- Re-entry rate: "On this visit, how many times did your personal group enter Yellowstone NP during your stay in the area (within 150 miles of the park)?"
- Domestic visitors: "For your personal group on this visit, what is your country of residence?"
- Trip Purpose: "How did this visit to Yellowstone NP fit into your personal group's travel plans?" Possible answers: "Primary destination", "One of several destinations", "Not a planned destination"
- Stay length: "For this trip, please list the total time your personal group spent in Yellowstone NP." This answer is reported in hours when the trip length was less than 24 hours and days when the trip lasted longer than 24 hours.
- Group size: "On this visit, how many people including yourself, were in your personal group?"

These questions allow me to calculate the five statistics of interest. When calculating the proportion of primary purpose trips, I count "One of several destinations" and "Not a planned destination" as non-primary purpose trips.

Using these survey data, I construct a dataset that contains these five statistics for each park in each season. For park-seasons when survey data are not available, I impute the missing statistics. I distinguish two cases in my imputation procedure. In the first, the park has conducted a survey at some point, but it is missing data for at least one season. For example, Acadia NP conducted a survey in summer, but it is missing data for spring, fall, and winter. In this case, I impute the missing data using the equation:

$$Y_{js} = \phi_j + \lambda_s + \epsilon_{js} \tag{6}$$

where Y is the statistic to be imputed (e.g., re-entry rate, proportion of domestic visitors); ϕ is a park fixed effect, and λ is a season-of-the-year fixed effect.

The second imputation case is when a park has never conducted a survey. In this case, I cannot estimate the park fixed effect like I do in equation 6. Instead, I estimate sixteen models that predict the survey statistic of interest using flexible functions of park attributes. For each statistic, I identify the model with the lowest mean-squared error in a ten-fold cross-validation exercise. I use these preferred models to impute the missing park-season statistics.

The survey data and imputation procedure provide the five statistics for each park in each season-of-the-year. The average statistics are: 1.81 entries per trip, 93 percent domestic visits, 53 percent primary purpose trips, 1.58 days per trip, and 3.49 visitors per group. I now describe how I use these statistics to adjust the raw visitor counts.

E.4 NPS Visitor Use Statistics

I adjust the raw Visitor Use Statistics visitor count data to count trips rather than park entries, drop non-primary purpose visits, and drop international visits. I adjust for re-entry, because if visitors enter a park multiple times on the same trip, they do not pay the full travel costs for each entry. I drop non-primary purpose visits to stay consistent with best practices in the recreation demand literature. Finally, I drop international visits, because my model and survey data consider only domestic visitation. These steps yield an estimate of the number of domestic, primary purpose visits to each national park.

To begin, I smooth the park-season-of-the-year panel of re-entry, primary destination, and domestic visitation statistics. I assume that a statistic applies to the midpoint of each season (e.g., July for summer), and I linearly impute the statistics between these midpoints. This smoothing process yields a park-month-of-the-year panel, and it prevents inter-season jumps in the adjusted visitor counts.

With a park-month-of-the-year panel of re-entry, primary destination, and domestic visitation statistics, I adjust the raw visitor counts using the following equation:

$$\begin{aligned} &Adj.\ Visits_{jt} = \\ &\quad \left(\frac{Visits_{jt}}{AvgEntries_{jm(t)}}\right) P\left(Domestic_{jm(t)} | PrimaryDestination_{jm(t)}\right) P\left(PrimaryDestination_{jm(t)}\right) \end{aligned} \tag{7}$$

where j indexes parks and $m(t)$ denotes the month-of-the-year of month-of-sample t. Note that this equation implicitly assumes that the average re-entry rate for primary purpose, domestic visits equals the average re-entry rate for all visits at the park in the season. Some version of this assumption is necessary, as I do not observe separate re-entry rates for primary purpose and non-primary purpose visits or domestic and international visits.

I further assume that no international visits are primary purpose visits. Again, some version of this assumption is necessary to simplify the conditional probability in equation 7. Given that international travel is often costly, it seems reasonable to assume that the vast majority of international trips have "several planned destinations", and thus, qualify as non-primary purpose trips for my analysis. This assumption simplifies the visit adjustment equation to:

$$Adj.\ Visits_{jt} = \left(\frac{Visits_{jt}}{AvgEntries_{jm(t)}}\right) P\left(PrimaryDestination_{jm(t)}\right) \tag{8}$$

Dividing by the average number of entries converts the raw visitor counts to trips, rather than park entries. Multiplying by the fraction primary destination trips yields the adjusted visitor count, or the number of domestic, primary purpose trips to park j in month-of-sample t.

Adjusted visitor counts are 36 percent of their corresponding raw counts, on average. For roughly 80 percent of the parks in my sample, total adjusted visitation across the entire sample is 20 to 40 percent of their raw visitation. Six parks have adjusted visitation less than 15 percent of their raw visitation: Big Cypress NPRES (7 percent), Cape Cod NSS (9 percent), Grand Teton NP (10 percent), Pipestone NM (12 percent), Curecanti NRA (13 percent), and Zion NP (14 percent). Two parks have adjusted visitation greater than 65 percent of their raw visitation: Biscayne NP (83 percent) and Delaware Water Gap NRA (66 percent). Yet, adjusted visitation remains highly correlated with raw visitation with an R-squared of 0.83 (figure E1).

Adjusting the visitor counts preserves overall visitation trends (figure E2). In particular, both adjusted and raw visitor counts reveal a large increase in visitation between 2013 and 2017.

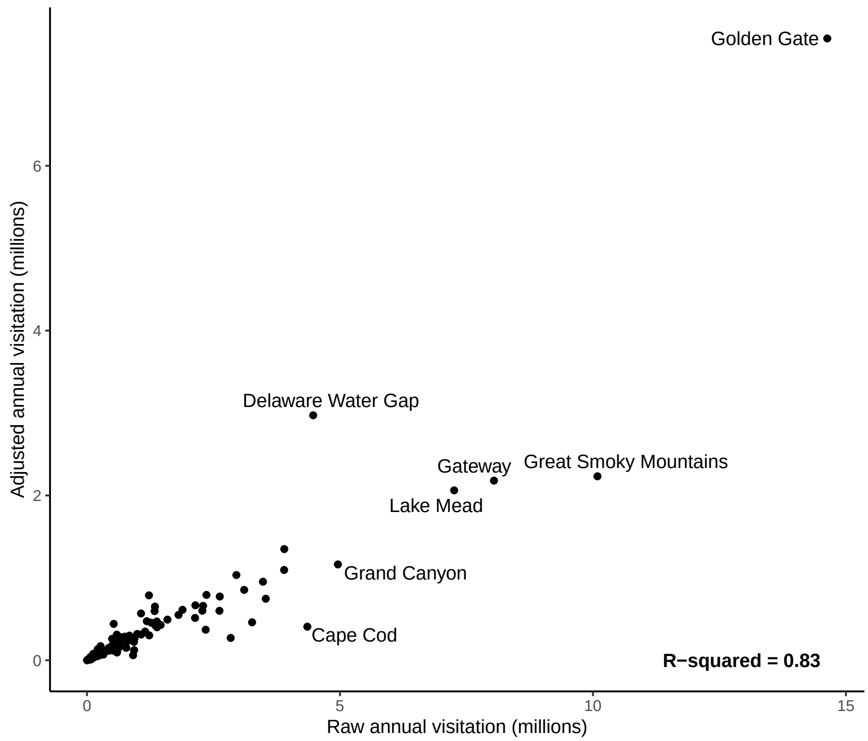
Adjusting visitor counts dampens seasonal visitation patterns (figure E3). Both raw and adjusted counts capture summer visitation peaks, but this peak is less dramatic when using adjusted counts. This is because summer trips tend to have higher re-entry rates (2.0 entries in summer versus an average of 1.76 in other seasons) and because summer trips are less likely to be primary purpose trips (47 percent versus 59 percent).

For the estimation procedure, I convert visitor counts to visitation shares. I assume the market size is the U.S. population times 0.716, which is the fraction of the 2008 CSAP respondents that "Strongly agree", "Somewhat agree", or "Neither agree nor disagree" with the statement "I plan to visit a unit of the National Park System within the next 12 months."

F Calculating travel costs

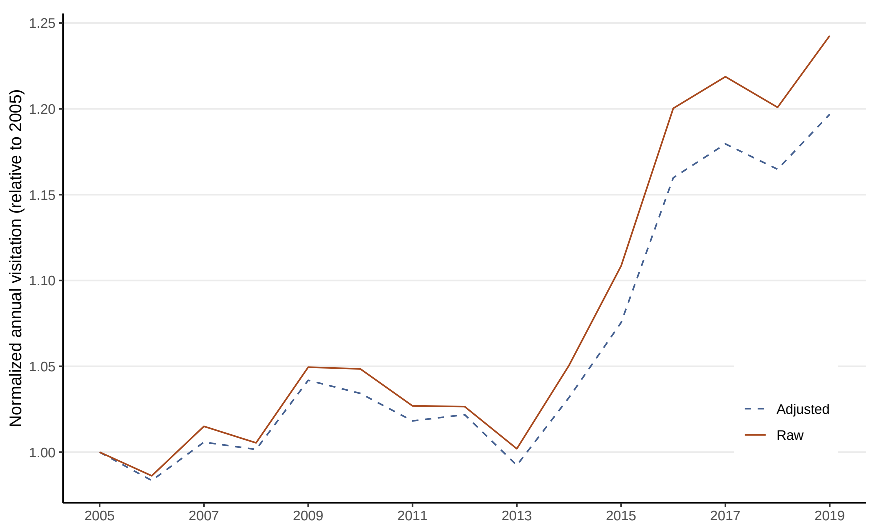
This appendix explains the procedure for calculating driving and flying travel costs. The procedure is based on English et al. (2018)'s travel cost calculations, which also compute driving and flying travel costs for respondents across the United States. I apply the procedure to calculate quarterly driving and flying travel

Figure E1: Comparing Raw and Adjusted Annual Visitation by Park



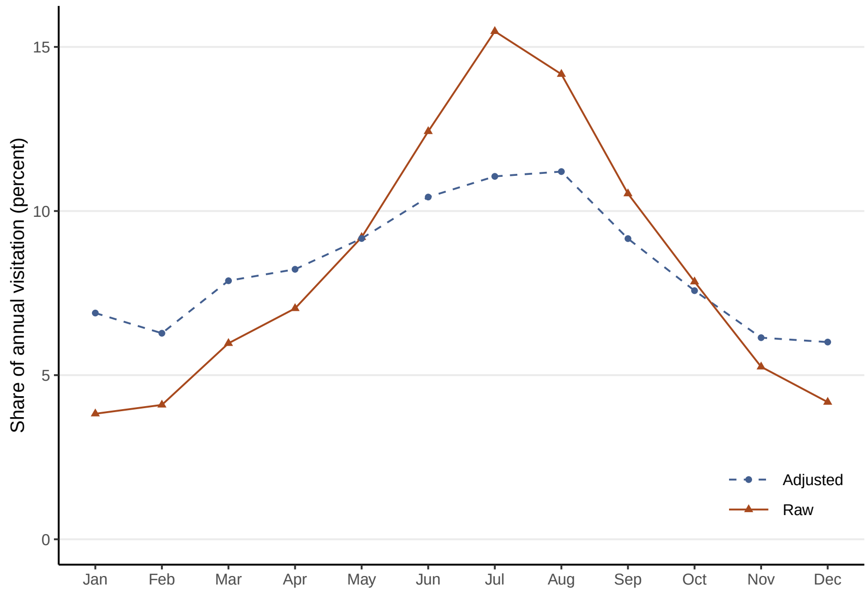
Note: The figure plots average annual adjusted visitation on the vertical axis and average annual raw visitation on the horizontal axis.

Figure E2: Comparing Raw and Adjusted Visitation Trends



Note: The figure plots annual system-wide visitation divided by 2005 visitation. The trend in adjusted visitor counts closely matches the trend in the raw visitor counts.

Figure E3: Comparing Raw and Adjusted Seasonal Visitation Patterns



Note: The figure compares the share of system-wide visitation occurring in each month-of-the-year using adjusted visitor counts and raw visitor counts.

costs for respondents in several datasets. First, I compute travel costs for respondents in the 2008 and 2018 waves of the Comprehensive Survey of the American Public (CSAP) telephone survey. I average respondents' travel costs across quarters to produce the travel cost variable that enters the estimation routine. Second, I compute quarterly travel costs for a 1 percent subsample of the annual American Community Survey microdata from 2005 to 2019. These computations produce 60 quarters (four quarters times fifteen years) of travel costs that enter the calibration procedure.

F.1 Calculating Driving Travel Costs

I calculate the round-trip driving travel cost (C_{ij}^D) beween each respondent's (i) home and each national park (j) in each quarter (q). The driving travel cost is a function of the one-way driving mileage between the respondent's home and the unit (d_{ij}) and the one-way driving time (t_{ij}). I calculate driving mileages and times using PC*Miler.[14] Given the driving mileages and times, I calculate the driving travel cost as

$$C_{ijq}^D = 2\left[\left(p_{iq}^d d_{ij} + p_q^h h_{ij}\right)/n + p_i^t t_{ij}\right] \tag{9}$$

where p_{iq}^d is the per-mile marginal cost of driving, p_q^h is the average nightly hotel rate, n is the average group

[14] I use the following settings when calculating driving mileages and times in PC*Miler: Routing type = "practical", Units = 0, Over Perm = 0, Height = 0, Width = 96, Length = 1, Weight = 1000, Axle = 2, LCV = 0.

size, and p_i^t is respondent i's per-hour cost of travel time. This equation is identical to English et al.'s except that it does not include toll costs, because my version of PC*Miler does not include toll cost calculations.

The per-mile marginal cost of driving (p_{iq}^d) is the sum of per-mile marginal costs of (1) maintenance, (2) depreciation, and (3) gas. I obtain per-mile maintenance and depreciation costs from annual AAA "Your Driving Costs" reports. I define maintenance costs as the sum of AAA's reported per-mile maintenance and tire costs for an Average Sedan. AAA reports depreciation costs relative to a 15,000-mile baseline, which I use to calculate per-mile depreciation costs. For example, the 2013 AAA report estimates that an Average Sedan that drives 10,000 miles would depreciate \$266 less than an Average Sedan that drives 15,000 miles and an Average Sedan that drives 20,000 miles would depreciate \$231 more than an Average Sedan that drives 15,000 miles. This implies a per-mile depreciation cost of \$0.050 = (\$266 + \$231) / 10,000 miles. Due to the availability and quality of cost data from the AAA reports, I impute per-mile maintenance costs for four years and per-mile depreciation costs for six years. I describe these imputations in more detail in section F.2.

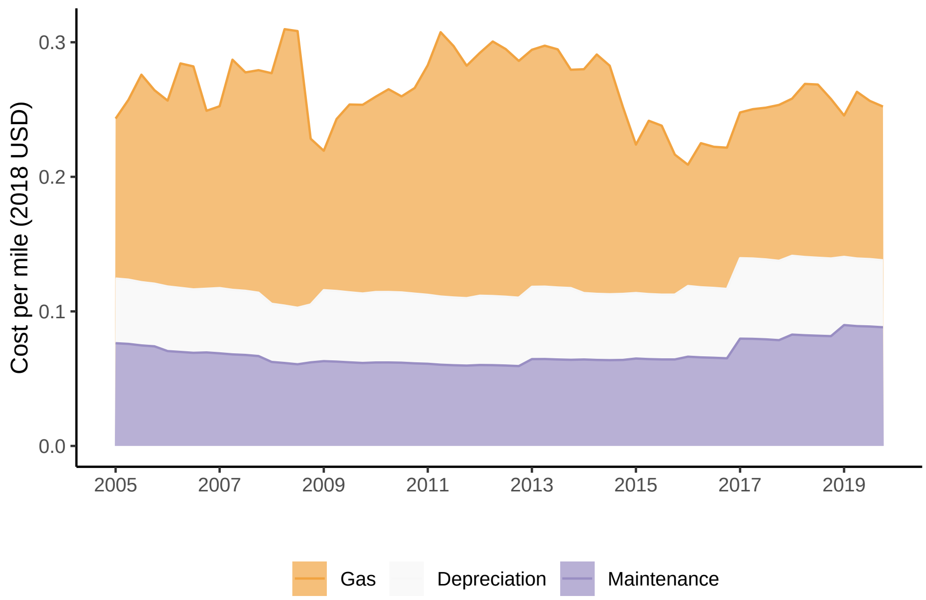
The final input to the per-mile marginal cost of driving is the per-mile cost of gas. I calculate quarterly per-mile gas costs using regional gasoline prices from the Energy Information Administration (U.S. Energy Information Administration, 2024) and average light duty vehicle fuel efficiency from the Bureau of Transportation Statistics (Bureau of Transportation Statistics, 2023). I average weekly gasoline prices to produce a region-quarter panel of gas prices from 2005 through 2019, then I divide gas prices by the average efficiency in the corresponding year to find the per-mile marginal cost of gas.

Figure F1 shows the components of the quarterly per-mile marginal cost of driving. The total per-mile marginal cost averages 26.4 cents from 2005 to 2019. Maintenance and depreciation costs are relatively stable, making up around 7 cents and 5 cents of the total per-mile cost. The per-mile gas cost makes up the largest portion of the total per-mile driving cost, and it varies more than maintenance and depreciation costs, ranging between 9 cents and 21 cents.

I calculate quarterly hotel rates using English et al.'s reported average nightly hotel rate of \$114 in 2012. I scale this rate by the "Other lodging away from home" component of the Consumer Price Index to find quarterly average hotel rates from 2005 through 2019. I calculate the number of hotel nights by dividing the one-way travel time by twelve hours and rounding down — i.e., I assume respondents can drive up to twelve hours in one day of travel.

Because I do not observe the average group size in my survey data, I incorporate additional on-site survey data. I describe these data in the Data Appendix. Averaging average group sizes across all parks and seasons yields an average group size of 3.49 people trip. I use this as the n in the driving travel cost equation. Finally, I assume the cost of an hour of travel time, p_i^t, is one-third of a respondent's hourly wage.

Figure F1: Per-mile driving costs over time



Note: The figure shows the components of the per-mile driving cost over time. Per-mile gas prices vary by region, and their national average is shown here.

I approximate each respondent's hourly wage by dividing their income by 2080 hours (40 hours per week times 52 weeks per year).

Given these inputs, I calculate the one-way driving travel cost for each respondent-park combination. I multiply by two to convert one-way costs to roundtrip costs, and I convert roundtrip driving travel costs into 2018 dollars.

Roughly two-thirds of the driving travel cost comes from the cost of time, rather than mileage and hotel costs. As an example, consider a road trip from Greenville, NC to Yellowstone National Park. The trip requires approximately 2,200 miles and 33 hours of driving one-way. The average per-mile driving cost is about 25 cents per-mile and 33 hours of one-way driving requires two nights in a hotel room at \$136 per night. Summing these mileage and hotel costs and dividing by the average group size of 3.43 yields one-way mileage and hotel costs of $\$240 = (0.25 * 2200 + 2 * 136)/3.43$. Meanwhile, the average cost of travel time for the 2008 survey respondents is \$12.57 per hour, which implies the one-way cost of time is \$415.

F.2 Imputing Maintenance and Depreciation Cost

To produce time series of maintenance and depreciation costs, I adjust some of the raw AAA driving cost data. These adjustments are necessary because (1) I could not find the AAA report for 2005, (2) the Average Sedan category was removed from reports beginning in 2017, and (3) depreciation costs in 2006 and 2007 are three times larger than other years.

To create an annual time series of maintenance costs for AAA's Average Sedan vehicle classification, I impute the 2005 maintenance cost by averaging the 2004 and 2006 maintenance costs. Then, I impute maintenance costs for Average Sedans in 2017, 2018, and 2019. For the 2017–2019 imputation I regress Average Sedan maintenance costs on Small, Medium, and Large Sedan maintenance costs for 2005 through 2016. Using the parameter estimates from this regression, I predict Average Sedan per-mile maintenance costs in 2017, 2018, and 2019. These two imputations produce an annual time series of per-mile maintenance costs for Average Sedans between 2005 and 2019.

I produce an annual time series of depreciation costs for Average Sedans in two steps. First, I impute per-mile depreciation costs for Small, Medium, and Large Sedans in 2005, 2006, and 2007 by regressing 2008–2019 depreciation rates for those sedan categories on the year, vehicle dummy variables, and the year interacted with the vehicle dummy variables. I use these parameter estimates to predict per-mile depreciation costs for Small, Medium, and Large Sedans for 2005, 2006, and 2007. After this step, I have a panel of depreciation rates for Small, Medium, and Large Sedans for 2005 through 2019. Second, I impute per-mile depreciation costs for Average Sedans by regressing Average Sedan per-mile depreciation costs on Small, Medium, and Large Sedan per-mile depreciation costs for 2008 to 2016. Using the parameter estimates from this regression and the 2005-2019 panel of depreciation rates for Small, Medium, and Large Sedans, I predict per-mile depreciation costs for Average Sedans for 2005–2007 and 2017–2019.

F.3 Calculating Flying Travel Costs

Following English et al., I sum five components to calculate flying travel costs: (1) the cost of driving from a respondent's home to the origin airport, (2) the cost of parking at the origin airport, (3) the cost of flying from the origin airport to the destination airport, (4) the cost of renting a car, and (5) the cost of driving from the destination airport to the national park. Because individuals may choose from several origin and destination airports when taking their trip, I calculate flying travel costs for all routes through four origin airports and four destination airports. This leads to sixteen possible airport combinations for each respondent-park-pair. For each respondent-park pair, I identify the minimum travel cost route and assign its travel cost as the respondent-park pair's flying travel cost.

I begin by identifying the origin airports. For each respondent, I calculate the driving mileage between their home and every airport with greater than 100,000 enplanements in 2012. I keep the four closest airports as their origin airports. If none of these four airports is a medium or large airport, as classified by the FAA's 2012 enplanement data (Federal Aviation Administration, 2024), then I replace the fourth closest airport with the closest medium or large airport. I repeat this process to identify the four destination airports for each national park.

Creating all combinations of these origin and destination airports produces sixteen possible routes for each respondent-park pair. I calculate respondent i's flying travel cost of reaching park j via their origin airport m and destination airport n in quarter q as

$$C^{F}_{imnjq} = 2C^{D}_{imq} + C^{Parking}_{mq} + 2C^{Flight}_{imnq} + C^{Rent}_{q} + 2C^{D}_{njq} \tag{10}$$

The first and last terms, C^{D}_{imq} and C^{D}_{njq}, represent the cost of driving from the individual's home to the origin airport and the cost of driving from the destination airport to the national park. I calculate these driving costs according to the steps outlined in section F.1.

The second term, $C^{Parking}_{mq}$, represents the cost of parking at the origin airport. It is the product of the average daily airport parking rate and the number of required parking days. I use separate parking rates for small airports and large/medium airports. I calculate the number of required parking days as the sum of the average time spent at the park on all national park visits (from the on-site survey data), the flight time, and the driving time from the destination airport to the park. I calculate the cost of renting a car, C^{Rent}_{q}, by taking the product of the national average rental care rate and the number of required rental car days. To estimate the rental car rate for each quarter, I take English et al.'s estimate of the 2012 national average rental car rate, \$54.11, and scale it by the Consumer Price Index for car rentals (U.S. Bureau of Labor Statistics, 2024). I calculate the number of required rental car days as the number of required parking days minus the flight time.

The final component of equation 10 is the cost of flying from the origin airport to the destination airport. The cost of the flight depends on the flight itinerary, as individuals could fly directly from origin airport m to destination airport n or have a layover. My flight data come from Table 6 of the Consumer Airfare Report, which includes information for single flight segments, effectively all direct flight itineraries. To more accurately represent the full set of itineraries between origin and destination airports, I generate all possible flight itineraries that can link origin and destination airports with at most one layover using the segments from the direct flights in Table 6 of the Consumer Airfare Report in that quarter.

I calculate individual i's cost of flying from origin airport m to destination airport n using itinerary z in quarter q as

$$C^{Flight}_{imnqz} = p^{t}_{i}\left(time^{airport} + time^{flight} + time^{layover}_{z}\right) + p^{airfare}_{mnqz} \tag{11}$$

The term $p^{airfare}_{mnqz}$ represents the monetary cost of airfare. For this, I use quarterly average airfare for all airport city-market pairs averaging more than ten passengers per day from Table 6 of the Consumer Airfare Report. For layover itineraries, I assume the airfare is the sum of the airfare for the two flight segments.

As in equation 9, the coefficient p_i^t represents individual i's cost of travel time. I decompose the time costs associated with flying into three components: (1) the time spent at the airport before and after the flight, (2) the flight duration, and (3) the time spent during layovers. I assume the time spent at the airport before and after the flight is two hours. I approximate the flight time using the distance between the airports and English et al.'s estimated parameters for the relationship between flight time and distance. In a simple regression of flight times on flight distances, they estimate an intercept of 42.5 and a slope of 0.1213. I use median layover times from English et al. that vary by airport size: 80 minutes for small airports, 55 minutes for medium airports, and 70 minutes for large airports.

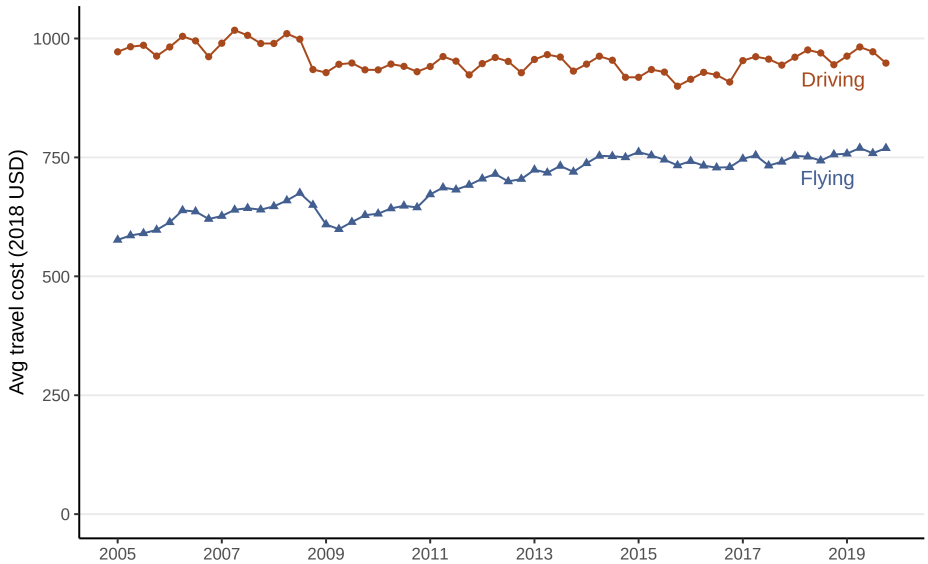
These calculations provide me with multiple flying travel costs for each respondent-park combination. If each destination airport can be reached from each origin airport in one layover or less, then there are sixteen possible origin-destination airport routes for each individual-park pair. Furthermore, each origin-destination airport route has multiple itineraries – it could be reached directly or via a layover. I take the minimum of flying travel costs across all routes and itineraries as respondent i's flying travel cost to reach national park j.

Although my flying travel cost calculations closely follow English et al., I do use different airfare and flight itinerary data. English et al. use the flight itinerary for the 30th percentile airfare between the origin and destination airports from DB1B Origin to Destination Surveys. Because my analysis period spans fifteen years and 60 quarters, replicating their calculations would require over 100GB of ticket-level data. I use the Consumer Airfare Report, which summarizes the ticket-level data and thus requires much less storage.

Figure F2 shows average driving and flying travel costs for each quarter of the survey period. Average driving travel costs remain consistent across the analysis period. Average flying travel costs steadily increase, beginning around \$600 and ending just above \$750.

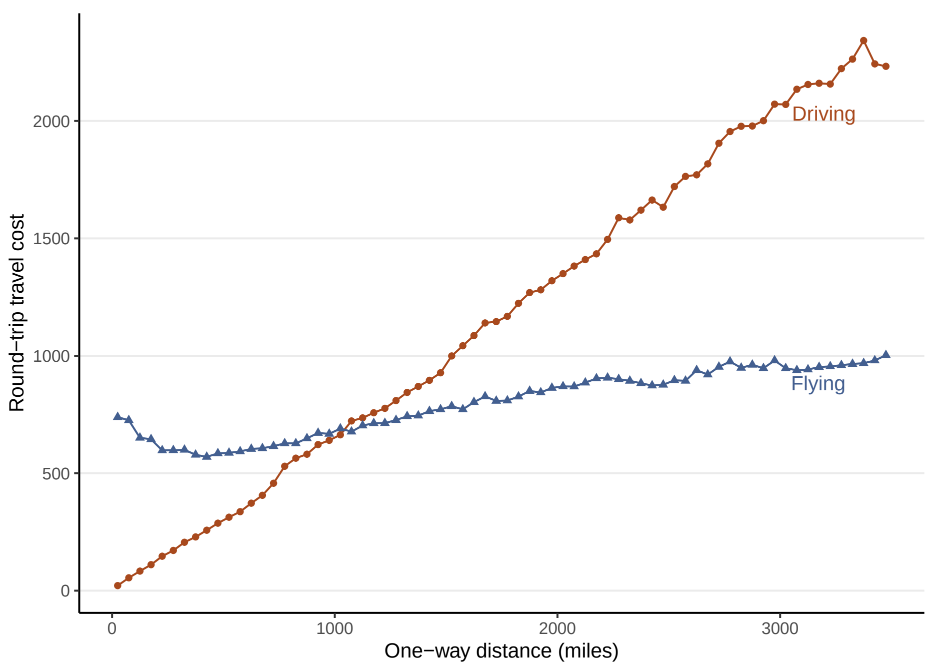
Figure F3 shows the average travel costs for 50-mile distance bins. Both driving and flying travel costs increase with distance, but flying travel costs increase much more gradually. On average, flying is more expensive than driving for trips under 1,000 miles (one-way), and it is cheaper than driving for longer-distance trips.

Figure F2: Average Driving and Flying Travel Costs



Note: The figure shows average round-trip driving travel costs (brown circles) and flying travel costs (blue triangles) for all respondent-park pairs in the 1 percent ACS sample for each quarter of the analysis period. All travel costs are reported in real 2018 dollars.

Figure F3: Travel costs increase with distance



Note: The figure plots survey respondents' average round-trip travel costs on one-way driving distance for 50-mile distance bins. The brown line with circles shows average driving travel costs, and the blue line with triangles shows average flying travel costs.