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

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Abstract

I develop a framework to study demand for 140 U.S. national parks. Using a travel cost RUM model, I generate a national park awesomeness index and explore which attributes make parks awesome. Iconic parks, like Glacier, Yellowstone, and Grand Canyon, consistently rank in the top ten. I apply the framework to estimate the welfare impacts of climate change. I find that the benefits of warming cold temperatures will outweigh losses from extreme heat, leading to annual welfare gains of $679 million by 2050. Large-scale resource changes and an increased frequency of natural disasters have the potential to erase these gains.

In 1916, the National Park Service was created to conserve the United States' most significant sites, scenery, and wildlife (Organic Act of 1916). More than a century later, the national parks are more popular than ever. The National Park System now encompasses over 400 parks, including world-famous destinations like Yellowstone and the Grand Canyon, seashores like Cape Hatteras and Point Reyes, historic sites, and much more. The national parks attract 300 million visits each year, generating surplus for visitors and supporting local

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economies. Their cultural significance has earned them the nickname, “America’s Best Idea” (Burns & Dayton, 2009).

The National Park Service aims to provide recreational enjoyment and preserve park resources. In recent years, achieving these objectives has become increasingly challenging. At some parks, vehicle traffic creates air pollution that rivals metropolitan areas (Keiser et al., 2018). Record visitation levels and stagnant funding have contributed to a $20 billion deferred maintenance backlog (NPS 2023). Meanwhile, climate change has already begun to alter the resources the National Park Service was created to protect. Sea level rise, wildfires, drought, and extreme weather events, amplified by climate change, pose threats to the United States’ most treasured resources. Understanding how these challenges impact visitor welfare aligns with the National Park Service’s mission of conservation for the enjoyment of present and future generations.

This paper creates a unified and versatile framework to analyze demand for the U.S. National Park System. I construct a travel cost random utility maximization (RUM) model of national park visitation that includes 140 parks throughout the contiguous United States. Individuals repeatedly choose whether to visit a park, which park to visit, and whether to drive or fly to the park. The model controls for travel costs and the quality of alternative parks to isolate the mean utility provided by visiting a park. I call these mean utilities “park effects”. In plain terms, the park effects provide a national park *awesomeness* index.

I combine two data sources to estimate the model: the 2008 and 2018 waves of the Comprehensive Survey of the American Public, a nationally representative telephone survey administered by the National Park Service, and monthly, park-level visitor counts from the National Park Service’s Visitor Use Statistics database. I first estimate the model parameters using data from the two survey periods. I then calibrate the model from January 2005 through December 2019, solving for the monthly park effects that match the visitation shares predicted for a nationally representative microdata sample (from the American Community Survey) to the visitation shares observed in the visitor count data. In effect, I filter the monthly visitor counts through the RUM model, transforming them into estimates of monthly park *awesomeness*. I explore variation in the park effects to understand which parks are most *awesome* and which attributes explain *awesomeness*.

The model and data infrastructure provide a versatile framework for studying the welfare impacts of resource and management changes across the National Park System. To demonstrate this versatility, I apply the framework to estimate the welfare impacts of climate change on national park visitation. I begin by specifying a second stage model in which park effects depend on both long-run average temperatures and short-run temperature shocks. This decomposition captures preferences for both gradual warming and the increased frequency of heat waves and cold snaps expected with climate change. I identify preferences for temperature by using a flexible set of fixed effects to isolate within-season variation at each park and control for unobservable attributes. The estimated preferences allow me to predict how climate change will impact park effects and, subsequently, visitor welfare.

This analysis produces three sets of findings. First, I find that iconic parks, like Yellowstone, Glacier, and Grand Canyon, consistently rank among the top ten most *awesome* parks. In addition to varying across parks, park effects vary substantially month-to-month. For parks with harsh winters, park effects peak in the summer months, while parks with moderate climates provide more stable utility throughout the year.

Second, I regress the park effects on park attributes and find that, on average, visitors prefer parks with iconic flora and wildlife, like redwood forests and bison, and more extensive trail and road networks. Many attributes vary little over time, posing a challenge for causal inference, but the month-to-month variation in my park effects makes a causal interpretation more plausible for attributes that vary across time. However, even with an extensive collection of attributes, I can explain only 52% of the variation in the park effects, suggesting it is difficult to quantify many of the features that make the parks so appealing.

Finally, I apply the model to estimate the welfare impacts of climate change on national park visitation. Abstracting from large-scale resource changes, I find that climate change will increase the average annual welfare from national park visitation by \$572 million in the 2030s, \$679 million in the 2040s, and \$1.2 billion in the 2050s (relative to a 2005 to 2019 baseline). Two features of visitor preferences underlie these gains. First, visitors have stronger preferences for long-run average temperatures than temperature shocks. Second, visitors dislike cold more than they dislike heat. Compared to an average temperature of 75°F, visiting a park when the average temperature is 30°F reduces average willingness to pay by \$400 per trip, while visiting when the average temperature is 95°F reduces average willingness to pay by just \$78. Consistent with these preferences, I find that large welfare gains in cooler months outweigh losses in summer months.

These welfare gains reflect the effect of improved visitor comfort but ignore other channels for climate impacts, such as an increased frequency of natural disasters and degrading park ecology (e.g., species loss). It is challenging to predict how climate change will alter park resources, let alone estimate the associated welfare impacts. However, it is feasible to evaluate the welfare impacts of plausible park closure scenarios. For example, a permanent closure of Cape Hatteras National Seashore, say, due to sea level rise, would decrease welfare by \$615 million per year between 2040 and 2049, offsetting 91% of the gains from improved visitor comfort.

This paper constitutes the most comprehensive analysis of demand for the national parks to date.[1] The closest study to mine is Neher et al. (2013) who value 58 national parks using park-specific surveys conducted between 1994 and 2009. They estimate WTP for visiting each park separately, then run a meta regression of WTP on park attributes. In addition to studying 80 additional parks, my analysis improves on Neher et al.'s by modeling demand spillovers and exploiting monthly variation in visitation and resource quality. Like me, several papers analyze visitation at the national level. Keiser et al. estimate the impact of air quality on national park visitation. Wichman (2024) studies the impact of social media,

[1] There is a diverse body of economic research on the National Park System. Other notable research focuses on volunteerism (Kotchen & Wagner, 2023), local economic impacts (Cullinane Thomas & Koontz, 2020), and valuation with stated preference methods (Haefele et al., 2020)

and Szabó and Ujhelyi (2024) study the impact of national park designations as part of a broader analysis of local economic impacts. Fisichelli et al. (2015) study the impact of climate change, as I do. They also predict that climate change will increase park visitation but use monthly visitation and temperature data averaged over 35 years. None of these visitation studies use individual-level data, estimate demand for the parks, or conduct welfare analysis.[2] Other papers apply recreation demand models to value parks and their resources, but 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 cost RUM model and Gellman et al. (2023) 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.

My analysis fills a void at the intersection of visitation and valuation studies. I preserve the ability to conduct valuation, while maintaining a national scope and studying visitation, rather than a specific activity. This approach has two practical benefits. First, valuation estimates are critical for informing policy and damage assessments, but many parks lack the resources to execute their own analyses. Even if parks have the resources, they typically execute surveys infrequently, so the sampling period may not capture resource changes of interest. The scope of my framework, covering 140 parks over fifteen years, fills these gaps. Second, nearly all national visitation studies assume that impacts at treated parks do not spill over to control parks. This assumption departs from much of the recreation demand literature, which prioritizes modeling inter-site substitution. By using a RUM framework, I explicitly model potential demand spillovers, making my approach a valuable point of comparison for estimates based on reduced-form models.

I also contribute to a growing literature valuing the nonmarket impacts of climate change, which are understudied inputs to the social cost of carbon (Burke et al., 2016). Within this literature, several papers have valued the impact of climate change on recreation (Chan &

[2]Other papers studying national park visitation at the national scale include Henrickson and Johnson (2013), Bergstrom et al. (2020), and Cai (2021).

Wichman, 2020; Chan & Wichman, 2022; Loomis & Crespi, 1999; Mendelsohn & Markowski, 1999; Parthum & Christensen, 2022). Methodologically, my analysis is most similar to Dundas and von Haefen (2020), who estimate climate impacts on recreational marine fishing using a travel cost RUM model. Our approaches have one important difference. My model allows temperature and precipitation to impact both participation and site choice, while in their model, temperature and precipitation impact only the participation choice. This feature is critical when modeling national park visitation, because weather conditions vary substantially across parks.

The paper proceeds as follows. Section 1 presents the model of national park visitation. Section 2 describes the nationally representative telephone surveys, monthly visitor counts, and the national park attribute data. Section 3 discusses the estimation and calibration procedure. Section 4 describes the results. Section 5 applies the framework to value the welfare impacts of climate change, and Section 6 concludes.

1 A Model of National Park Visitation

In this section, I present a model of national park visitation. The model departs from the standard recreation travel cost model in two dimensions. 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 often focuses on participation and site choice, with the transportation literature, which often focuses on travel mode choice (McFadden, 1974).[3] Second, the model includes a panel of park-by-month fixed effects (park effects), rather than time-invariant (or infrequently varying) park fixed effects. In this respect, the model shares similarities Chintagunta et al.'s (2005) model of demand for margarine, which includes time-varying product fixed effects.

Suppose that each month individuals choose whether to visit a national park, which

[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.

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 $\mathcal{M} = \{D, F\}$, where D 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 visits to 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

$$U_{ijmt} = \begin{cases} \delta_0 Z_i + \epsilon_{i0t} & j = 0 \\ \delta_{jt} + \beta_{TC} TC_{ijDt} + \epsilon_{ijDt} & j \in \{1, ..., J\}, m = D \\ \delta_{jt} + \beta_F + \beta_{TC} TC_{ijFt} + \epsilon_{ijFt} & j \in \{1, ..., J\}, m = F \\ \delta_{J+1,t} + \epsilon_{i,J+1,t} & j = J + 1 \end{cases} \tag{1}$$

In equation 1, coefficient β_{TC} represents the marginal disutility of travel costs, and coefficient β_F represents the preference for flying relative to driving after controlling for travel costs, TC. Z_i contains a vector of socioeconomic variables, and ϵ_{ijmt} is unobservable to the econometrician. For $j \in \{1, ..., J\}$, I call the 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 decompose the park effects using observable park attributes, X_{jt}, by writing:

$$\delta_{jt} = X_{jt}\alpha + \nu_{jt}, \tag{2}$$

where α is a coefficient vector, and ν_{jt} contains all unobservable park attributes.

Assume the error term, ϵ_{ijmt} follows a Generalized Extreme Value distribution with a two-level nesting structure such that the no visit alternative, $j = 0$, is in its own nest. This assumption implies the independence of irrelevant alternatives (IIA) assumption holds for any two alternatives within the visit nest, but it relaxes IIA for the no visit alternative and each of the visit alternatives. Thus, the nested logit model can capture more flexible substitution patterns than the conditional logit model. Under this nesting structure, the probability of choosing each alternative has a closed form:

$$P_{ijmt} = \begin{cases} \dfrac{\exp(V_{0t})}{\exp(V_{0t}) + (\sum_{k=1}^{J+1} \sum_{n \in \mathcal{M}} \exp(\frac{V_{iknt}}{\lambda}))^{\lambda}} & , \text{ if } \ j = 0 \\ \dfrac{(\sum_{k=1}^{J+1} \sum_{n \in \mathcal{M}} \exp(\frac{V_{iknt}}{\lambda}))^{\lambda}}{\exp(V_{0t}) + (\sum_{k=1}^{J+1} \sum_{n \in \mathcal{M}} \exp(\frac{V_{iknt}}{\lambda}))^{\lambda}} \ \dfrac{\exp(\frac{V_{ijmt}}{\lambda})}{\sum_{k=1}^{J+1} \sum_{n \in \mathcal{M}} \exp(\frac{V_{iknt}}{\lambda})}, & \text{ if } \ j \in \{1, ..., J\} \\ \dfrac{(\sum_{k=1}^{J+1} \sum_{n \in \mathcal{M}} \exp(\frac{V_{iknt}}{\lambda}))^{\lambda}}{\exp(V_{0t}) + (\sum_{k=1}^{J+1} \sum_{n \in \mathcal{M}} \exp(\frac{V_{iknt}}{\lambda}))^{\lambda}} \ \dfrac{\exp(\frac{V_{i,J+1,t}}{\lambda})}{\sum_{k=1}^{J+1} \sum_{n \in \mathcal{M}} \exp(\frac{V_{iknt}}{\lambda})}, & \text{ if } \ j = J + 1 \end{cases} \tag{3}$$

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

Two terms comprise the choice probabilities for the visit alternatives. The first is the probability of choosing a visit alternative. The second is the probability of visiting a specific park using a specific travel mode 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 literature often refers to the parameter, λ, as 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.

2 Data

My main data sources describe individual-level visitation, aggregate park-level visitation, and the physical and institutional attributes of the national parks. The individual-level visitation data come from the National Park Service's Comprehensive Survey of the American Public, a telephone survey designed to learn about visitor experiences and gauge public sentiment towards the National Park Service and its management practices. Each interview lasts approximately fifteen minutes and includes several questions regarding respondents' visitation histories. I observe 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% 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, while the 2018 wave did not collect travel mode information. The seasonal timing of interviews also varies slightly 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% 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 B. 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. 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 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. 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 CSAP respondents. Respondents made five visits in the past two years, on average, and 62% visited at least once. Of the respondents who visited a park less than two years before their interview and answered the travel mode question, about 13% 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.

I use park-level visitor count data from the National Park Service's 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. The vast majority of nationwide visitation studies use these Visitor Use Statistics (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. I aggregate counts at national parks that were not protected for their natural resources. These sites make up the historic site alternative in the choice set, $j = J + 1$. I use National Park Service designations to identify sites protected for their natural resources. For all national parks in the contiguous United States, the choice set 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 include all other parks (e.g., National

Monuments less than 150 acres, Historic Sites, Battlefields, and Memorials) as part of 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. The adjustment addresses three specific factors: international visitation, non-primary purpose trips, and park re-entry. I drop international visitors and non-primary purpose trips, because the survey data include only U.S. residents and Lupi et al. (2020) recommend dropping non-primary purpose trips in recreation demand analyses. 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. To execute the adjustment, I use park-specific statistics on international visitation, trip purpose, and re-entry from 109 on-site surveys conducted by the National Park Service between 1995 and 2019. I discuss these on-site survey data and the visitor count adjustment in more detail in Appendices A3 and A4.

To understand visitor preferences for park attributes, I compile several datasets describing the national parks themselves. Table 2 shows the full list of data sources and the variables I generate from them.

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). The ACS reports the county of residence for about 60% of the sample. 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 the telephone survey sample.

3 A two-step approach to estimate demand

This section describes an estimation and calibration procedure designed for the model and data from the previous two sections. In Step 1a, I estimate the travel cost, flying dummy, and demographic coefficients. In Step 1b, I calibrate the panel of park effects. Finally, in Step 2, I regress the park effects on park attributes. Removing the calibration step (1b) from my procedure makes it nearly identical to Murdock's (2006) two-stage estimation approach. My procedure also shares similarities with Berry et al. (2004), who combine micro and macro-level demand data in a maximum likelihood estimation.

3.1 Step 1a: Maximum likelihood estimation

I begin by estimating the parameters in equation 1 via 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: the location of the 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 drop the t subscript from the model and estimate two cross-sections of park effects, one for each survey period.

Using the choice probabilities from equation 3, the likelihood of observing individual i's visitation history is

$$L_i(\beta, \delta) = \underbrace{(\Pi_{j=0}^{J} \Pi_{m \in \mathcal{M}} P_{ijm}^{y_{ijm}})}_{(1)} \underbrace{(1 - P_{i0})^{v_i}}_{(2)} \underbrace{(P_{i0})^{24-1-v_i}}_{(3)} \tag{4}$$

where v_i is the number of visits in the two years before the interview, excluding the most recent, and y_{ijm} equals one if respondent i visits park j using travel mode m 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 prior to the interview. The third term represents the likelihood from all non-visits in the two years prior to 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. 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): $\delta^{n+1} = \delta^n + \lambda \left[ln(s) - ln(\hat{s}(\delta^n, \beta))\right]$. As the optimization routine iterates over values of β, the contraction mapping solves for the unique vector of 2008 and 2018 park effects, δ, that matches the observed (s) and predicted ($\hat{s}$) visitation shares in each survey period.

Incorporating the contraction mapping has several practical 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 only over the remaining first-stage parameters, reducing the computational burden. Third, the contraction mapping allows me to estimate park effects for parks that are never chosen in the survey data. This is not possible with survey data alone.

By estimating two cross-sections of park effects, I eliminate for bias from unobserved park attributes when estimating the remaining first-stage parameters. Any unobserved park attributes are completely captured by the park effects (Murdock, 2006). Geographic sorting remains an identification concern (Parsons, 1991). Individuals who value national parks may choose their residential location 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 and bias willingness to pay estimates towards zero. The magnitude of this potential bias is unclear due to the limited attention it receives in the travel cost literature and the dearth of national travel cost studies.

3.2 Step 1b: Calibrating a monthly panel of park effects

Step 1a yields estimates of the first-stage parameters including two cross-sections of park effects, one for the 2008 survey period and another for the 2018 period. Now, in Step 1b, I toss out these cross-sections of park effects and use the remaining first-stage parameters, annual American Community Survey (ACS) microdata, and the monthly 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 sample period. I account for these demographic changes by calibrating the model using annual ACS microdata samples from 2005 to 2019 rather than the survey data. The calibration procedure also requires an assumption on the stability of the first-stage parameters. I assume that the first-stage parameters are constant across the entire fifteen-year calibration period. While this is not necessary, early iterations of this analysis allowed first-stage parameters 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 model of recreational marine fishing and obtain fairly stable estimates from 2004 through 2009.

Given these assumptions, I calculate choice probabilities for each individual in the ACS microdata.[4] Summing these choice probabilities generates predicted visitation shares for each park in each month. Recall that the visitor counts also have a monthly panel structure. Beginning with January 2005, I 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 applying the contraction mapping to solve for park effects does not require individual-level choice data. One only needs estimates

[4] I use a random 1% sample of the ACS microdata to reduce the computational burden. In earlier iterations of the analysis, the calibrated park effects were nearly identical whether I used a 1% subsample or a 5% subsample.

of the first-stage parameters, a microdata sample, and observed visitation shares.

3.3 Step 2: Estimating preferences for park attributes

In Step 2, I regress park effects on various park attributes (equation 2). Previous recreation demand research using a two-stage estimation approach has run cross-sectional second-stage regressions (Murdock, 2006; Timmins & Murdock, 2007). A cross-sectional second stage can leave estimates susceptible to omitted variable bias unless the researcher has an instrumental variable or stated preference data. My second-stage regression uses panel variation, rather than cross-sectional variation, allowing more strategies for dealing with omitted variables. For example, I include park-by-season fixed effects when estimating preferences for average temperatures and temperature shocks in my application.

Despite the panel structure of my park effects, there are complications in estimating preferences for many park attributes at once. Some attributes, like elevation, do not change meaningfully across my fifteen-year analysis period. Other attributes, like temperature, vary across parks and across time. While including a flexible set of fixed effects (e.g., park or park-by-season) has the attractive property of controlling for unobserved attributes that are constant across time, the fixed effects would subsume preferences for time-invariant attributes.

I use a correlated random effects model with a Mundlak device to address this issue. Specifically, I use OLS to estimate

$$\delta_{jt} = X_j\alpha_1 + X_{jt}\alpha_2 + \bar{X}_{js(t)}\alpha_3 + \nu_{jt}, \tag{5}$$

where X_j includes time-invariant attributes, X_{jt} includes time-varying attributes, and $\bar{X}_{js(t)}$ is the mean of time-varying attributes at park j in the season of the year $s(t)$. When attributes vary over time, the Mundlak device allows me to recover the same coefficient estimates as a model with park-by-season fixed effects. At the same time, it preserves cross-sectional variation to recover preferences for time-invariant attributes (Mundlak, 1978; Wooldridge, 2019).

4 Results: Which parks are most awesome, and why?

Table 3 shows estimates of the first-stage parameters. The travel cost coefficient is negative and significant, as expected. The "fly" parameter capturing 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 $173 on average to drive rather than fly to their chosen site. I interact several sociodemographic variables with the outside option. College graduates and individuals with higher household incomes are more likely to visit national parks. Seniors and people with at least one child under 18 are less likely to visit. In terms of racial and ethnic diversity, white, non-Hispanics are more likely to visit the parks than Asian, Black and Hispanic individuals. These racial and ethnic participation differences align with visitation statistics and anecdotal observations that note a lack of diversity among national park visitors (Mott, 2016). Unlike previous studies, I can rule out park locations as the reason for the differences in visitation rates. Even conditional on having the same travel costs, income, and education level, minority groups are less likely to visit the national parks than white, non-Hispanics. The dissimilarity coefficient is between zero and one, implying the nested logit model is consistent with utility-maximizing behavior.

The first-stage estimates allow me to calibrate the monthly 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 $995 more on average to visit Glacier in July rather than January. Great Smoky Mountains displays more muted seasonality with a less pronounced peak and valley. Similar patterns at other parks suggest that climate and weather drive seasonal variation in park effects, providing motivation for my climate change application in section 5.

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.[5] 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.

Table 4 shows how park attributes impact the park effects. Variables with asterisks change over time, and I identify these coefficients using within-park-season variation. Variables without an asterisk do not change meaningfully between 2005 and 2019, either due to data availability or geophysical processes. I identify their coefficients with only cross-sectional variation. Conditional on other observable attributes, visitors are willing to pay more to visit parks with iconic flora and fauna, like redwood forests and bison, as well as more extensive trail and road networks. Population density in surrounding counties is also positively correlated with the park effects. This estimate reflects nearby amenities, such as restaurants, hotels, and other attractions, but it is likely biased upward, because desirable, unobserved park attributes attract visitors and generate local economic impacts. The land cover coefficient estimates suggest that visitors appreciate barren land (exposed rock and sand) more than other land cover types, such as forest, wetland, and grassland. Willingness to pay is lower for parks with grizzly bears and coastal parks. Estimates described in this paragraph should be interpreted with caution, however, because they are identified with

[5] 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.

cross-sectional variation.

I use within-season-of-the-year variation at each park to identify coefficients on time-varying attributes. An additional rainy day decreases willingness to pay by \$2, while visitors are willing to pay \$4 for a one-degree increase in average monthly temperature at the mean temperature of 66°F. Increasing park acreage seems to have little impact on WTP. Charging an entrance fee decreases WTP by \$15 on average, and conditional on charging an entrance fee, visitors are willing to pay more to visit parks with higher entrance fees. Although, this estimate is not statistically significant. The slight preference for parks with higher entry fees may seem counterintuitive, but there are at least two reasonable explanations. First, many visitors purchase annual or lifetime passes that provide access to all national parks. An entrance fee increase will not matter much to these visitors; they can gain access without paying the fee. Therefore, if many visitors own annual or lifetime passes, then the coefficient on entrance fee size will be close to zero, as I find here. Second, if a park experiences visitation growth, it may increase its entrance fee to try and temper the growth, ameliorate crowding concerns, and raise revenue. This strategic pricing behavior means that entrance fee hikes could be correlated with unobserved, favorable shocks to park attributes, and thus, it is possible that my estimate of the entrance fee coefficient is biased upwards.

The national park designation coefficient reflects the impact of switching a park's designation to National Park from one of the various other designations — e.g., National Lakeshore or National Monument. Anecdotal wisdom suggests bestowing the official National Park designation will increase visibility and attract visitors. Giving parks National Park status has even been proposed as a method to reduce crowding at more popular parks nearby (Hotakainen, 2021). Using variation from the three National Park redesignations in my sample period (Pinnacles, Gateway Arch, and Indiana Dunes), I estimate that an official National Park designation actually decreases WTP for a visit. When analyzing a broader set of redesignations, Szabó and Ujhelyi (2024) find that a National Park redesignation does increase visitation. Adding this context, my results suggest that redesignations have heterogeneous impacts and are not an all-powerful tool for attracting visitors.

Even with this broad array of park attributes, 48% of the variation in park effects remains unexplained. Given the unique resources the parks protect, this unexplained variation is not surprising. It is difficult to estimate the value of iconic park attributes, such as Arches' arches or Yellowstone's Old Faithful geyser, which are often idiosyncratic and, famously, remain largely unchanged over time.

By capturing mean utilities after controlling for travel costs, monthly park effects provide a national park *awesomeness* index. To create the index, 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} are the maximum and minimum of all park effects from January 2005 through December 2019. This ranking offers an attractive alternative to rankings from the popular media, which are typically based on travel bloggers' personal experiences or raw visitation counts. Unlike experience-based 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 5 shows the top ten parks for 2018 based on each national park's maximum park effect throughout the year. Appendix D provides a full ranking of all 140 parks. The top ten includes many of the most famous national parks, such as Glacier, Yellowstone, Grand Canyon, and Zion. Surprisingly, Golden Gate National Recreation Area tops the list. Golden Gate provides views of the Golden Gate Bridge, beaches, hiking trails, and popular attractions like Alcatraz Island, but for several reasons, it is likely overrated. 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 are coming from people living farther away, biasing the park effect upward.

I report welfare losses from monthly park closures in Appendix C. These estimates could be useful for park managers seeking to estimate the lost recreational value from any event or management decision that impacts visitation, such as the Yellowstone flooding of June 2022. Unlike the national park *awesomeness* index, welfare loss estimates are affected by the travel costs of reaching a site. For example, Cape Cod National Seashore and Gateway Recreation Area, located near Boston and New York City, are among the most valuable parks, despite the fact that they rank 19th and 26th in the *awesomeness* index.

My park closure welfare loss estimates are reasonable when compared to Parsons et al.'s (2021) estimates. They estimate that closing Grand Canyon for the entirety of June 2002 would decrease welfare by between \$52 million and \$73 million, while I estimate the welfare loss to be \$32 million (on average across 2005 to 2019). My more conservative estimate may reflect the fact that only 20% to 43% of visits (depending on the season) to Grand Canyon are primary purpose visits. I drop these non-primary purpose trips from the visitor count data, following most of the recreation demand literature, while Parsons et al.'s innovative model captures the value of these multi-purpose trips. Our estimates are more similar for Bryce Canyon (\$15 million versus their \$10–\$15 million), Canyonlands (\$5 million versus their \$3–\$4 million), Mesa Verde (\$14 million versus their \$6–\$8 million), Petrified Forest (\$8 million versus their \$5–\$8 million), and Zion (\$27 million versus their \$28–\$41 million).[6]

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

5 Application: Climate Change and Visitor Welfare

The model, data infrastructure, and estimates presented above provide a versatile foundation for studies seeking to estimate the welfare impacts of resource or management changes throughout the National Park System. In this section, I demonstrate the power of my framework by valuing the welfare impacts of climate change.

5.1 Model

To value climate impacts, I adjust my park effect decomposition to focus on temperature specifically, rather than many attributes at once. Because park visitors may respond to long-run average temperatures differently than short-run temperature shocks, I base my model on Bento et al.'s (2023) "unifying approach" to estimating climate impacts and decompose the park effects as

$$\delta_{jt} = \sum_b (\alpha_b^{AVG} \mathbb{1}(\overline{temp}_{jt} \in b)) + \sum_b (\alpha_b^{SH} temp_{jt}^{SH} \mathbb{1}(\overline{temp}_{jt} \in b)) + \alpha^X X_{jt} + \gamma_{js(t)} + \phi_t + \nu_{jt} \quad (6)$$

The primary coefficients of interest are α^{AVG} and α^{SH}, which capture preferences for long-run average temperatures and short-run temperature shocks. The variable $\overline{temp}$ represents the average temperature at a park in a given calendar month over the past ten years (e.g., the average temperature at Yellowstone over the previous ten Mays if j = "Yellowstone" and t corresponds to the month of May). The variable $temp_{jt}^{SH} = temp_{jt} - \overline{temp}_{jt}$ represents the deviation from this average, or the temperature shock, that occurs at a park in a given month. Roughly, the average temperature reflects the weather a visitor could expect to observe at a park in a certain month. This expected weather is relevant for people planning their trip more than a few weeks in advance. The temperature shock captures short-run events, like heatwaves and cold snaps. My specification allows for a flexible relationship between temperature and the park effects by estimating separate α^{AVG} coefficients for 5°F bins. It also allows preferences for shocks, α^{SH}, to vary by average temperature by interacting the temperature shock with the average temperature bin. Thus, individuals can prefer warmer-than-average temperatures when the average temperature is cold and cooler-than-average temperatures when the average temperature is hot. The set of control variables, X_{jt}, includes the number of days with precipitation in each month. The month-of-sample fixed effects, ϕ_t, capture system-wide shocks to the park effects and absorb variation in the quality of the outside option, allowing for a more natural interpretation of park effects relative to the average park effect in each month.

Equation 6 also includes park-by-season-of-the-year fixed effects, which play a critical role in identifying preferences for temperature. These parameters control for all observed and unobserved park characteristics constant throughout a season, such as infrastructure or elevation. Including these fixed effects leaves within-season variation at each park to identify preferences for temperature. For example, the estimation will attribute variation in Yellowstone's March, April, and May park effects to variation in average temperatures and temperature shocks across these months, after controlling for system-wide shocks and precipitation.

Many park attributes vary within a season and are correlated with temperature, such as fall foliage and seasonal road closures. It is tempting to control for these intra-season resource changes, say by including a park-by-month-of-year fixed effects, to isolate variation in weather conditions. However, many intra-season resource changes are, in fact, caused by climate and weather conditions. The National Park Service has already documented evidence of advancing spring onset, e.g., trees gaining their leaves earlier in the season (Monahan et al., 2016), and the timing of seasonal road closures is often determined by heavy snow. Controlling for these resource changes would therefore control for part of climate change's causal effect, leading to the "over-controlling" problem (Dell et al., 2014). Thus, I opt not to include higher-frequency fixed effects, and my estimated preferences for temperature reflect both the direct impact of temperature on visitor comfort as well as how temperature may impact park attributes within each season.

The parameter estimates from equation 6 allow me to compare the welfare provided by national park visitation under different climate and weather conditions. Given temperature and precipitation forecasts from a climate projection, I predict a panel of park effects, which I denote

$$\hat{\delta}_{jt} = \sum_{b}(\hat{\alpha}_b^{AVG}\mathbb{1}(\overline{temp}_{jt} \in b)) + \sum_{b}(\hat{\alpha}_b^{SH} temp_{jt}^{SH}\mathbb{1}(\overline{temp}_{jt} \in b)) + \hat{\alpha}^X X_{jt} + \hat{\gamma}_{js(t)} + \bar{\phi}_{m(t)} \quad (7)$$

where $\bar{\phi}_{m(t)}$ denotes the average month-of-sample fixed effect estimate for month of the year, $m(t)$. Climate projections provide daily weather forecasts for future years, allowing me to calculate ten-year moving average temperatures, $\overline{temp}$, temperature shocks, $temp^{SH}$, and the number of precipitation days, just as I do with historical weather observations.

The compensating variation (CV) of climate and weather conditions in month t relative to baseline month t_0 is given by

$$CV_i(\hat{\delta}_t) = \frac{-1}{\beta_i^{TC}}\left[EU_i(\hat{\delta}_t) - EU_i(\hat{\delta}_{t_0})\right], \quad (8)$$

where EU_i represents the expected utility of a choice occasion

$$EU_i(\hat{\delta}_t) = \ln\left[1 + \left(\sum_j \sum_m \exp\left(\frac{\hat{V}_{ijmt}}{\lambda}\right)\right)^{\lambda}\right]. \quad (9)$$

In equation 9, the term $\hat{V}_{ijmt}$ is the predicted deterministic portion of the utility function (equation 1).

Predicting future welfare changes requires assumptions on how variables and parameters evolve over time. Over a long enough horizon, variables and parameters are likely to change. Visitors may acclimate to warmer temperatures; park resources will change, impacting park-season fixed effects; and more efficient transportation options may lower travel costs. It is feasible to estimate welfare impacts under any number of alternative assumptions. Yet, it is difficult to predict which assumptions will best approximate future conditions. For simplicity, my welfare calculations fix demographics and travel costs at 2019 levels and assume preferences for temperature and precipitation, park-season fixed effects, average month-of-sample fixed effects, and first-stage parameters remain constant across time.

5.2 Data

To estimate preferences for temperature, I use weather observations from the Global Historical Climatology Network's Global Summary of the Month (Lawrimore et al., 2016). These data document temperature and precipitation observations collected by weather monitoring stations. I extract two monthly variables for each station: the average daily high temperature and the number of days with more than 0.1 inches of precipitation.

Parks often have several weather stations in their vicinity. For each park, I select the nearest station with at least 50% complete data as the "primary station." On average, primary stations are 2 miles from the park they represent. When primary stations are missing data, which occurs for 18% of the station-months, I impute missing temperature and precipitation variables using nearby PRISM weather observations. Appendix A describes the imputation process in more detail.

To characterize long-run average temperatures, I calculate the ten-year moving average of the month's average daily high temperature at each park (e.g., the average daily high temperature in Yellowstone National Park over the ten previous Aprils). To calculate the short-run temperature shock, I take the difference between the observed average daily high temperature and the long-run average (e.g., the average daily high temperature in Yellowstone this April minus the average daily high temperature in Yellowstone over the previous ten Aprils).

To describe temperature and precipitation under climate change, I compute ten-year moving average temperatures, temperature shocks, and precipitation day variables from 2005 through 2070 variables using downscaled CMIP5 Climate Projections (Bureau of Reclamation, 2013). When reporting welfare estimates, I compare annual welfare in future years to the average annual welfare under climate projection conditions from 2005 through 2019. There are dozens of CMIP5 climate projections available. I use the Community Earth System Model Contributor's projection for representative concentration pathway (RCP) 4.5, a middle ground between low-warming RCP2.6 projections and high-warming RCP8.5 projections.

Unlike the weather station data, climate projections are gridded products; they provide predictions every 1/8th degree of latitude and longitude (roughly eight miles in the contiguous United States). I select one grid point to represent each park by comparing historic weather observations at nearby projection grid points to observations at the park's primary weather station. I select the grid point with the most similar weather as the park's "primary grid point." Appendix A provides more details on the climate projection data and the grid point selection procedure.

By selecting a "primary station" and a "primary grid point" for each park, I abstract from within-park weather variation, which is substantial in some cases. An alternative method might average station observations or use a gridded product and average points within each park. I prefer using primary stations and grid points for two reasons. First, weather stations are often located near visitor centers or gateway communities. Both are heavily trafficked by park visitors, meaning the weather observed at stations typically aligns with the weather visitors experience. Second, weather conditions may vary dramatically within parks, particularly those with rugged terrain and expansive, yet lightly trafficked, backcountry. A technique that averages grid points or stations is more likely to be influenced by these backcountry locations, which may be irrelevant to the vast majority of visitors.

5.3 Results

My first set of results focuses on preferences for temperature. Figure 2 shows that visiting a park provides the most surplus when average temperatures fall between 60°F and 80°F. WTP decreases sharply as temperatures become colder. Relative to 75°F, visiting when the average temperature is 30°F reduces individual WTP by almost $400 per trip on average. Hotter temperatures reduce WTP less dramatically. Visiting a park when the average high temperature is 95°F reduces WTP by just $78.

Preferences for temperature shocks depend on the average temperature (figure 3). When the average temperature is between 35°F and 50°F, a positive temperature shock increases WTP by about $5 per degree. At average temperatures above 80°F, WTP for temperature shocks is not statistically significant. However, I cannot rule out potential adverse effects of heatwaves, because estimates have large standard errors at average temperatures above 90°F.

Figure 4 combines these results, comparing the impact of equal-sized changes in average temperatures and temperature shocks. Warming temperatures has the largest impact between 35°F and 55°F. In this range, a positive 5°F shock raises WTP by up to $31, and a 5°F increase in average temperature raises WTP by up to $95. In the ideal temperature range, WTP for changes in average temperatures and temperature shocks is small. At hot temperatures, estimates have larger standard errors, and the noise obfuscates any clear trend.

The magnitude of WTP for changes in average temperatures is almost always greater than the magnitude of WTP for temperature shocks. This result may be driven by visitors that plan trips far in advance. In this case, visitors cannot observe temperature shocks when making their recreation decision. After committing to their trip, it may be costly to cancel or substitute to another location, minimizing the observable response to temperature shocks. Visitors may also respond to temperature shocks by changing their behavior on a trip. For example, they could spend less time in a park or shift their visit to a different time of day. These responses are not captured in my survey or visitor count data, which may lead me to understate preferences for temperature shocks. Even still, it is clear that both average temperatures and temperature shocks influence the visitation decision, and my results suggest stronger preferences for average temperatures.

To summarize, these temperature preference estimates yield two main findings. First, individuals have a strong preference against cold temperatures and a more modest preference against hot temperatures. Second, preferences for average temperatures are stronger than preferences for equal-sized temperature shocks. Therefore, ignoring this distinction would lead to incorrect estimates of future welfare changes.

In my model, climate change affects visitor welfare by changing park effects. Figure 5 shows predicted changes in park effects under an RCP4.5 climate projection. In the winter, warming temperatures increase park effects at nearly all parks. Parks in the Mid-Atlantic see some of the largest increases, in part because their average temperatures are between 35°F and 50°F where marginal temperature increases are most valuable. In the spring, middle to upper Mountain West parks see the largest increases, while park effects decrease in the South. In the summer, most parks experience average temperatures above the 60°F to 80°F ideal range, and warming temperatures cause park effects to decrease at 115 out of 140 parks. Averaging these changes over the entire year reveals that climate change tends to increase park effects. Again, it is important to keep in mind that these predicted park effect changes, and the subsequent welfare estimates abstract from large-scale resource changes.

The increased park effects, in turn, increase the welfare generated by national park visitation (figure 6). Average annual welfare (solid-black line) increases \$572 million in the 2030s, \$679 million in the 2040s, and \$1.2 billion in the 2050s, relative to a 2005 to 2019 baseline. The dashed-grey line isolates the welfare impact of changes in average temperatures by setting all temperature shocks equal to zero and fixing the number of precipitation days at average 2005 to 2019 levels. The decomposition reveals that average temperature changes drive the overall welfare gains. Over the next fifty years, the climate model predicts temperature shocks and precipitation will be less favorable than the baseline period, decreasing the welfare gains from average temperature changes by between 7% and 28% depending on the decade.

The annual welfare gains are driven by gains in cooler months, which outweigh losses in the summer (figure 7). This result is consistent with the preferences for temperature, which showed WTP to warm cool temperatures is greater than WTP to avoid extreme heat. As the temperature changes become larger over time, seasonal welfare changes become more pronounced.

The seasonal welfare changes suggest that inter-temporal substitution, such as shifting a visit from July to October, could play an important role in determining the welfare impacts. As an example, consider a family who is only able to visit in the summer months, perhaps due to their children's school schedule. They will not be able to avoid the summer heat, and they cannot take advantage of the improved spring, summer, and fall conditions. These constraints are not explicitly incorporated into my model, but my estimates do capture them to some extent. Park effects tend to peak in the summer, in part, due to secular visitation patterns, like school schedules. High summer park effects influence welfare estimates, because all else equal, changing a park's *awesomeness* has a larger welfare impact when it is more likely to be visited.

Figure 8 shows how welfare impacts vary geographically. In the winter, warming temperatures increase welfare across the country, with the largest impacts in California, the Southeast, Mid-Atlantic, and eastern Midwest. Welfare increases across the country in the spring as well, and the Mountain West experiences some of the largest benefits, possibly due to warming temperatures at popular high-elevation parks like Yellowstone, Grand Teton, Glacier, and Rocky Mountain. With the exception of the West Coast, the entire country suffers welfare losses in summer months. Losses are largest in the eastern Midwest, Mid-Atlantic, and Southeast. Parks in these areas experience some of the largest park effect decreases in the summer. Despite these summer losses, gains in winter, spring, and fall (not shown) lead to annual welfare increases throughout the country. Annual welfare increases are largest in the West and Northeast, between \$0.50 to \$1 per person.

These welfare estimates abstract from large-scale resource changes, but climate change may bring unexpected and dramatic changes to park resources and ecology, as well as an increased frequency of natural disasters. It is challenging to estimate welfare impacts of these large-scale resource changes, which could be caused by wildfire, sea level rise, or invasive species. One challenge is predicting the frequency and scale at which these changes will occur. A second challenge is to estimate how these changes will impact demand. It is difficult to determine, for instance, how *awesome* Glacier NP would be without its glaciers.

To get some sense of how these damages might compare to the gains from improved visitor comfort, I calculate welfare losses from several park closure scenarios. Park closures could become more frequent due to climate-induced resource changes and natural disasters. For example, park managers face significant challenges maintaining access to Cape Hatteras National Seashore, and some have questioned whether the barrier island will "wash away" completely due to sea level rise and rapid erosion (Gaul, 2023). I estimate that removing Cape Hatteras from the choice set in the 2040s would cause average annual welfare losses of \$615 million. While this is a dramatic (yet plausible) example, many other parks have close temporarily in response to natural disasters. Motivated by previous closures caused by flooding and wildfires, I estimate the welfare loss of closing Yellowstone for the month of June is \$63 million on average in the 2040s, and the loss of closing Yosemite for October is \$43 million. Losing Cape Hatteras alone would eliminate 91% of the gains from improved visitor comfort over the same time period. Thus, park closures and large-scale resource changes have the potential to erase the welfare gains of improved comfort.

I run several checks to gauge the sensitivity of the aggregate welfare estimates (table 6). One sensitivity check uses the CESM RCP8.5 projection, which predicts more warming than the RCP4.5 projection. Under the RCP8.5 projection, average annual welfare increases are smaller in the 2020s and 2030s but larger in the 2040s and 2050s. A second sensitivity check drops Golden Gate Recreation Area from the analysis. Recall that Golden Gate had surprisingly high park effect estimates. Dropping Golden Gate reduces welfare gains by roughly 50% in each decade, a substantial change. However, it does not change the fundamental takeaway. Climate change will bring more favorable weather for park visitation, increasing welfare, but large-resource changes and more frequent park closures could offset these gains.

6 Conclusion

This paper conducts the most comprehensive analysis of demand for the U.S. national parks to date. I estimate preferences for over 140 parks throughout the contiguous United States, producing a park *awesomeness* index that provides a systematic, revealed-preference alternative to existing rankings. I find that visitors prefer parks with redwood forests, bison, and extensive trail and road networks. Nevertheless, a full 48% of the variation in park *awesomeness* is unexplained by my collection of observable attributes, suggesting that idiosyncratic, unobservable, or difficult-to-quantify attributes play an important role in driving visitation.

My model, data infrastructure, and estimation procedure are valuable tools for studying demand for the U.S. National Parks System. I demonstrate one application by estimating how climate change will impact the welfare generated by national park visitation. Abstracting from large-scale resource changes, I find that climate change will lead to substantial welfare gains, because gains from milder winters will outweigh the losses caused by hotter summers. This pattern is largely consistent across the United States. To gauge the potential magnitude of impacts from large-scale resource changes and natural disasters, I estimate the welfare impacts of plausible park closure scenarios. I find that such closures have the potential to erase the gains from improved visitor comfort.

My methods could be used in future studies of how climate change may impact recreation. My paper makes advances by allowing temperatures to impact the participation and site choices in a RUM framework. Exploring higher-frequency responses to weather and estimating the losses caused by less predictable weather could be fruitful paths for future research.

This paper also provides a framework for valuing other resource and management changes throughout U.S. National Park System. Many studies use reduced-form models to study the impact of some resource change on national park visitation. My model and data infrastructure can be used to estimate recreational welfare impacts, rather than visitation changes alone. My work could also be applied to value some of the resource changes that, as of now, are difficult to incorporate into my climate impact estimates, such as more frequent wildfires. Such analyses would help to maximize the impact of recent legislation, which provides new funding to help conserve the country's most treasured resources.

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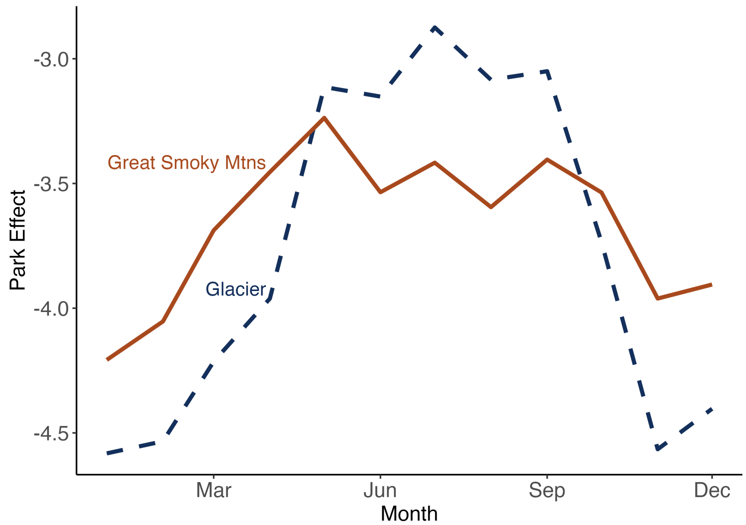

Figure 1: Park effects vary month-to-month

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

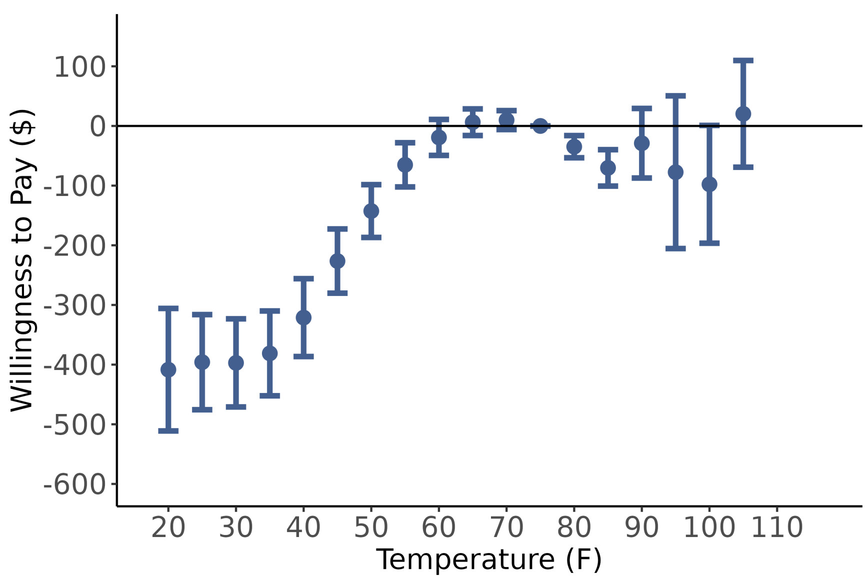

Figure 2: WTP for long-run average temperatures

Note: The figure shows how visitors' willingness to pay for a park visit varies for different long-run average temperatures. All estimates are relative to the 75°F bin.

Table 1: Survey Respondent Demographics

Variable	CSAP Unweighted	CSAP 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 = 1537)	13.5	12.6	
Sample size	6762	6762	

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 data compared to statistics from 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: Park Attribute Data Sources

Source	Variables
USGS National Map	Elevation range, mean elevation, trail miles, number of lakes > 40 acres, area of lakes > 40 acres
NPS Administrative Data	Designation (Park, Lakeshore, Seashore, etc), acreage, coastal, miles of shoreline, species presence, entrance fees
2004 NLCD	Share of land by landcover type, mode landcover type, landcover diversity
Census	Road miles, population density of overlapping counties
NCEI	Monthly average high temperature, days with precipitation > 0.1", monthly ten-year average temperature and precipitation days

Note: The table shows data sources for park attributes and variables generated from them. NPS Administrative Data include the *NPSpecies* database, Annual Acreage Reports, and a 2011 Resource Report on Shoreline length. NCEI data come from weather station-based Global Summary of the Month reports. NLCD - National Land Cover Database, NCEI - National Centers for Environmental Information.

Table 3: First Stage Estimates

Variable	Estimate	Std. Error
Fly	-0.298	0.004
Travel cost ($100)	-0.172	0.001
Interacted with outside option		
$10k < income < $25k	0.061	0.052
$25k < income < $50k	-0.316	0.032
$50k < income < $75k	-0.471	0.032
$75k < income < $100k	-0.549	0.033
$100k < income < $150k	-0.760	0.029
Income > $150k	-0.773	0.031
Has kid(s)	0.048	0.018
Senior	0.493	0.039
White, non-Hispanic	-0.182	0.027
Black	0.364	0.033
Hispanic	0.068	0.032
College graduate	-0.302	0.011
Dissimilarity coefficient	0.348	0.000

Table 4: Second Stage Estimates

Variable	Coefficient	WTP ($)
Redwoods present	0.867	505
	(0.266)	
Bison present	0.247	144
	(0.189)	
Coastal x elevation range	0.017	10
	(0.038)	
Land cover share: barren land	0.007	4
	(0.004)	
Avg max temperature (F)*	0.007	4
	(0.001)	
Trail miles (10 miles)	0.006	3
	(0.003)	
Nearby population density (100 per sq mile)	0.004	2
	(0.001)	
Road miles (10 miles)	0.003	2
	(0.002)	
Elevation range (1000 ft)	0.001	1
	(0.018)	
Park charges entry fee x entry fee*	0.002	1
	(0.002)	
Lake acreage (100 acres)	0.000	0
	(0.000)	
Avg max temperature squared*	0.000	0
	(0.000)	
Acreage (1,000s)*	0.000	0
	(0.001)	
Trail miles x elevation range	0.000	0
	(0.001)	
Land cover share: emergent wetland	-0.001	-1
	(0.006)	
Land cover share: shrub/scrub	-0.001	-1
	(0.002)	
Precipitation days*	-0.003	-2
	(0.001)	
Land cover share: mixed forest	-0.005	-3
	(0.004)	
Land cover share: grassland	-0.007	-4
	(0.003)	
National Park designation*	-0.020	-12
	(0.012)	
Park charges entry fee*	-0.025	-15
	(0.060)	
Coastal	-0.031	-18
	(0.132)	
Grizzly bears present	-0.159	-93
	(0.173)	
R-squared:	0.520	

* indicates variables that vary over time. Estimates for time-varying variables are equivalent to estimates from a model including park-by-season-of-the-year fixed effects. Other coefficients are identified using only between-park variation. Willingness to pay (WTP) is calculated by dividing each coefficient estimate by the travel cost coefficient and multiplying by 100 to convert units to dollars.

Table 5: Park Awesomeness Index – Top 10

Rank	Park	Rating
1	Golden Gate RA	99.3
2	Glacier	95.8
3	Yellowstone	95.4
4	Grand Canyon	94.1
5	Grand Teton	93.9
6	Zion	93.4
7	Olympic	93.0
8	Bryce Canyon	92.2
9	Mount Rainier	92.2
10	Gulf Islands SS	92.1

Note: The table shows the ten most awesome national parks 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. I rank parks by their maximium 2018 rating.

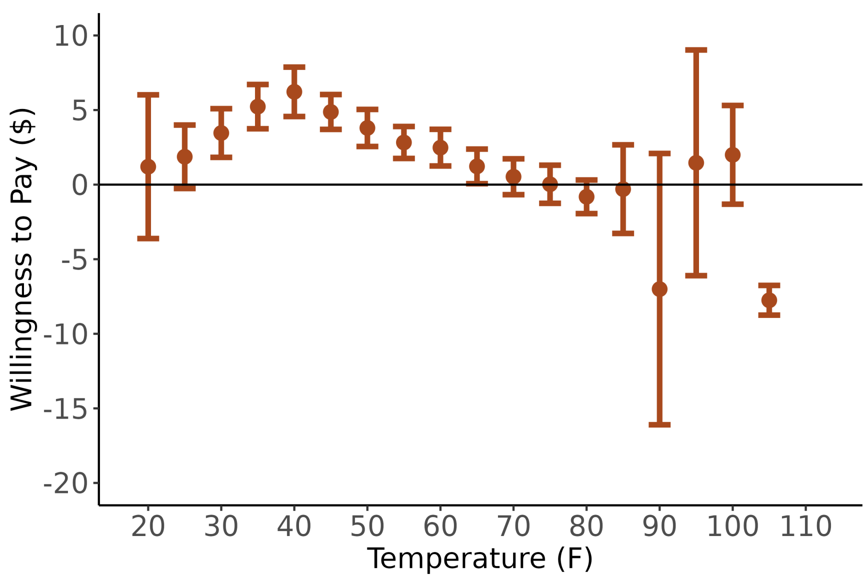

Figure 3: WTP for temperature shocks by long-run average temperature

Note: The figure shows visitors' willingness to pay for a positive one-degree temperature shock at different long-run average temperatures.

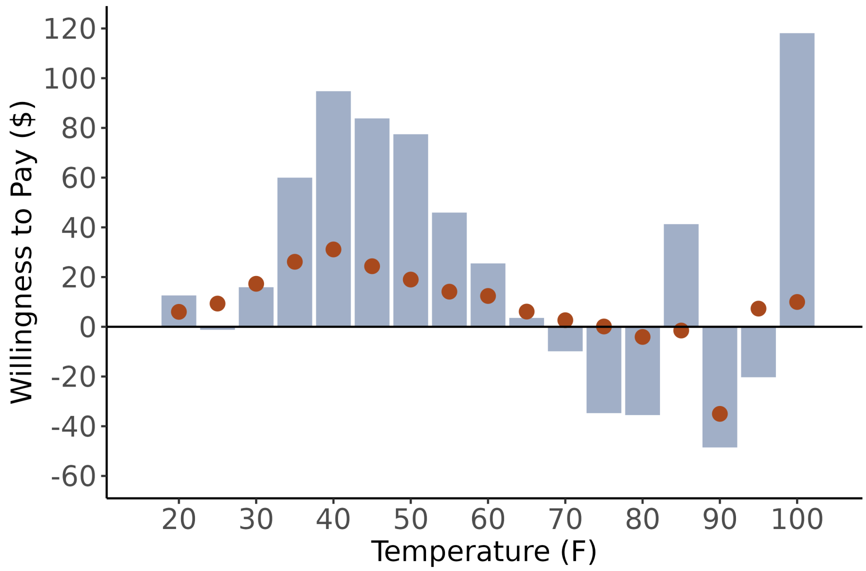

Figure 4: WTP for temperature shocks and higher average temperatures

Note: The figure shows visitors' willingness to pay for a positive five-degree temperature shock (brown dots), as well as willingness to pay for a five-degree increase in the long-run average temperature (blue bars) across different long-run average temperatures. It provides a uniform change in temperature for comparing estimates displayed in figures 2 and 3.

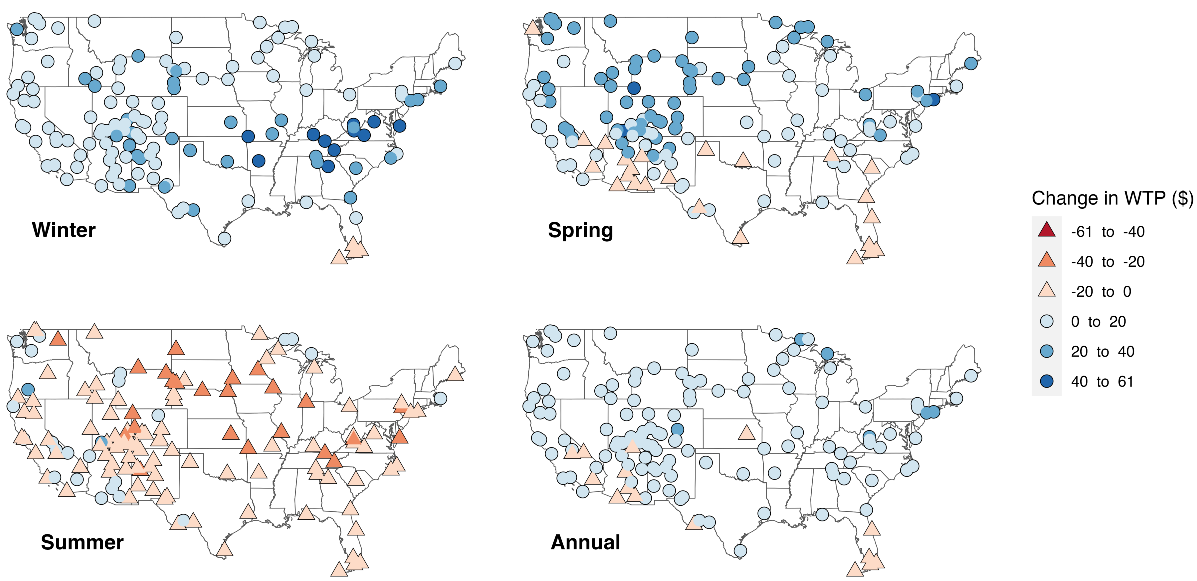

Figure 5: Predicted park effect changes 2040–2059 relative to 2000–2019

Note: The figure shows the predicted change in average park effects (in WTP terms) for winter, spring, summer, and annual averages. Red-triangles denote park effect decreases and blue circles denote park effect increases. The map showing predicted changes for the fall season is omitted.

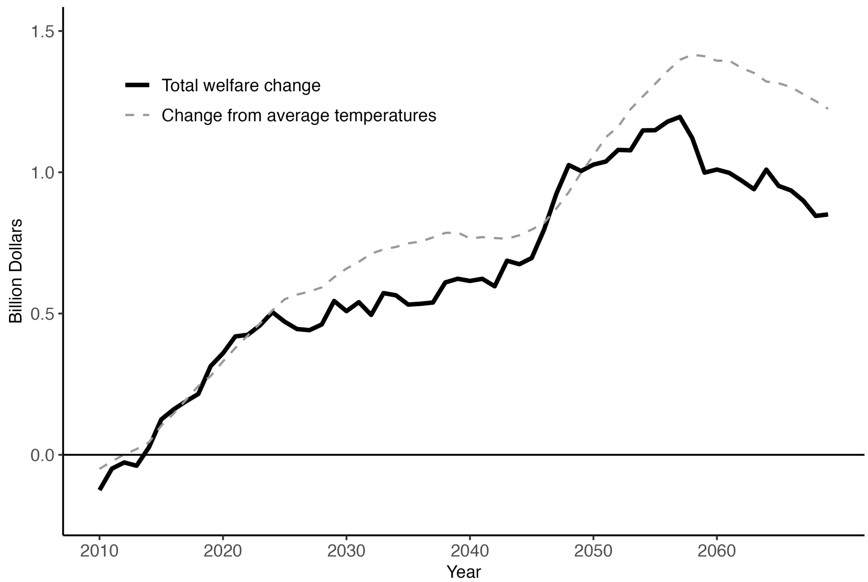

Figure 6: Predicted welfare change under RCP4.5

Note: The figure shows the predicted annual welfare from national park visitation under RCP4.5 conditions relative to the average annual welfare from 2005 and 2019. The solid black line represents an eleven-year moving average of annual welfare changes (five years before through five years after the x-axis year). The light gray line also plots an eleven-year moving average, but it isolates the impact of changes in long-run moving temperatures. Specifically, it takes the moving average of annual welfare impacts when all temperature shocks are set to zero and the number of precipitation days is fixed at its average 2005 to 2019 level for each park and month of the year.

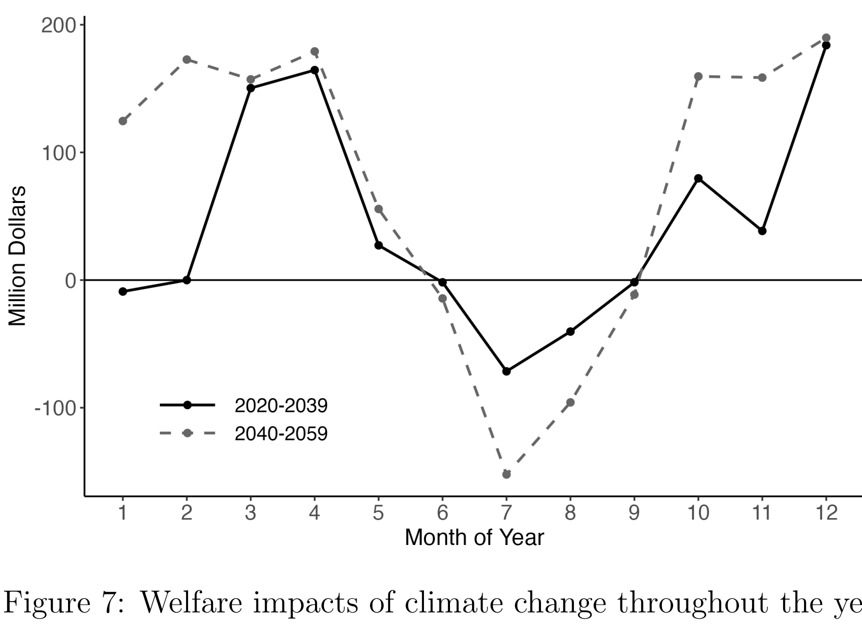

Figure 7: Welfare impacts of climate change throughout the year

Note: The figure shows how climate change impacts the welfare generated by national park visitation in different months of the year. The solid line (dashed line) shows average welfare in each month of the year for 2020 to 2039 (2040 to 2059) relative to the average welfare in each month of the year for 2005 to 2019.

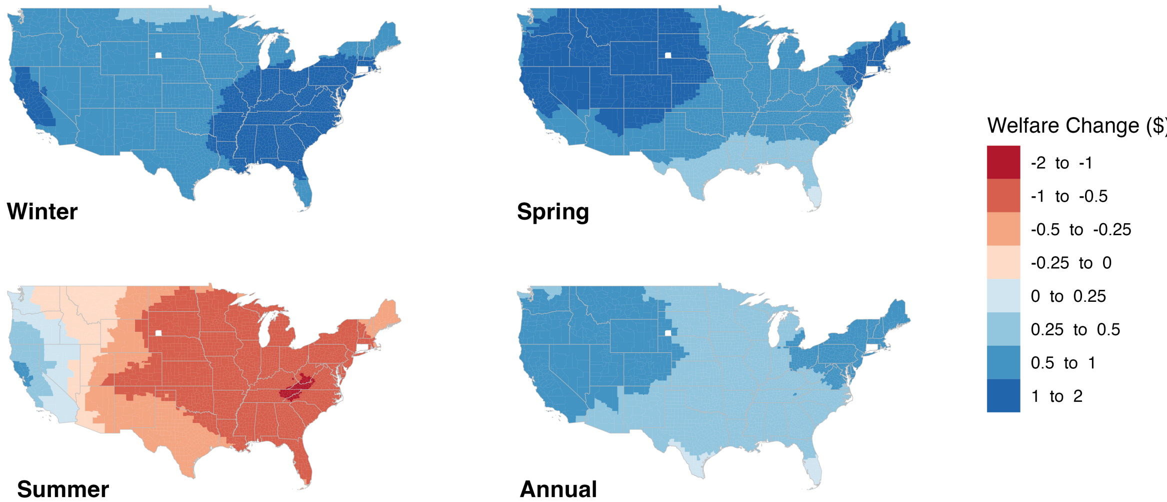

Figure 8: County-level welfare impacts

Note: The figure shows the change in average monthly welfare (2040–2059 minus 2005–2019) experienced by a representative individual in each county for winter, spring, summer, and the entire year. Red indicates a welfare decrease and blue indicates a welfare increase. Darker colors indicate larger magnitude gains or losses. All counties experience gains in winter, spring, and when averaging across the entire year. Most of the country experiences losses in the summer, with the exception of the West Coast and Nevada. I omit the fall map for brevity.

Table 6: Sensitivity Checks

Decade	Baseline	CESM 8.5	Change flying cutoff	Drop GOGA	Group extreme temps
2020	468.1	108.8	474.9	242.2	466.3
		(-76.8%)	(1.4%)	(-48.3%)	(-0.4%)
2030	571.9	557.8	578.8	289.1	568.5
		(-2.5%)	(1.2%)	(-49.4%)	(-0.6%)
2040	678.6	969.1	687.8	340.8	675.3
		(42.8%)	(1.4%)	(-49.8%)	(-0.5%)
2050	1168.5	1413.6	1183.4	617.9	1163.2
		(21.0%)	(1.3%)	(-47.1%)	(-0.5%)

Note: The table shows average annual welfare impact of climate change for several sensitivity checks across different decades. The percentage difference between each sensitivity check and the baseline model is shown in parentheses. "CESM 8.5" uses the CESM RCP8.5 climate projection instead of the CESM RCP4.5 projection. "Change flying cutoff" drops all flying alternatives within 200 miles of a respondent (the baseline cutoff is 400 miles). "Drop GOGA" drops Golden Gate Recreation Area from the analysis. "Group extreme temperatures" combines all temperature bins above 100F when estimating preferences for temperature in the second stage.

Appendix A Data

A.1 Weather Data

In the second-stage regressions, I use a park-by-month panel of weather variables from 2005 through 2019. To generate this panel, I obtain monthly weather observations between 1984 and 2019 and use these monthly observations to calculate long-run average temperatures and temperature shocks for the 2005 to 2019 sample period. I begin by describing the 1984 to 2019 panel.

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 closely 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 146 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.[7] For each primary station, I regress non-missing primary station observations on the nearest

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

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 value 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.

With a monthly panel of average high temperatures and precipitation days from 1984 to 2019, I calculate the weather variables for my second-stage regressions. First, I calculate long-run average temperatures using a monthly ten-year moving average. For Yellowstone in May 2019, for example, I average the average daily high temperature at Yellowstone across the previous ten May's. Second, I calculate the temperature shock, which I define as the difference between the average high temperature in the month and the long-run average temperature. Finally, I use the number of days with precipitation greater than one tenth of an inch as an additional control.

A.2 Climate Projection Data

To predict future park effects and value climate impacts, I use bias-corrected and downscaled CMIP5 climate projections from the U.S. Bureau of Reclamation. The climate projections predict daily high temperatures and precipitation amounts for a 1/8th degree grid (roughly 8 miles) across the contiguous United States. I convert these daily predictions into monthly weather statistics to match with the weather variables described in the previous subsection. My main analysis features Community Earth System Model Contributors (CESM-BGC)

RCP4.5 projections, which predict an average warming of around 2°C, and I conduct sensitivity tests with the CESM RCP8.5 predictions, which predicts more dramatic warming.

Because climate projections are not available at the exact location of each primary weather station, I select one "primary grid point" for each park and take climate projections at this grid point as the park's climate projection. To select each park's primary grid point, I calculate the difference between the weather at the park's primary station and the weather at all grid points within 0.5 degrees of the weather station. I select the grid point with the weather most similar to the park's primary station as the park's primary grid point. Specifically, I select the grid point that solves

$$\arg\min_{g} \sum_{t} 0.9\left(stationTemp_{jt} - gridTemp_{jgt}\right) + 0.1\left(stationPrecip_{jt} - gridPrecip_{jgt}\right) \quad (10)$$

for each park j, where g indexes grid points and t indexes months from January 1985 through December 1994. The temperature variables capture average daily high temperature and the precipitation variables reflect the number of precipitation days.

The mean absolute error between primary grid points and primary station observations is 0.99°F for average high temperatures and 1.52 days for the number of precipitation days. Primary grid point and primary station weather are highly correlated outside this selection period as well. From 1995 to 1999, the mean absolute error is 1.08°F for average high temperatures and 1.63 days for precipitation days. These statistics suggest that the measurement error introduced by using gridded climate projection data is reasonably small.

Table 7 shows mean (across parks and months) values for several statistics derived from the RCP4.5 climate projection. Long-run average temperatures increase about 3.3°F from the 2000's to mid-century. Temperature shocks tend to be positive, causing the long-run averages to increase. The magnitude of temperature shocks is consistent across time, between 2.6°F and 2.8°F. The average number of precipitation days is around 6 days per month in

Table 7: Climate Projection Statistics

Decade	Moving Avg Temperature	Temperature Shock	Absolute Temperature Shock	Monthly Precipitation Days
2000	66.8	0.4	2.7	6.0
2010	67.5	0.3	2.8	6.0
2020	68.3	0.4	2.7	5.8
2030	68.8	0.0	2.8	6.0
2040	68.9	0.4	2.6	5.8
2050	70.1	0.3	2.7	5.9
2060	70.1	-0.2	2.7	6.1
2070	69.9	0.2	2.8	6.2
2080	70.3	0.3	2.7	6.0
2090	70.5	-0.3	2.7	6.3

Note: The table shows the predicted mean (across parks and months) ten-year moving average temperature, temperature shock, absolute temperature shock and number of days per month with more than one-tenth of an inch of precipitation for each decade under the CESM RCP4.5 climate projection.

every decade.

Projected warming is most extreme in the upper Midwest (figure 9). The CESM RCP4.5 projection predicts average temperatures in this region will rise by around 3.5°F from the 2010's and 2050's. Mississippi National River & Recreation Area, which runs through Minneapolis, is projected to experience the largest warming, with its ten-year moving average temperature increasing 3.8°F from the 2010's to the 2050's. Parks on the West Coast and in the southeast experience the least warming, with moving average temperatures increasing by between 1°F and 1.5°F.

A.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

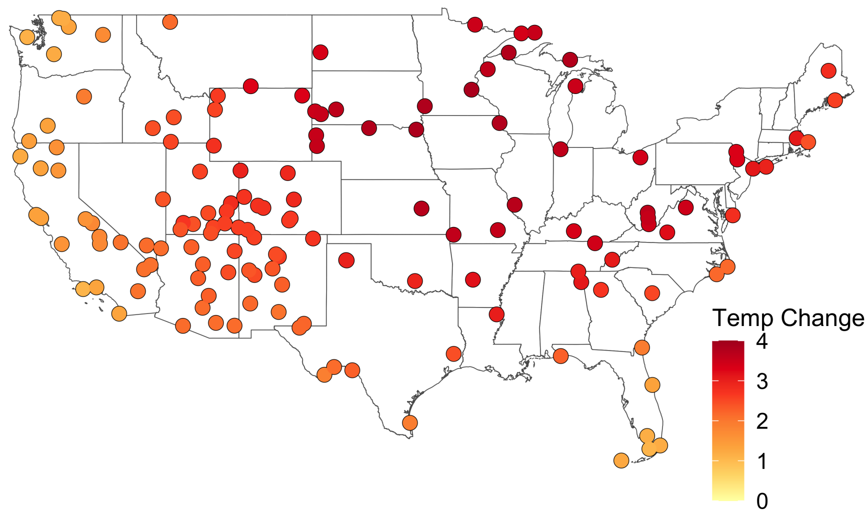

Figure 9: Temperature changes under RCP4.5

Note: The figure shows changes in average (across all months in the decade) ten-year moving average temperatures between the 2010's and the 2050's under the CESM RCP4.5 projection. A darker shading indicates a larger change.

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 (SESRC) and Socioeconomic Monitoring survey responses from the National Park Services 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 themselves 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:

$$Y_{js} = \phi_j + \lambda_s + \epsilon_{js} \tag{11}$$

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 11. Instead, I estimate nineteen models that predict the survey statistic of interest using flexible functions of park attributes. I select the model with the lowest adjusted R-squared as the imputation model.

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.

A.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. I adjust the raw visitor counts using the following equation:

$$\begin{aligned} &Adj.\ Visits_{jt} = \\ &\left(\frac{Visits_{jt}}{AvgEntries_{js(t)}}\right) P\left(Domestic_{js(t)} | PrimaryDestination_{js(t)}\right) P\left(PrimaryDestination_{js(t)}\right) \end{aligned} \tag{12}$$

where j indexes parks and $s(t)$ denotes the season-of-the-year of month 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 all international visits are multi-purpose visits. Again, some version of this assumption is necessary to simplify the conditional probability in equation 12. If this seems unreasonable, consider that for an international visit to count as a primary purpose trip, the visitor must visit one park as the primary purpose for their travel. 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:

$$Adj.\ Visits_{jt} = \left(\frac{Visits_{jt}}{AvgEntries_{js(t)}}\right) P\left(PrimaryDestination_{js(t)}\right) \tag{13}$$

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 31 percent of their corresponding raw counts, on average. They range between 7 percent to 68 percent of raw counts, and over 60 percent of adjusted counts are between 20 and 45 percent of their raw count. The adjusted counts are highly correlated with raw counts with an R-squared value of 0.79 (figure 10).

The adjustment reduces visitor counts most at Big Cypress NPRES, Isle Royale NP, Cape Cod NS, Grand Teton NP, and Shenandoah NP. It reduces raw counts the least at Lake Roosevelt NRA, Delaware Water Gap NRA, Pinnacles NP, Cabrillo NM, and Mount Rainier NP.

Adjusting the visitor counts preserves overall visitation trends (figure 11). In particular, both adjusted and raw visitor counts reveal a large increase in visitation between 2013 and 2017. This is reassuring, but not surprising, as adjusted counts merely scale the raw counts.

Adjusting visitor counts dampens seasonal visitation patterns (figure 12). Both raw and

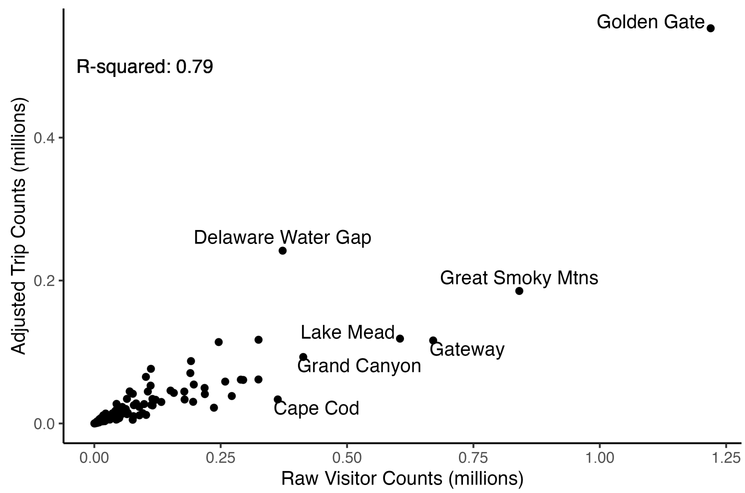

Figure 10: Comparing Raw and Adjusted Annual Visitation by Park

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

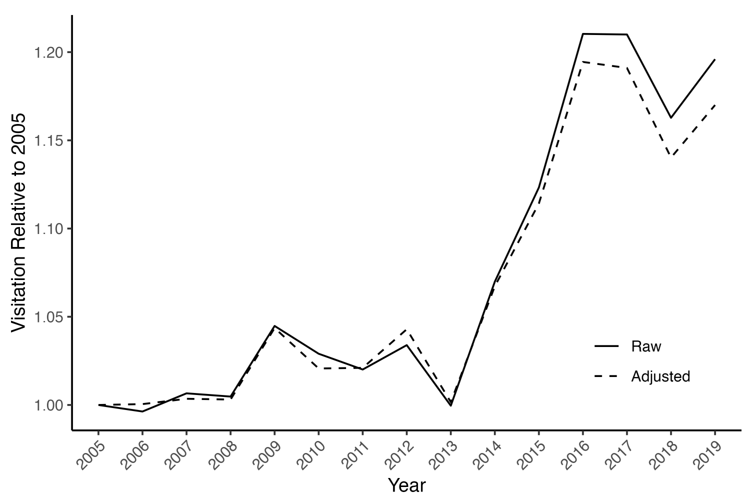

Figure 11: Comparing Raw and Adjusted Visitation Trends

Note: The figure plots annual total visitation (monthly visitation summed across parks and months) divided by 2005 visitation. Adjusted visitor counts closely match the trend observed in the raw visitor counts.

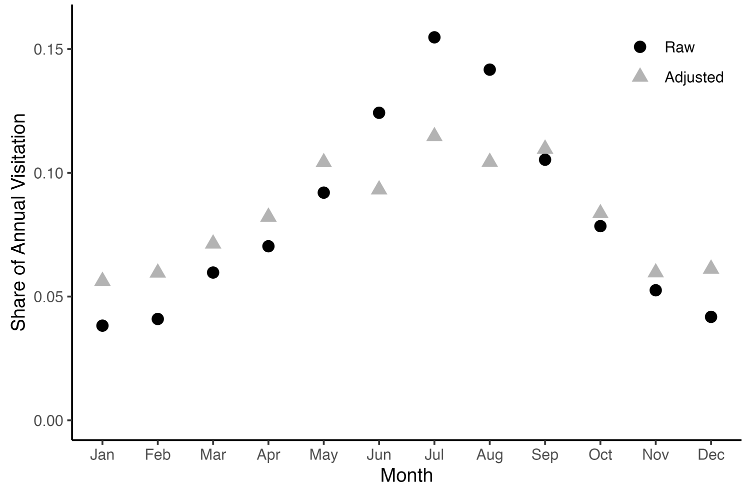

Figure 12: Comparing Raw and Adjusted Seasonal Visitation Patterns

Note: The figure compares the share of total visitation occurring in each month-of-the-year using adjusted visitor counts (grey triangles) and raw visitor counts (black circles). Adjusted visitor counts have a flatter summer peak.

adjusted counts capture summer visitation peaks, but his peak is less dramatic when using adjusted counts. This is because summer trips tend to have higher re-entry rates (1.96 entries in summer versus 1.71 to 1.80 in other seasons) and because summer trips are less likely to be primary purpose trips (43 percent versus 55–58 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."

Appendix B 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 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.

B.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.[8] Given the driving mileages and times, I calculate the driving travel cost as

$$C_{ijq}^D = 2\left[\left(p_{iq}^d d_{ij} + p_q^h h_{ij}\right)/n + p_i^t t_{ij}\right] \tag{14}$$

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 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

[8] 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.

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 B.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 13 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

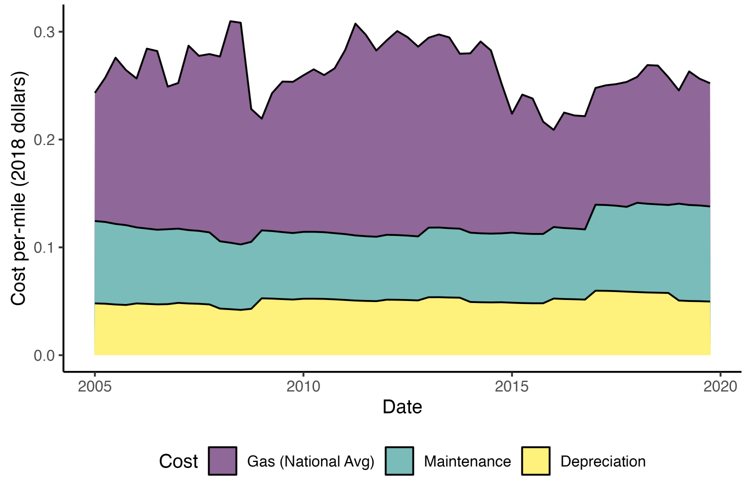

Figure 13: Per-mile driving costs over time

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.

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. 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 CSAP2 respondents is \$12.57 per hour, which implies the one-way cost of time is \$415.

B.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 estimated parameter values 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.

B.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

$$C^{F}_{imnjq} = 2C^{D}_{imq} + C^{Parking}_{mq} + 2C^{Flight}_{imnq} + C^{Rent}_{q} + 2C^{D}_{njq} \tag{15}$$

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 B.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_q^{Rent}, 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 15 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

$$C_{imnqz}^{Flight} = p_i^t \left(time^{airport} + time^{flight} + time_z^{layover} \right) + p_{mnqz}^{airfare} \tag{16}$$

The term $p_{mnqz}^{airfare}$ 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 14, 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 our flying travel cost calculations are nearly identical, I use different airfare and flight itinerary data than English et al. They use the flight itinerary for the 30th percentile airfare between the origin and destination airports from DB1B Origin to Destination Surveys. Because my sample period spans fifteen years and 60 quarters, replicating their calculations would required over 100GB of ticket-level data. Using the Consumer Airfare Report, which summarizes the ticket-level data, requires much less storage.

Figure 14 shows average driving and flying travel costs for each quarter of the survey period. On average, driving travel costs remain consistent across the sample period. Average flying travel costs steadily increase, beginning around \$600 and ending around \$800.

Figure 15 shows how travel cost vary with distance for a subset of the survey sample. Driving travel costs increase approximately linearly with driving distance. The rays correspond to different income bins. Higher income respondents have higher opportunity costs of time, and their driving travel costs increase more quickly. Flying travel costs increase more gradually. On average, flying is more expensive than driving for trips under 700 miles (one-way), and it is cheaper than driving for longer-distance trips.

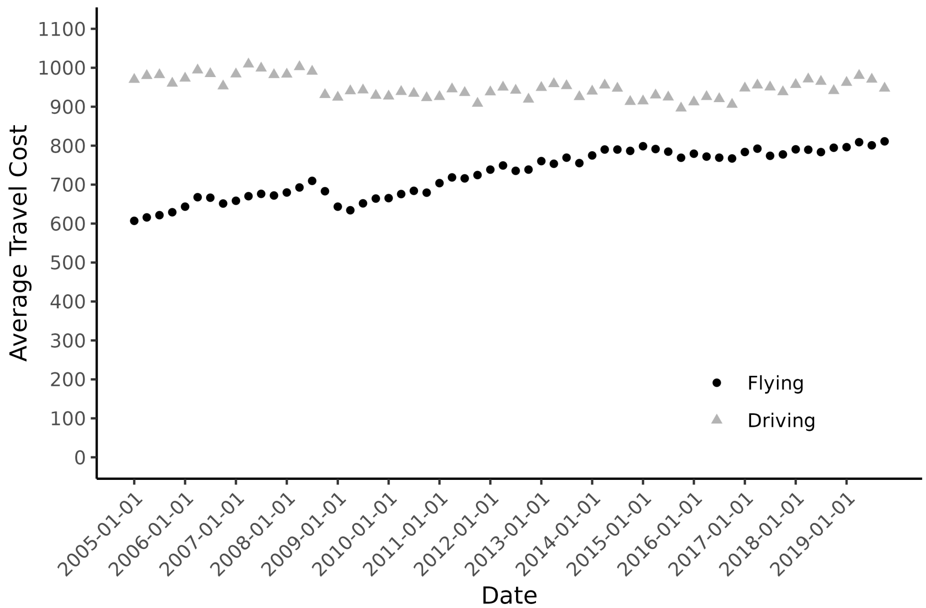

Figure 14: Average Driving and Flying Travel Costs

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

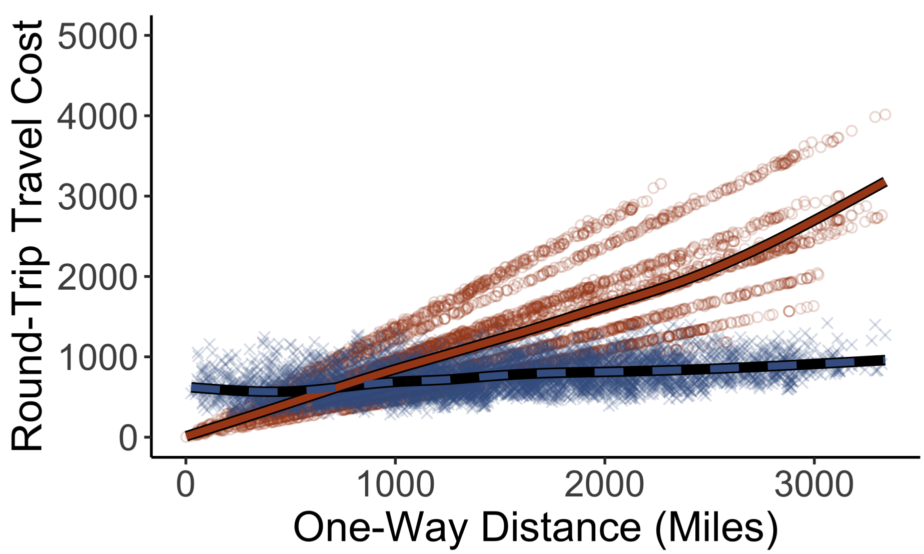

Figure 15: Travel costs increase with distance

Note: The figure plots round trip travel costs on one-way driving distance for a three percent subset of the 2008 suvery sample. Brown circle show driving travel costs, and blue x's show flying travel costs. Lines show average travel costs conditional on distance for both driving (brown-solid) and flying (blue-dashed). On average, flying travel costs increase more gradually with distance.

Appendix C Park Values

Table 8: Park Values in Millions of 2018 Dollars

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Acadia	2.51	2.47	3.16	9.64	24.97	31.20	52.97	57.65	60.81	42.87	5.53	2.41
Agate Fossil Beds M	0.02	0.03	0.07	0.09	0.31	0.28	0.35	0.36	0.27	0.11	0.04	0.03
Alibates Flint Quarries M	0.02	0.03	0.07	0.08	0.16	0.05	0.04	0.05	0.08	0.12	0.03	0.02
Amistad RA	12.47	15.50	20.78	17.81	17.34	12.04	10.94	8.62	9.84	9.36	7.84	10.25
Apostle Islands LS	0.57	1.69	1.88	0.61	1.82	2.67	5.61	5.95	3.66	1.64	0.36	0.35
Arches	3.21	4.68	12.82	17.01	23.08	14.16	13.90	13.14	20.10	13.51	5.90	4.76
Assateague Island SS	8.38	8.48	13.56	24.23	37.09	32.30	54.30	50.45	36.75	20.20	11.87	8.68
Aztec Ruins M	0.19	0.25	0.60	0.82	1.04	0.70	0.77	0.55	0.76	0.64	0.32	0.37
Badlands	1.75	1.62	2.13	3.06	8.96	14.57	18.43	16.75	12.72	4.28	1.80	1.67
Bandelier M	1.06	1.24	2.95	3.66	4.94	2.49	2.70	2.22	2.74	2.88	1.60	1.38
Big Bend	3.76	4.64	5.33	3.92	3.02	1.26	1.03	1.13	1.69	2.43	3.19	3.61
Big Cypress Preserve	13.94	17.59	11.80	8.52	6.04	2.88	3.11	2.87	4.03	5.10	7.05	12.45
Big South Fork River and Recreation Area	5.39	5.50	5.82	8.55	10.74	6.42	6.10	5.13	6.90	7.39	4.91	6.66
Big Thicket Preserve	1.23	1.14	1.11	1.49	1.96	1.14	1.33	1.30	1.62	1.83	1.81	2.04
Bighorn Canyon RA	0.77	0.71	0.96	1.58	2.57	2.42	3.19	2.87	2.20	1.01	0.63	0.80
Biscayne	6.32	6.27	5.77	6.52	7.27	4.48	5.42	4.10	4.15	5.51	4.20	6.51
Black Canyon of Gunnison	0.87	0.76	0.91	1.43	4.12	3.07	3.56	3.16	4.12	2.61	1.23	0.84
Bluestone SR	0.01	0.01	0.02	0.03	0.58	0.60	0.78	0.59	0.48	0.45	0.02	0.02
Booker T Washington M	0.14	0.20	0.32	0.40	0.47	0.34	0.33	0.25	0.29	0.31	0.23	0.19
Bryce Canyon	2.95	3.64	5.93	11.50	20.48	15.19	16.03	15.35	27.24	14.93	4.98	4.23
Cabrillo M	14.03	13.89	14.78	13.94	13.06	7.84	10.17	9.31	9.75	8.79	9.90	12.62
Canaveral Seashore	16.44	21.98	26.51	26.36	28.59	13.71	14.82	12.11	13.69	11.40	10.76	14.76
Canyon de Chelly M	11.44	9.41	12.00	14.07	14.97	8.86	9.21	9.34	10.74	6.30	5.49	8.89
Canyonlands	0.84	1.52	4.79	7.50	9.61	4.90	4.26	4.38	7.94	6.40	2.23	1.28
Cape Cod SS	24.66	25.40	34.46	52.64	66.22	55.48	91.98	103.34	83.11	53.76	28.85	27.46
Cape Hatteras SS	11.85	11.81	23.87	32.65	44.98	39.50	44.44	39.27	39.27	24.96	17.80	14.11
Cape Lookout SS	3.11	2.44	4.18	9.65	9.75	7.62	9.42	7.84	8.93	7.02	7.19	3.80
Capitol Reef	1.72	2.15	6.07	11.71	18.06	8.80	8.46	7.79	13.81	10.36	3.05	2.21
Capulin Volcano M	0.21	0.24	0.77	0.38	0.93	1.07	1.48	0.85	0.67	0.44	0.30	0.32
Carlsbad Caverns	3.05	3.42	7.72	5.02	6.02	4.93	6.61	3.84	3.60	3.61	3.09	4.83

Table 8: Park Values in Millions of 2018 Dollars *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Casa Grande Ruins M	1.92	2.77	2.73	1.41	0.77	0.31	0.30	0.26	0.44	0.66	0.87	1.17
Cedar Breaks M	2.31	1.65	1.74	1.94	7.59	9.30	14.00	12.03	15.72	10.23	4.68	3.68
Channel Islands	2.89	3.55	3.76	3.83	3.97	2.93	3.56	3.21	3.53	2.60	2.09	2.64
Chattahoochee River RA	53.71	59.18	60.86	65.78	74.04	46.33	40.87	39.58	37.61	33.64	32.73	57.24
Chickasaw RA	4.39	5.20	7.09	7.27	11.99	10.49	10.75	9.33	7.65	5.09	4.61	4.10
Chiricahua M	0.72	1.05	1.25	0.93	0.59	0.19	0.20	0.18	0.30	0.42	0.44	0.59
City of Rocks R	0.09	0.08	0.14	0.54	1.74	1.30	1.07	1.05	1.39	1.08	0.56	0.42
Colorado M	3.05	3.32	5.68	7.20	9.26	5.10	5.17	5.06	6.74	5.41	3.65	3.45
Congaree	1.55	2.05	2.90	2.50	2.80	1.13	0.97	1.00	1.29	1.55	1.49	1.77
Crater Lake	1.31	1.09	1.10	2.10	4.70	6.32	11.06	9.94	10.45	3.89	1.46	1.02
Craters of the Moon M	0.38	0.49	0.61	1.01	2.40	2.48	3.16	3.17	3.32	1.33	0.46	0.32
Cumberland Island SS	0.47	1.10	1.47	1.41	1.18	0.52	1.23	0.34	0.56	0.92	0.62	0.54
Curecanti RA	3.14	3.02	3.14	5.62	13.59	12.35	16.81	14.57	13.21	6.89	3.79	2.74
Cuyahoga Valley	27.36	26.70	25.35	37.98	49.88	32.62	35.17	34.93	31.28	29.53	17.34	29.51
Death Valley	10.35	12.44	18.07	17.04	14.61	6.99	8.74	9.92	15.96	13.24	11.20	11.31
Delaware River Water Gap RA	31.09	31.52	34.90	42.89	49.91	37.98	42.61	42.26	37.74	36.27	30.92	35.42
Devil's Postpile M	0.00	0.00	0.00	0.00	0.34	1.02	3.44	3.29	2.72	1.34	0.00	0.00
Devils Tower M	0.44	0.46	1.09	1.59	5.63	9.19	11.92	11.66	7.67	2.38	0.76	0.52
Dinosaur M	0.83	1.00	1.57	3.05	5.93	5.37	6.11	5.08	4.58	2.47	1.12	0.94
Dry Tortugas	0.98	0.99	0.96	0.94	1.02	0.62	0.63	0.47	0.44	0.36	0.56	0.97
Effigy Mounds M	0.60	0.85	0.79	0.82	1.45	0.92	1.32	1.06	1.32	1.72	0.34	0.38
El Malpais M	1.02	1.09	2.08	2.32	2.66	1.51	1.67	1.38	1.93	1.75	1.02	1.10
El Morro M	0.43	0.47	0.75	0.89	1.21	0.61	0.70	0.66	0.79	0.74	0.48	0.46
Everglades	13.77	14.26	12.52	8.52	5.80	3.03	3.17	3.19	3.50	4.30	5.64	12.16
Fire Island SS	1.50	1.72	2.08	3.32	6.19	6.27	13.07	14.65	8.31	3.18	2.27	2.29
Florissant Fossil Beds M	0.29	0.32	0.49	0.59	1.20	1.09	1.39	1.16	1.30	0.80	0.31	0.28
Fossil Butte M	0.02	0.03	0.09	0.15	0.51	0.66	0.85	0.67	0.68	0.25	0.07	0.03
Gateway RA	47.54	48.05	50.53	65.40	91.44	75.59	91.58	86.15	87.24	60.98	56.25	54.51
Gauley River RA	0.17	0.37	0.62	0.67	0.89	0.79	0.94	0.76	3.72	1.93	0.30	0.21
George Washington Carver M	0.22	0.30	0.55	0.92	1.03	0.51	0.51	0.31	0.66	0.65	0.41	0.20

Table 8: Park Values in Millions of 2018 Dollars *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Gila Cliff Dwellings M	0.30	0.46	1.16	0.90	0.93	0.49	0.60	0.40	0.54	0.52	0.38	0.32
Glacier	1.33	1.39	1.44	2.72	11.14	21.83	39.24	35.11	28.46	5.34	1.38	1.35
Glen Canyon RA	3.46	3.67	7.51	13.08	18.37	20.89	20.90	17.33	13.79	9.33	4.85	3.48
Golden Gate RA	167.65	167.93	145.28	150.67	152.25	99.81	102.48	101.09	136.52	129.89	115.17	167.81
Grand Canyon	18.43	19.43	31.07	35.58	40.35	32.02	37.37	35.24	37.18	31.09	20.31	25.61
Grand Portage M	0.14	0.17	0.37	0.34	0.95	1.31	2.20	2.87	1.62	0.75	0.24	0.28
Grand Teton	6.21	5.99	5.56	5.45	22.60	35.46	46.58	41.83	39.09	13.91	3.68	5.75
Great Basin	0.24	0.33	0.53	0.98	1.63	1.36	1.78	1.44	2.25	1.06	0.35	0.34
Great Sand Dunes	0.30	0.43	1.62	1.65	5.80	5.21	5.36	4.22	4.19	2.34	0.74	0.44
Great Smoky Mtns	33.43	33.66	51.35	66.46	75.35	73.21	82.04	64.29	75.97	89.10	52.88	51.23
Guadalupe Mountains	1.69	2.23	3.33	2.63	2.41	1.21	1.26	1.09	1.53	2.37	2.23	2.23
Gulf Islands SS	36.44	40.45	60.32	68.67	84.73	48.38	49.91	42.36	44.33	38.27	34.18	47.85
Hagerman Fossil Beds M	0.14	0.21	0.61	0.64	1.11	0.68	0.72	0.57	0.64	0.38	0.24	0.13
Hot Springs	13.88	14.69	17.79	16.37	20.26	13.91	15.24	14.20	19.51	18.44	13.87	15.07
Hovenweep M	0.08	0.11	0.40	0.68	0.88	0.43	0.39	0.33	0.64	0.51	0.17	0.10
Indiana Dunes LS	13.27	13.97	21.74	23.11	37.24	29.73	43.13	33.45	30.30	19.95	14.24	12.44
Isle Royale	0.00	0.01	0.00	0.01	0.08	0.21	0.38	0.43	0.18	0.02	0.00	0.01
Jefferson National Expansion ML	10.52	11.75	27.97	30.13	36.75	28.31	70.31	28.97	17.80	17.05	12.21	14.69
Jewel Cave M	0.05	0.06	0.36	0.43	1.20	2.52	4.13	2.79	1.84	0.48	0.13	0.06
John Day Fossil Beds M	0.40	0.52	1.57	2.47	3.93	2.64	2.94	2.80	3.15	1.60	0.64	0.47
Joshua Tree	28.00	32.48	36.72	32.33	22.00	7.79	7.22	7.62	11.42	16.01	20.56	32.46
Kings Canyon	2.91	2.42	2.31	3.37	6.69	5.64	7.48	6.62	6.97	4.89	2.33	2.67
Lake Chelan RA	0.10	0.11	0.11	0.19	0.36	0.34	0.54	0.53	0.55	0.27	0.10	0.11
Lake Mead RA	34.30	38.00	35.49	42.81	45.70	38.49	37.32	35.04	40.36	33.39	27.85	32.45
Lake Meredith RA	5.83	10.42	7.75	8.57	10.95	9.41	10.15	7.54	7.29	5.64	5.38	5.97
Lake Roosevelt RA	3.72	5.26	5.59	7.22	9.47	12.68	20.53	18.08	9.35	5.35	3.24	4.34
Lassen Volcanic	1.55	1.21	0.96	1.35	3.55	4.96	8.38	7.72	7.45	4.14	0.99	1.39
Lava Beds M	0.66	0.89	1.04	1.22	2.35	1.99	2.42	1.96	1.93	1.32	0.79	0.73
Little River Canyon Preserve	2.07	2.59	3.20	3.40	4.93	3.87	3.51	2.96	2.26	2.40	1.67	2.29
Mammoth Cave	2.32	2.22	5.77	7.66	7.31	6.62	9.43	6.63	4.69	4.86	2.64	3.05

Table 8: Park Values in Millions of 2018 Dollars *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mesa Verde	1.20	1.36	3.61	6.04	12.37	13.95	15.26	12.73	12.97	7.40	2.24	1.84
Mississippi River & RA	1.26	1.32	1.27	1.02	2.44	1.11	1.31	1.26	1.38	1.16	0.89	1.21
Missouri Recreational River	0.48	0.46	0.64	1.07	1.72	1.51	1.74	1.65	2.10	1.28	0.78	0.52
Mojave Preserve	4.66	5.18	4.67	4.46	4.28	2.74	2.28	2.50	3.65	3.84	5.47	5.23
Montezuma Castle M	5.68	7.41	11.79	11.03	9.32	4.60	4.65	4.21	6.13	6.82	5.23	5.04
Mount Rainier	5.42	4.73	5.55	6.89	17.62	23.06	37.71	39.13	33.54	13.59	9.22	5.35
Muir Woods M	9.15	8.95	13.82	15.02	15.68	10.60	14.13	12.90	12.45	10.46	8.59	11.50
Natural Bridges M	0.19	0.28	1.02	2.04	3.24	1.32	1.13	0.99	2.13	1.55	0.48	0.26
New River Gorge R	3.17	3.75	5.83	8.63	14.13	12.16	15.88	13.44	9.04	11.78	3.95	3.99
Niobrara SR	0.06	0.04	0.08	0.11	0.29	0.65	1.44	1.16	0.29	0.09	0.04	0.04
North Cascades	0.00	0.01	0.01	0.02	0.09	0.18	0.48	0.54	0.47	0.08	0.01	0.01
Obed Wild and Scenic River	1.09	1.20	2.03	2.55	2.69	2.27	1.92	1.68	1.42	1.50	1.18	1.58
Olympic	10.83	11.00	10.08	12.94	25.82	23.34	29.31	43.05	31.75	14.62	9.15	9.85
Oregon Caves Monument and Preserve	0.17	0.17	0.61	0.64	1.43	1.09	1.37	1.28	1.19	0.80	0.29	0.22
Organ Pipe Cactus M	5.05	6.57	5.22	3.89	2.38	1.23	1.23	1.01	1.78	2.11	2.35	3.67
Ozark Scenic River	2.54	2.74	5.67	7.89	12.34	15.06	21.25	19.79	13.05	8.11	6.43	4.87
Padre Island Seashore	5.85	7.29	10.93	9.31	11.38	8.41	9.97	7.02	6.17	5.39	4.70	4.60
Petrified Forest	3.71	4.12	6.85	6.79	8.53	7.67	7.84	6.11	6.32	6.42	3.59	4.55
Petroglyph M	1.55	1.64	2.67	2.59	2.52	1.39	1.43	1.18	1.57	2.72	1.59	1.81
Pictured Rocks LS	3.40	4.35	3.26	2.59	6.49	8.09	15.56	15.75	13.18	7.29	1.26	1.87
Pinnacles	2.23	2.88	3.56	4.58	3.83	1.67	1.69	1.78	1.73	1.74	1.70	2.63
Pipestone M	0.10	0.14	0.28	0.60	1.88	1.21	1.71	1.45	1.32	0.77	0.25	0.17
Point Reyes SS	31.06	31.12	35.18	39.37	39.87	24.29	28.26	26.98	32.83	25.57	25.49	30.20
Rainbow Bridge M	0.03	0.03	0.20	0.80	2.07	1.90	2.39	1.76	1.89	0.86	0.13	0.04
Redwood	3.38	3.14	3.31	4.21	5.57	4.90	6.06	5.22	5.90	4.00	2.48	3.70
Rio Grande Wild and Scenic River	0.00	0.01	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.01
Rocky Mountain	13.04	11.49	12.81	12.80	28.69	43.44	59.24	51.18	56.22	27.04	9.95	12.33
Ross Lake RA	0.53	0.54	0.47	1.74	6.79	7.16	10.40	9.26	8.45	5.28	1.26	0.56
Russell Cave M	0.15	0.24	0.35	0.46	0.67	0.30	0.28	0.25	0.33	0.38	0.26	0.25
Saguaro	15.77	18.92	17.19	11.65	7.55	3.13	3.51	3.50	4.67	6.23	8.14	13.35

Table 8: Park Values in Millions of 2018 Dollars *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Saint Croix SR	0.14	0.10	0.08	2.07	5.28	5.53	10.54	10.81	6.24	1.69	0.31	0.19
Salinas Pueblo Missions M	0.30	0.38	0.52	0.56	0.66	0.34	0.37	0.32	0.50	0.57	0.32	0.28
Santa Monica Mountains RA	7.14	6.94	6.69	6.05	7.34	4.12	3.90	3.91	4.70	4.64	4.59	5.51
Scotts Bluff M	0.48	0.59	1.21	1.51	2.61	2.15	2.57	2.09	2.32	1.21	0.62	0.74
Sequoia	4.97	4.47	5.70	7.62	12.78	9.69	13.34	13.15	12.73	7.73	4.75	5.90
Shenandoah	2.79	2.90	5.11	11.62	17.19	11.25	13.66	13.42	15.84	27.04	11.61	3.63
Sleeping Bear Dunes LS	1.70	2.17	2.84	4.95	13.05	22.09	50.14	44.54	21.65	13.39	2.80	1.77
Sunset Crater Volcano M	1.20	1.24	2.94	3.59	3.54	2.21	2.29	1.94	2.55	2.27	1.40	1.25
Tallgrass Prairie Preserve	0.07	0.09	0.18	0.26	0.49	0.40	0.28	0.22	0.39	0.38	0.17	0.09
Theodore Roosevelt	0.34	0.45	0.88	2.96	8.11	8.86	11.54	10.65	10.16	7.83	2.74	0.76
Timpanogos Cave M	0.02	0.02	0.05	0.09	1.20	1.99	2.72	2.17	1.11	0.38	0.02	0.03
Tonto M	0.99	1.41	1.98	1.17	0.71	0.25	0.24	0.20	0.34	0.49	0.55	0.62
Upper Delaware Scenic and Rec. River	0.56	0.55	0.42	0.75	3.13	2.40	4.80	4.33	3.16	0.74	0.35	0.41
Voyageurs	0.74	1.46	0.50	0.05	3.64	3.73	4.25	3.93	3.01	1.05	0.23	0.07
Whiskeytown- Shasta-Trinity RA	3.87	4.34	4.54	5.91	9.64	9.94	11.14	8.14	6.66	4.19	2.77	3.12
White Sands M	4.24	5.02	10.84	8.35	8.76	5.60	6.78	5.06	6.05	5.64	4.85	5.61
Wind Cave	2.71	2.59	4.16	7.83	11.35	11.11	13.83	12.44	10.94	3.87	2.24	2.73
Yellowstone	2.98	3.44	1.80	2.97	27.05	39.55	51.01	44.83	41.45	12.63	0.99	2.12
Yosemite	14.01	14.66	14.49	22.37	34.57	30.32	36.56	36.03	37.62	26.83	13.29	17.21
Zion	9.93	11.31	23.87	33.83	37.60	26.63	27.64	25.60	31.78	25.48	13.93	12.70

Note: The table shows average park values for each month of the year in millions of 2018 dollars. I define and calculate park values as the total lost welfare of removing a park from the choice set. To calculate average park values, I calculate park values every month from January 2005 through December 2019 and average the values across years.

Table 9: Park Values per Visit (2018 dollars)

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Acadia	212.04	211.87	150.78	150.94	151.40	91.26	91.63	91.83	137.43	136.74	134.93	210.34
Agate Fossil Beds M	207.75	207.68	193.98	193.85	193.72	109.87	109.79	109.72	152.96	152.85	152.74	206.23
Alibates Flint Quarries M	208.01	207.86	194.16	194.03	193.89	110.02	109.94	109.86	153.18	153.08	152.97	206.40
Amistad RA	145.85	145.94	113.96	113.62	113.45	73.68	73.55	73.47	99.36	99.30	99.28	144.42
Apostle Islands LS	205.28	205.34	199.27	199.03	198.94	113.76	113.76	113.71	157.07	156.87	156.70	203.75
Arches	206.63	206.59	147.48	147.43	147.40	88.56	88.44	88.40	132.26	132.06	131.77	205.11
Assateague Island SS	204.21	204.03	198.64	198.78	198.98	113.80	114.10	114.06	156.75	156.13	155.88	202.55
Aztec Ruins M	208.14	207.99	194.31	194.17	194.04	110.13	110.05	109.97	153.35	153.24	153.13	206.54
Badlands	178.81	178.66	128.40	128.32	128.38	79.17	79.13	79.08	116.37	116.05	115.90	177.40
Bandelier M	204.79	204.65	188.70	188.57	188.47	107.22	107.14	107.06	148.99	148.91	148.78	203.22
Big Bend	126.33	126.28	92.47	92.33	92.23	59.75	59.70	59.66	85.51	85.48	85.48	125.30
Big Cypress Preserve	134.25	134.42	99.62	99.32	99.14	63.98	63.93	63.88	89.85	89.86	89.99	132.93
Big South Fork River and Recreation Area	179.16	179.01	143.56	143.50	143.42	88.81	88.73	88.66	100.80	100.75	100.67	177.79
Big Thicket Preserve	186.93	186.77	144.08	143.98	143.89	88.35	88.29	88.23	127.93	127.86	127.80	185.53
Bighorn Canyon RA	139.74	139.62	108.01	107.94	107.88	70.54	70.49	70.44	95.71	95.62	95.55	138.65
Biscayne	190.16	189.97	135.88	135.75	135.66	82.70	82.65	82.57	122.29	122.31	122.22	188.60
Black Canyon of Gunnison	214.52	214.34	153.00	152.91	152.88	91.29	91.23	91.16	136.84	136.72	136.59	212.84
Bluestone SR	132.07	131.96	126.65	126.57	126.49	79.20	79.21	79.15	93.78	93.71	93.55	130.92
Booker T Washington M	208.14	207.99	194.29	194.16	194.02	110.13	110.05	109.97	153.34	153.23	153.13	206.53
Bryce Canyon	157.93	157.84	107.43	107.47	107.54	62.01	61.94	61.91	111.96	111.65	111.31	156.76
Cabrillo M	209.85	209.63	195.55	195.16	194.87	110.55	110.53	110.46	153.98	153.87	154.08	207.95
Canaveral Seashore	204.23	204.49	196.38	195.89	195.70	111.92	111.82	111.70	153.93	153.77	153.82	202.32
Canyon de Chelly M	228.56	228.16	204.90	204.74	204.53	104.47	104.37	104.33	123.66	123.48	123.45	226.48
Canyonlands	166.08	166.00	119.91	119.87	119.80	74.49	74.42	74.38	108.93	108.86	108.68	164.81
Cape Cod SS	206.08	205.93	199.87	200.25	200.42	114.85	115.59	116.18	159.10	157.92	157.07	204.40
Cape Hatteras SS	205.06	204.86	201.32	201.29	201.43	115.02	114.87	114.77	158.32	157.77	157.66	203.50
Cape Lookout SS	204.44	204.22	200.64	200.69	200.50	114.24	114.17	114.08	157.45	157.30	157.31	202.87
Capitol Reef	203.71	203.58	148.57	148.64	148.66	85.71	85.61	85.56	117.50	117.39	117.09	202.14
Capulin Volcano M	207.99	207.83	194.26	194.10	193.99	110.10	110.03	109.94	153.28	153.17	153.06	206.48
Carlsbad Caverns	212.27	212.14	151.18	150.89	150.80	90.30	90.26	90.14	135.04	134.96	134.90	210.76

Table 9: Park Values per Visit (2018 dollars) *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Casa Grande Ruins M	208.30	208.22	194.44	194.20	194.02	110.11	110.03	109.95	153.32	153.23	153.15	206.60
Cedar Breaks M	207.71	207.49	193.75	193.61	193.69	109.87	109.87	109.78	153.11	152.88	152.62	206.18
Channel Islands	178.00	177.93	127.87	127.75	127.65	78.61	78.57	78.51	115.60	115.48	115.41	174.54
Chattahoochee River RA	300.80	300.97	253.63	252.90	252.69	133.22	132.74	132.77	162.24	162.07	162.42	297.98
Chickasaw RA	92.60	92.56	76.65	76.57	76.59	53.36	53.30	53.26	64.05	63.96	63.95	91.85
Chiricahua M	169.13	169.02	128.65	128.54	128.44	77.78	77.73	77.67	104.18	104.12	104.05	167.80
City of Rocks R	169.43	169.30	123.44	123.36	123.31	77.45	77.38	77.33	98.81	98.74	98.66	168.14
Colorado M	206.31	206.17	191.40	191.27	191.16	108.44	108.34	108.28	150.84	150.74	150.64	204.72
Congaree	230.76	230.62	191.09	190.91	190.78	111.09	111.00	110.93	147.24	147.15	147.06	228.96
Crater Lake	187.87	187.69	134.48	134.43	134.45	82.20	82.27	82.20	121.67	121.27	121.16	186.52
Craters of the Moon M	145.86	145.76	107.60	107.53	107.49	69.16	69.11	69.07	98.07	97.95	97.86	144.72
Cumberland Island SS	203.82	203.71	198.91	198.75	198.59	113.31	113.24	113.14	156.06	155.98	155.86	202.23
Curecanti RA	176.57	176.42	139.75	139.72	139.82	86.39	86.38	86.30	110.98	110.77	110.65	175.15
Cuyahoga Valley	255.71	255.39	202.55	202.62	202.68	116.11	115.94	115.95	132.74	132.69	132.44	253.61
Death Valley	177.03	177.00	155.45	155.18	154.90	89.24	89.20	89.18	147.76	147.65	147.63	175.63
Delaware River Water Gap RA	137.83	137.73	122.00	121.86	121.80	76.39	76.28	76.30	95.53	95.54	95.64	136.77
Devil's Postpile M					164.51	96.17	96.18	96.11	125.26	125.51		
Devils Tower M	208.06	207.90	194.23	194.11	194.13	110.31	110.25	110.21	153.49	153.19	153.02	206.45
Dinosaur M	212.92	212.77	201.53	201.45	201.41	111.58	111.50	111.41	150.05	149.89	149.75	211.27
Dry Tortugas	208.77	208.61	148.48	148.36	148.26	89.00	88.94	88.87	132.92	132.82	132.76	207.13
Effigy Mounds M	207.95	207.81	194.08	193.94	193.82	109.94	109.87	109.79	153.07	152.99	152.83	206.31
El Malpais M	197.07	196.92	174.37	174.24	174.12	100.60	100.53	100.46	139.18	139.09	138.98	195.54
El Morro M	208.06	207.90	194.21	194.07	193.94	110.04	109.96	109.89	153.22	153.11	153.01	206.44
Everglades	122.02	121.93	88.34	88.04	87.87	54.64	54.60	54.57	72.87	72.86	72.93	120.83
Fire Island SS	198.13	197.99	198.77	198.67	198.63	115.03	115.11	115.12	122.41	122.17	122.08	196.63
Florissant Fossil Beds M	207.56	207.40	193.70	193.56	193.45	109.63	109.55	109.47	152.60	152.48	152.35	205.94
Fossil Butte M	281.43	281.21	275.36	275.17	275.00	184.09	183.96	183.83	254.62	254.42	254.23	279.24
Gateway RA	150.89	150.71	117.75	117.67	118.04	76.61	76.59	76.58	102.95	102.33	102.78	149.67
Gauley River RA	149.04	148.93	117.30	117.22	117.14	75.66	75.60	75.55	101.37	101.27	101.16	147.88
George Washington Carver M	208.15	208.00	194.31	194.18	194.05	110.13	110.06	109.98	153.36	153.25	153.14	206.53

Table 9: Park Values per Visit (2018 dollars) *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Gila Cliff Dwellings M	208.13	207.98	194.31	194.16	194.02	110.11	110.03	109.95	153.31	153.21	153.10	206.51
Glacier	116.13	116.04	85.47	85.44	85.63	56.48	56.70	56.63	80.57	79.82	79.62	115.22
Glen Canyon RA	81.91	81.85	62.91	62.93	62.93	43.77	43.71	43.66	53.42	53.34	53.27	81.26
Golden Gate RA	157.92	157.55	119.19	118.08	117.38	76.14	75.68	75.89	104.13	104.54	105.51	155.77
Grand Canyon	110.67	110.58	82.02	81.93	81.87	54.15	54.13	54.11	76.97	76.91	76.78	110.03
Grand Portage M	208.10	207.94	194.26	194.11	194.01	110.13	110.07	110.02	153.35	153.20	153.07	206.50
Grand Teton	137.52	137.38	109.69	109.56	109.91	69.31	69.33	69.28	91.83	91.26	90.92	136.39
Great Basin	206.24	206.09	146.83	146.74	146.65	88.21	88.15	88.08	131.61	131.49	131.38	204.64
Great Sand Dunes	152.56	152.45	127.89	127.79	127.80	79.50	79.44	79.37	121.17	121.04	120.91	151.38
Great Smoky Mtns	100.47	100.35	86.87	86.84	86.77	58.53	58.45	58.31	74.14	74.43	74.11	100.05
Guadalupe Mountains	204.64	204.53	145.80	145.65	145.52	87.63	87.57	87.50	130.63	130.58	130.52	203.08
Gulf Islands SS	201.85	201.88	183.64	183.28	183.39	106.31	106.07	105.94	145.32	145.17	145.40	200.67
Hagerman Fossil Beds M	296.60	296.38	305.49	305.27	305.08	181.60	181.47	181.34	264.20	264.00	263.82	294.29
Hot Springs	219.65	219.49	157.23	156.94	156.88	93.29	93.21	93.16	140.34	140.28	140.20	217.87
Hovenweep M	208.08	207.93	194.25	194.12	193.99	110.08	110.00	109.92	153.28	153.17	153.05	206.47
Indiana Dunes LS	209.24	209.09	208.99	208.67	208.95	117.54	117.64	117.43	162.24	161.84	161.71	207.41
Isle Royale	142.07	141.96	103.32	103.25	103.18	65.72	65.67	65.63	94.82	94.75	94.68	140.97
Jefferson National Expansion ML	205.42	205.34	199.83	199.49	199.42	115.52	116.25	115.34	123.60	123.54	123.45	204.00
Jewel Cave M	208.03	207.87	194.19	194.06	193.95	110.10	110.05	109.95	153.26	153.11	152.99	206.41
John Day Fossil Beds M	206.77	206.63	192.53	192.45	192.39	109.03	108.94	108.86	151.69	151.51	151.34	205.17
Joshua Tree	195.63	195.82	143.14	142.50	141.78	82.10	81.99	81.97	112.45	112.65	113.15	194.27
Kings Canyon	152.41	152.25	110.37	110.31	110.34	69.59	69.57	69.52	100.97	100.85	100.70	151.19
Lake Chelan RA	144.53	144.42	112.79	112.72	112.65	73.18	73.13	73.08	98.87	98.79	98.71	143.41
Lake Mead RA	85.62	85.62	64.89	64.86	64.78	45.60	45.48	45.47	60.37	60.31	60.36	84.80
Lake Meredith RA	146.39	146.56	114.53	114.43	114.37	74.19	74.12	74.04	99.85	99.75	99.74	145.21
Lake Roosevelt RA	126.74	126.83	99.42	99.39	99.33	67.09	67.21	67.11	71.78	71.64	71.56	125.78
Lassen Volcanic	189.95	189.77	137.66	137.57	137.56	84.32	84.34	84.28	110.08	109.90	109.69	188.45
Lava Beds M	203.49	203.37	186.20	186.06	185.99	106.13	106.06	105.97	147.34	147.22	147.10	201.92
Little River Canyon Preserve	192.39	192.26	151.63	151.50	151.42	93.60	93.52	93.45	102.28	102.22	102.14	190.88
Mammoth Cave	168.52	168.38	126.97	126.90	126.78	79.66	79.62	79.54	101.91	101.85	101.75	167.24

Table 9: Park Values per Visit (2018 dollars) *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mesa Verde	232.02	231.86	219.76	219.70	219.79	136.67	136.54	136.41	193.46	193.13	192.75	230.27
Mississippi River & RA	97.15	97.07	78.09	78.02	78.00	53.41	53.37	53.34	62.47	62.43	62.39	96.42
Missouri Recreational River	131.35	131.25	123.06	122.98	122.91	77.28	77.23	77.18	91.47	91.39	91.32	130.33
Mojave Preserve	107.31	107.25	81.28	81.19	81.12	54.52	54.46	54.43	76.22	76.19	76.24	106.48
Montezuma Castle M	208.59	208.57	194.95	194.65	194.37	110.23	110.13	110.05	153.52	153.49	153.40	206.88
Mount Rainier	255.18	254.69	249.72	249.56	250.84	134.02	134.81	134.99	186.65	184.26	184.10	253.04
Muir Woods M	209.15	208.95	195.46	195.24	195.04	110.67	110.70	110.61	154.10	153.95	153.90	207.72
Natural Bridges M	207.38	207.23	193.56	193.47	193.37	109.49	109.40	109.33	152.41	152.30	152.15	205.77
New River Gorge R	130.77	130.69	119.64	119.59	119.58	75.61	75.58	75.51	89.42	89.43	89.24	129.76
Niobrara SR	92.74	92.67	92.04	91.97	91.91	60.88	60.85	60.81	58.16	58.12	58.07	92.02
North Cascades	147.99	147.83	107.41	107.25	107.26	67.91	67.87	67.83	98.32	98.22	98.15	146.67
Obed Wild and Scenic River	132.10	132.00	126.67	126.58	126.49	79.24	79.18	79.12	93.73	93.67	93.61	131.08
Olympic	121.48	121.39	88.81	88.80	89.29	58.42	58.41	58.96	83.67	82.84	82.65	120.28
Oregon Caves Monument and Preserve	200.76	200.61	157.30	157.18	157.12	94.68	94.62	94.55	135.65	135.54	135.42	199.21
Organ Pipe Cactus M	180.31	180.28	144.88	144.67	144.49	86.43	86.36	86.30	118.43	118.38	118.34	178.76
Ozark Scenic River	130.57	130.48	118.77	118.70	118.69	75.22	75.21	75.18	88.97	88.83	88.79	129.64
Padre Island Seashore	199.99	199.99	182.75	182.37	182.30	105.87	105.82	105.66	144.93	144.80	144.76	198.21
Petrified Forest	182.05	181.93	130.67	130.53	130.46	80.09	80.01	79.93	117.93	117.89	117.76	180.67
Petroglyph M	207.53	207.37	193.68	193.52	193.36	109.52	109.44	109.36	152.44	152.39	152.26	205.93
Pictured Rocks LS	205.43	205.34	198.60	198.38	198.39	113.58	113.66	113.64	157.06	156.76	156.40	203.67
Pinnacles	191.11	191.03	158.98	158.89	158.71	95.34	95.26	95.20	121.88	121.81	121.75	189.65
Pipestone M	208.14	207.98	194.29	194.17	194.09	110.16	110.09	110.01	153.38	153.26	153.13	206.53
Point Reyes SS	205.59	205.37	195.36	195.08	194.69	111.62	111.57	111.54	153.74	153.37	153.82	203.69
Rainbow Bridge M	208.27	208.41	194.30	194.20	194.11	110.19	110.12	110.03	153.42	153.28	153.07	206.53
Redwood	197.64	197.45	141.01	140.93	140.86	85.37	85.32	85.24	126.80	126.65	126.52	196.11
Rio Grande Wild and Scenic River	131.94	131.74	126.27	126.18	125.66	78.80	78.52	78.97	93.19	93.26	93.24	130.92
Rocky Mountain	163.21	162.90	127.95	127.76	128.05	78.91	79.03	78.94	105.56	104.81	104.33	161.74
Ross Lake RA	139.99	139.89	108.23	108.25	108.49	71.00	71.02	70.93	96.37	96.23	95.85	138.90
Russell Cave M	208.13	207.98	194.29	194.15	194.02	110.12	110.04	109.96	153.33	153.23	153.12	206.52
Saguaro	205.00	205.06	145.82	145.37	145.07	87.37	87.31	87.26	130.21	130.22	130.36	203.08

Table 9: Park Values per Visit (2018 dollars) *(continued)*

Park	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Saint Croix SR	130.23	130.12	117.40	117.39	117.39	74.47	74.51	74.49	88.16	87.97	87.88	129.23
Salinas Pueblo Missions M	208.07	207.92	194.22	194.08	193.95	110.05	109.98	109.90	153.24	153.14	153.02	206.45
Santa Monica Mountains RA	137.52	137.38	105.54	105.38	105.34	69.09	69.01	68.98	93.59	93.55	93.55	136.27
Scotts Bluff M	207.89	207.74	194.06	193.92	193.82	109.93	109.85	109.77	153.04	152.90	152.78	206.29
Sequoia	158.69	158.51	114.70	114.66	114.73	71.93	71.94	71.92	104.75	104.51	104.38	157.49
Shenandoah	185.36	185.21	132.87	132.90	132.90	81.29	81.24	81.20	120.08	120.35	119.97	183.94
Sleeping Bear Dunes LS	205.37	205.24	201.85	201.77	201.92	114.80	115.33	115.25	157.57	157.20	156.68	203.76
Sunset Crater Volcano M	207.94	207.78	194.16	194.02	193.86	109.94	109.85	109.77	153.06	152.96	152.83	206.33
Tallgrass Prairie Preserve	199.44	199.29	156.02	155.91	155.81	94.23	94.16	94.09	134.87	134.78	134.68	197.89
Theodore Roosevelt	207.56	207.41	147.72	147.71	147.78	88.88	88.84	88.78	132.69	132.57	132.29	205.99
Timpanogos Cave M	139.51	139.40	136.26	136.16	136.10	84.97	84.92	84.85	86.01	85.94	85.87	138.43
Tonto M	208.13	208.01	194.31	194.11	193.95	110.05	109.89	109.89	153.23	153.13	153.04	206.48
Upper Delaware Scenic and Rec. River	130.61	130.50	119.21	119.14	119.11	75.31	75.29	75.24	89.15	89.04	88.97	129.58
Voyageurs	182.35	182.28	130.77	130.65	130.69	80.19	80.13	80.08	118.15	117.99	117.88	180.86
Whiskeytown- Shasta-Trinity RA	146.53	146.45	114.70	114.65	114.67	74.43	74.36	74.18	100.02	99.88	99.79	145.32
White Sands M	183.92	183.83	172.69	172.37	172.21	117.23	117.16	117.04	156.81	156.71	156.66	182.56
Wind Cave	218.55	218.36	206.62	206.62	206.56	114.66	114.60	114.53	154.43	154.08	153.94	216.82
Yellowstone	111.37	111.31	86.41	86.37	86.84	57.64	57.66	57.59	73.91	73.34	72.97	110.43
Yosemite	126.38	126.29	91.15	91.26	91.46	59.56	59.57	59.58	75.95	75.70	75.35	125.53
Zion	136.05	135.99	102.30	102.36	102.25	63.89	63.79	63.76	85.25	85.17	84.96	135.07

Note: The table shows average park values per visit for different months of the year. I calculate value per visit by dividing the estimated aggregate park value by the VUS visitor count for the month. To get the average value per visit, I calculate value per visit for all parks and months between January 2005 and December 2019, then I average across years.

Appendix D Full Park Ranking

Table 10: Park Awesomeness Index – All Parks

Rank	Park	Rating
1	Golden Gate RA	98.4
2	Glacier	95.3
3	Yellowstone	94.5
4	Gulf Islands SS	93.7
5	Grand Teton	93.6
6	Grand Canyon	93.5
7	Zion	93.4
8	Olympic	92.6
9	Mount Rainier	92.3
10	Bryce Canyon	91.6
11	Rocky Mountain	91.4
12	Point Reyes SS	91.3
13	Arches	91.2
14	Yosemite	91.1
15	Capitol Reef	91.1
16	Acadia	91.0
17	Lake Mead RA	90.8
18	Glen Canyon RA	90.5
19	Cape Cod SS	90.2
20	Joshua Tree	89.9
21	Great Smoky Mtns	89.6
22	Chattahoochee River RA	89.5
23	Cape Hatteras SS	89.3
24	Ross Lake RA	88.8
25	Lake Roosevelt RA	88.3
26	Gateway RA	88.3
27	Death Valley	88.1
28	Canaveral Seashore	86.6
29	Mesa Verde	86.4
30	Sleeping Bear Dunes LS	86.1
31	Crater Lake	85.9
32	Canyonlands	85.8
33	Theodore Roosevelt	85.6
34	Redwood	85.4
35	Black Canyon of Gunnison	84.4
36	Badlands	84.4
37	Assateague Island SS	84.2
38	Sequoia	84.2
39	Curecanti RA	84.0

40	Canyon de Chelly M	84.0
41	Cuyahoga Valley	83.9
42	Muir Woods M	83.9
43	Saguaro	83.8
44	Wind Cave	83.8
45	Amistad RA	83.7
46	White Sands M	83.4
47	Delaware River Water Gap RA	83.1
48	Jefferson National Expansion ML	82.9
49	Devils Tower M	82.6
50	Hot Springs	82.4
51	Colorado M	82.4
52	Dinosaur M	82.4
53	Petrified Forest	82.4
54	Cabrillo M	82.3
55	Cedar Breaks M	82.2
56	Lake Meredith RA	82.2
57	Pictured Rocks LS	82.0
58	Whiskeytown- Shasta-Trinity RA	81.7
59	Great Sand Dunes	81.7
60	John Day Fossil Beds M	81.1
61	Indiana Dunes LS	81.0
62	Padre Island Seashore	80.7
63	Montezuma Castle M	80.4
64	Lassen Volcanic	80.1
65	Biscayne	79.9
66	Carlsbad Caverns	79.4
67	Santa Monica Mountains RA	79.4
68	Chickasaw RA	79.4
69	Kings Canyon	79.2
70	Shenandoah	79.1
71	Bandelier M	78.7
72	Everglades	78.5
73	Saint Croix SR	78.4
74	Petroglyph M	78.0
75	Ozark Scenic River	77.9
76	Natural Bridges M	77.8
77	Craters of the Moon M	77.8
78	Cape Lookout SS	77.7
79	Bighorn Canyon RA	77.6
80	Big South Fork River and Recreation Area	77.4
81	Big Bend	76.8
82	New River Gorge R	76.8
83	Little River Canyon Preserve	76.7
84	Jewel Cave M	76.3
85	Mojave Preserve	76.2

86	Channel Islands	76.2
87	Big Cypress Preserve	76.1
88	Guadalupe Mountains	76.0
89	Voyageurs	75.9
90	Rainbow Bridge M	75.5
91	Apostle Islands LS	75.5
92	Devil's Postpile M	74.9
93	El Malpais M	74.8
94	Scotts Bluff M	74.5
95	City of Rocks R	74.4
96	Lava Beds M	74.4
97	Pinnacles	74.2
98	Organ Pipe Cactus M	74.1
99	Oregon Caves Monument and Preserve	73.0
100	Sunset Crater Volcano M	72.9
101	Great Basin	72.9
102	Mammoth Cave	72.7
103	Big Thicket Preserve	72.4
104	Congaree	72.1
105	Gila Cliff Dwellings M	71.4
106	Mississippi River & RA	71.1
107	El Morro M	71.0
108	Fire Island SS	71.0
109	Timpanogos Cave M	70.9
110	Aztec Ruins M	70.6
111	Grand Portage M	70.4
112	Hovenweep M	70.0
113	Hagerman Fossil Beds M	69.6
114	Pipestone M	69.3
115	Capulin Volcano M	69.3
116	Florissant Fossil Beds M	69.0
117	Casa Grande Ruins M	68.0
118	Missouri Recreational River	67.7
119	Chiricahua M	67.5
120	Upper Delaware Scenic and Recreational River	66.2
121	Fossil Butte M	66.1
122	North Cascades	66.1
123	Dry Tortugas	66.0
124	Obed Wild and Scenic River	65.9
125	Salinas Pueblo Missions M	65.4
126	Gauley River RA	65.2
127	Tonto M	64.8
128	Niobrara SR	64.6
129	Lake Chelan RA	64.5
130	Cumberland Island SS	63.8
131	Effigy Mounds M	63.0

132	Agate Fossil Beds M	62.7
133	George Washington Carver M	62.5
134	Tallgrass Prairie Preserve	59.1
135	Isle Royale	58.3
136	Alibates Flint Quarries M	55.5
137	Bluestone SR	55.5
138	Russell Cave M	55.2
139	Booker T Washington M	54.3
140	Rio Grande Wild and Scenic River	38.8