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

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Abstract

The U.S. National Park System protects some of the worlds' most spectacular resources and attracts 300 million visits each year, generating surplus for visitors and supporting local economies. I create a versatile and unified framework to analyze demand for U.S. national parks. Combining nationally representative surveys with park-level visitor counts, I estimate a discrete-choice model of demand from 2005 through 2019. The model controls for changing travel costs and inter-park substitution, while permitting the use of causal inference techniques. I apply the framework to analyze how long-run average temperatures and short-run temperature shocks impact demand. At the monthly level, visitors respond three times more strongly to average temperatures than shocks. Visitors are willing to pay an extra \$503 for average temperatures between 70°F and 85°F rather than 30°F. The response to temperature shocks exhibits intuitive heterogeneity. The results provide insight on the welfare impacts of climate change, and the framework is broadly applicable to management challenges facing U.S. national parks.

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1 Introduction

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 100 years later, the National Park System includes over 400 parks, which collectively attract 300 million visits each year. The parks generate surplus for visitors and support nearby gateway communities (Cullinane Thomas, Flyr, and Koontz 2022). They are so quintessentially American that Ken Burns featured them in a documentary titled, "America's Best Idea."

Conserving important and popular resources creates complex management challenges. At the most famous parks, large crowds create air pollution that rivals metropolitan areas (Keiser, Lade, and Rudik 2018). In rare cases, parks have turned away visitors because they had too little space left. Crowds also exacerbate challenges caused by stagnant political funding. The result is a $21.8 billion deferred maintenance backlog ("NPS 2022"). Although, recent legislation, including the Great American Outdoors Act and Bipartisan Infrastructure Plan, provides critical financial support. 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 visitation aligns with the National Park Service's core mission of conservation for the enjoyment of present and future generations.

This paper creates a versatile and unified framework for studying the U.S. National Park System. I introduce a random utility maximization model of visitation for 140 national parks, in which individuals repeatedly choose which park to visit and whether to drive or fly.[1] The model includes a full set of park-by-month fixed effects. These park-month effects represent the mean utility provided by a park after controlling for the travel costs of accessing

[1]Each National Park Service unit carries an official designation (e.g. National Park, National Lakeshore, National Monument), but all units are commonly referred to as "national parks." This paper focuses on parks conserved for their natural resources. The system also includes historic sites that I do not explicitly model (e.g. Theodore Roosevelt Birthplace National Historic Site).

it. Thus, they, roughly, provide an index of national park *awesomeness*.

I introduce a two-step estimation procedure that combines two nationally representative telephone surveys, a 15-year monthly panel of park-level visitor counts, and a rich collection of park attribute statistics. The first step uses the contraction mapping introduced by Berry (1994) to combine the survey and visitor count data. In effect, it filters the visitor counts through the model to produce a panel of park-month effects from January 2005 through December 2019. This technique accounts for changing travel costs and demand system spillovers, while facilitating welfare analysis and flexible policy simulations.

In the second step, I regress the panel of park-month effects on park attributes. I leverage variation both between and within parks to estimate willingness to pay for a variety of attributes, including ruggedness, land cover, and wildlife presence. Because the first step preserves the visitor counts' panel structure, popular causal inference techniques, like difference-in-differences and event study designs, can be applied within the structural model.

I demonstrate the versatility of the framework by estimating the impact of temperature on demand. I decompose the temperature effect into long-run changes in average temperatures and short-run temperature shocks. Using a flexibility set of fixed effects, I identify the impact of long-run changes in average temperatures from within park-season variation. This is likely similar to the variation induced by changes in long-run average temperatures caused by climate change.

I find that "bucket list" parks like Yellowstone, Glacier, and Grand Canyon consistently rank in the top ten of the national parks *awesomeness* index. Estimated park-month effects reveal previously unexplored seasonal variation in park mean utilities. The seasonal variation is particularly dramatic for parks with harsh winters. Observable attributes explain 46 percent of the variation in park-month effects. Potential visitors tend to prefer parks with redwood forests, bison, and shoreline, but most attributes vary little across time, ruling out a causal interpretation.

Applying the framework, I find cold deters potential visitors more than heat, and long-run average temperatures impact demand more than short-run shocks. Relative to the ideal long-run average temperatures of 70°F to 85°F, potential visitors are willing to pay \$503 less per visit in months when the average temperature is 30°F and \$107 less when the average temperature is 95°F. Positive temperature shocks increase demand at temperatures below 80°F and have no impact at higher temperatures. Without accounting for climate impacts to park resources, this suggests that warming temperatures may increase visitor welfare.

Many previous studies analyze recreation demand for the National Park System, and a few of these have a national scope. Neher, Duffield, and Patterson (2013) employ count data models to study visitation to 58 national parks and estimate the average willingness to pay to visit each unit. They perform a meta-regression of willingness to pay on park attributes. This paper differs by using within and between park variation to estimate park attributes, mitigating potential omitted variable bias. Henrickson and Johnson (2013) use annual visitor counts and a reduced-form spatial econometric approach to study visitation to 56 national parks. They conclude that a five percent increase in gas prices would decrease overall visitation by 1.96 million and a 2°F increase in average temperature would increase visitation by 3.42 million. This paper differs by structurally modeling individual decisions. I also exploit monthly, rather than annual, visitation variation.

This study builds on a broad environmental economics literature applying random utility maximization models to analyze recreation demand. These studies typically estimate the value of recreation sites or environmental characteristics (Egan et al. 2009; Parsons et al. 2013, 2020). Methodologically, this paper relates closely to Murdock (2006), which uses the Berry (1994) contraction mapping technique to estimate a full cross-section of site fixed effects. Murdock's approach eliminates bias from omitted site characteristics when estimating the travel cost coefficient. My approach also estimates a full set of site fixed effects, obtaining the benefits of Murdock's procedure, but it goes further by repetitively applying the contraction mapping to obtain a monthly panel of site fixed effects, what I call park-month effects. Extending the contraction mapping procedure outside the survey period, I show how to estimate an extended panel of park-month effects. The panel structure allows for causal inference techniques to be used to recover willingness to pay estimates, a recent point of emphasis in the travel cost literature (Lupi, Phaneuf, and von Haefen 2020). This also provides a technique for estimating demand systems across time without continual individual-survey efforts.

Several recent papers explore the impact of climate change on recreation demand, typically focusing on the effect of temperature changes. Dundas and von Haefen (2020) estimate the welfare impacts of temperature shocks on participation in recreational marine fishing. Their approach is similar to this paper, because they estimate climate impacts within a random utility maximization model. My approach differs by specifying the park-month effects as a function of temperature. In Dundas and von Haefen's model, temperature does not impact site mean utilities. Instead, the participation decision is a direct function of temperature. Fisichelli et al. (2015) estimate the impact of temperature on visitation at 340 national parks. Their approach uses binomial count models and within-park variation to estimate the effect of long-run average temperatures. My approach permits welfare analysis, and I decompose the impact of temperature into two effects: changes in long-run average temperatures and short-run deviations from averages, similar to Bento et al. (2020). I also use more precise, within-park-season variation to estimate the impact of long-run temperature changes.

This paper also relates closely to English et al. (2018), which quantifies the value of recreation lost due to the Deepwater Horizon oil spill at beaches throughout the entire Gulf Region. The authors use an extensive nationally representative survey with over 41,000 respondents and calculate travel costs on a national scale. They also estimate how the amenity value of sites change over time in response to the spill by calibrating the model to visitor count data. In addition to studying a different setting, my approach differs in two main ways. First, I explicitly apply panel data econometric methods to study changes in site mean utilities, whereas English et al. estimate all parameters. Second, I leverage a long-term panel of visitor counts to estimate park month effects outside the survey period and at a monthly level, while English et al. focus on a single difference between spill and non-spill conditions. The panel of visitor counts also greatly reduces, but does not eliminate, the need for costly mail or telephone surveys.

Section 2 describes the nationally representative telephone survey, monthly visitor counts, and park attributes data. Section 3 outlines how travel costs are calculated for both driving and flying travel modes. Section 4 presents the model of national park visitation. Section 5 details the two-step estimation procedure and its benefits. Section 6 describes the general results, and section 7 applies the framework to study the impact of temperature on demand. Section 8 concludes.

2 Park Visitation and Attributes Data

The main data sources for this project describe (i) visitation at the individual level, (ii) visitation at the park level, and (iii) physical and institutional attributes of the national parks. This section describes these data sources.

2.1 Individual-Level Visitation Data

The individual-level visitation data come from the National Park Service's Comprehensive Survey of the American Public. The survey conducts telephone interviews of individuals throughout the United States with the primary goal of gauging sentiment towards the National Park System. The roughly 15-minute interview includes several questions regarding individuals' visitation history over the previous two years. These questions provide the location of the most recent national park visit and the number visits. A random subset of the sample was also asked about how they traveled on their most recent visit.

Several characteristics of the Comprehensive Survey of the American Public make it a uniquely useful data source for studying national park visitation. First, it includes both visitors and non-visitors. This allows me to model the extensive-margin of choosing not to visit a national park. Second, the survey is nationally representative. Phone numbers are selected using a regionally-stratified random sampling design, and individuals are randomly selected within each sampled household. The data include weights to account for the regional stratification and match sample demographics statistics to the Census, so weighted mean demographics from the survey closely match mean demographics of the general population (Table 1). I use these weights throughout my analysis. Second, the survey was conducted in 2008 and 2009 and repeated in 2018. The two iterations are very similar, and visitation history questions are identical. The 2008 and 2009 interviews were split 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 Comprehensive Survey of the American Public also has important limitations. Most importantly, I observe respondents' home location imprecisely. In the 2008 iteration, the data include the area code of each respondent's telephone number and their state of residence. In the 2018 survey, the data only include respondents' 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 for calculating travel costs. When I only observe the state of residence, I randomly sample a home city according to the state's population distribution. The other limitation of these data is that many national parks are never the location of any respondent's most recent visit. Thus, to estimate a full set of mean utilities I must incorporate the visitor count data.

2.2 Park-Level Visitor Counts

The National Park Service publishes monthly, park-level visitor counts in their Visitor Use Statistics database. The counts have a broad temporal and geographic scope, dating back to 1905 for some of the oldest parks and currently covering 383 national parks. I use counts from January 2005 through December 2019, because this period overlaps closely with the telephone survey data.

Table 1: Pooled Telephone Survey Descriptive Statistics

	Unweighted	Weighted	Census
Age			
18-29	0.119	0.213	0.236
30-39	0.135	0.163	0.169
40-49	0.167	0.167	0.184
50-59	0.242	0.208	0.176
60-69	0.186	0.143	0.121
70+	0.152	0.105	0.114
Income			
Less than $10,000	0.045	0.061	0.126
$10,000 to $25,000	0.095	0.110	0.151
$25,000 to $50,000	0.203	0.232	0.236
$50,000 to $75,000	0.208	0.223	0.189
$75,000 to $100,000	0.173	0.159	0.136
$100,000 to $150,000	0.155	0.132	0.108
Greater than $150,000	0.121	0.083	0.054
Education			
Some High-School	0.036	0.056	
High School Grad	0.368	0.470	
College Grad	0.358	0.321	
Graduate Degree	0.229	0.146	
Number of Children	0.547	0.651	0.707
White, Non-Hispanic	0.750	0.679	0.638
Region			
Alaska	0.141	0.002	0.002
DC only	0.117	0.002	0.002
Intermountain	0.149	0.150	0.151
Midwest	0.146	0.230	0.226
Northeast	0.151	0.229	0.233
Pacific	0.149	0.169	0.173
Southeast	0.147	0.218	0.213
Visited in Past 2 Years	0.679	0.617	
Avg Number of Visits	9.225	4.709	
Flew (Subsample N = 1537)	0.136	0.127	
Sample Size	6762	6762	

Note: The table shows variable means for the Comprehensive Survey of the American Public telephone survey data compared to statistics from 2010 Census data. Weights are included in the survey and match survey statistics to Census averages. Thus, the weighted variable means align closely with Census means. The unweighted sample tends to be older, richer, and more White, Non-Hispanic than the general population.

Table 2: Park Attribute Data Sources

Source	Variables
USGS National Map	Ruggedness (Elevation SD), Avg Elevation, Hiking Trail Miles, Biking Trail Miles, Number of Lakes > 40 acres, Area of Lakes > 40 acres
NPS Administrative Data	Designation (Park, Lakeshore, Seashore, etc), Acreage, Miles of Shoreline, Species Presence
2004 NLCD	Acres by Landcover Type, Share of land by Landcover Type, Mode landcover type, Landcover Diversity (Herfindahl-Hirschman Index)
Census	Road Miles, Population density of overlapping counties
NCEI	Monthly Avg Max Temperature, Precipitation > 0.1" days, Monthly 10-year Avg Temperature

Note: The table shows data sources for park attributes and variables generated from them. NLCD - National Land Cover Database. NCEI - National Center for Environmental Information. 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.

Counting procedures vary by park and typically involve counting by National Park Service rangers at entry booths and/or with strategically placed vehicle counters. Parks use person per vehicle multipliers to convert vehicle counts to person counts. The number of visitors, available resources, and often remote locations make it difficult to obtain exact counts. Nonetheless, the Visitor Use Statistics are used administratively and in many academic studies of national park visitation (Fisichelli et al. (2015), Keiser, Lade, and Rudik (2018), Henrickson and Johnson (2013)).

I adjust the raw visitor count data to make them suitable for recreation demand modeling. This proccess accounts for re-entry, group size, international visitation, and the primary purpose of trips using on-site surveys conducted by the National Park Service. I provide more details on the adjustment procedure in the Appendix.

2.3 A Statistical Atlas of the National Parks

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

3 How much does it cost to visit the national parks?

This section describes the procedure for computing travel costs. I calculate travel costs at a quarterly frequency for every individual in the nationally representative telephone surveys, as well as every individual in American Community Survey microdata between 2005 and 2019. I use these microdata to calibrate the model outside the survey period. Travel costs include the time and money required for individuals to drive or fly to each of the national parks. These calculations closely follow English et al. (2018), which also computes driving and flying travel costs at a national scale.

To compute driving travel costs, I calculate the driving mileage and time from each respondent's home location to each national park using PC*Miler. I multiply mileage by the variable cost of driving, provided by annual AAA reports. For every twelve hours of driving, I add the average U.S. hotel rate. I also make a standard assumption that the cost of time is one-third of a respondent's hourly wage rate.

Flying travel costs include travel time, plus the cost of driving to the origin airport, airfare, and the cost of driving from the destination airport to the park, which may include rental car prices. Quarterly average airfare data come from the U.S. Department of Transportation's Consumer Airfare report, which includes the average airfare for flights between city markets, rather than individual airports. I use the 2012 average rental car price from English et al. (2018), adjusting for inflation to approximate rental car prices in other years. I compute travel costs for several routes for each individual-park pair, allowing individuals to choose to fly out of and into up to four different city markets. I select the cheapest route for each individual-park pair as the flying travel cost.

Figure 1 shows the flying and driving travel costs for a subset of the telephone survey sample. Driving travel costs increase approximately linearly with one-way driving distance, with different slopes for each income bin. Flying is more expensive for nearby parks, but eventually becomes cheaper than driving for long-distance trips.

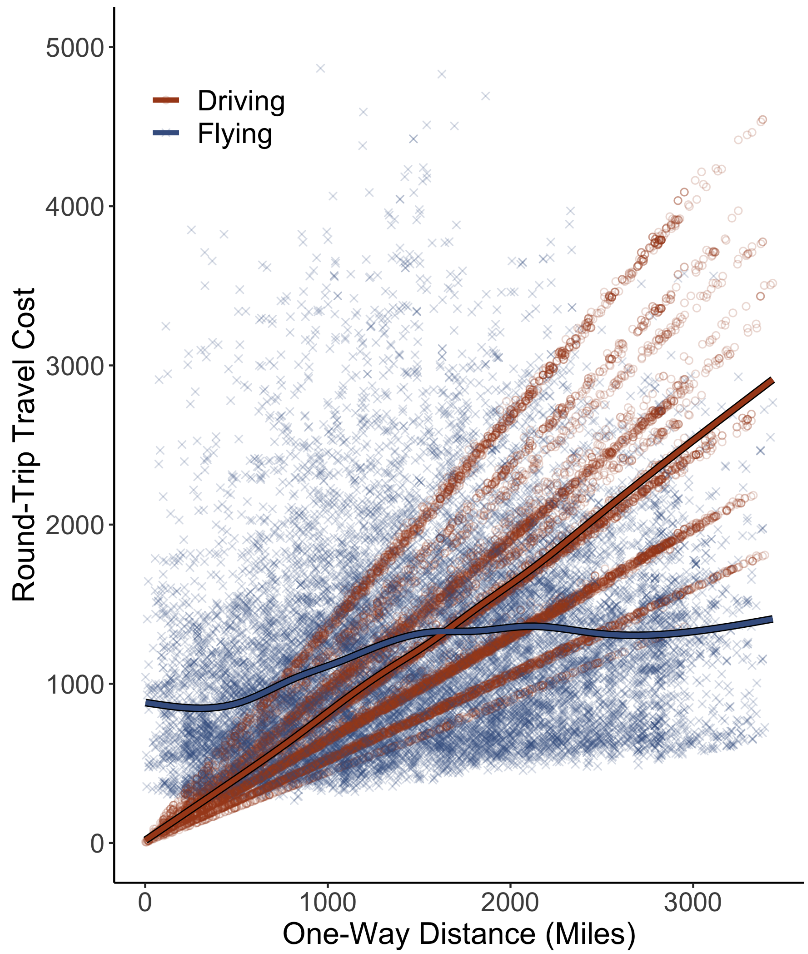

Figure 1: The graph plots calculated round trip travel costs on one-way driving distance for a three percent subset of the 2008 survey sample. Brown circles show driving travel costs, and blue x's show flying travel costs. Solid lines show average travel costs by distance. Driving travel costs increase linearly with distance. Flying travel costs increase at a slower rate.

4 A model of national park visitation

In this section, I outline a model describing the choices of which national park to visit and how to travel. By jointly modeling the choice of park and the choice of travel mode, I draw on the recreation demand literature, which typically focuses solely on the park choice, and the transportation literature, which has a rich history modeling travel mode choices (McFadden 1974).[2] The model also shares similarities with work by Chintagunta, Dubé, and Goh (2005), which allows for time-varying mean utilities when modeling demand for margarine.

Suppose that each month individuals choose whether to visit a national park, which national park to visit, and whether to drive of 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 $j = 0$ denote the outside option. This represents each individuals' best way of spending the month that does not involve visiting a national park. Because visits to the National Park System historic sites are included in the data but differ from visits to nature-centered national parks, I group visits to historic sites into a pseudo-outside option $j = J$. Given this choice set, let U_{ijmt} denote the utility individual i receives from visiting national park j using travel mode m during month t, where

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

[2] An exception, Hausman, Leonard, and McFadden (1995) model the travel mode choice in a recreation demand context. They introduce a model to quantify the recreational use losses of the *Exxon Valdez* oil spill.

$$\equiv \begin{cases} V_{0t} + \epsilon_{i0t} & j = 0 \\ V_{ijmt} + \epsilon_{ijmt} & j \in \{1, ...J-1\}, m \in \{D, F\} \\ V_{Jt} + \epsilon_{iJt} & j = J \end{cases} \tag{2}$$

In equation (1), β_{TC} represents the marginal disutility of travel costs. β_F represents the fixed cost of flying relative to driving. For $j \in \{1, ..., J-1\}$, δ_{jt} is a park-month effect that captures the mean utility provided by park j in month t after controlling for travel costs. Ranking the vector of park-month effects, δ, produces the national park *awesomeness* index. The park-month effects include the utility provided by observable park attributes, X_{jt}, and unobservable attributes, ν_{jt}.

$$\delta_{jt} = X_{jt}\alpha + \nu_{jt} \tag{3}$$

Assume the error term, ϵ_{ijmt} follows a Generalized Extreme Value distribution implying a two nest structure such that the no visit alternative is in its own nest. This assumption allows error terms for visit alternatives to be correlated and relaxes the Independence of Irrelevant Alternatives assumption imposed by conditional logit models. The nested logit model still imposes the Independence of Irrelevant Alternatives assumption within the visit nest. With this assumption, the probability of choosing each alternative has a closed form:

$$P_{ijmt} = \begin{cases} \dfrac{\exp(V_{0t})}{\exp(V_{0t}) + (\sum_{k=1}^{J}\sum_{n\in\mathcal{M}}\exp(\frac{V_{iknt}}{\lambda}))^{\lambda}} & \text{if} \quad j = 0 \\ \dfrac{\exp(\frac{V_{ijmt}}{\lambda})}{\sum_{k=1}^{J}\sum_{n\in\mathcal{M}}\exp(\frac{V_{iknt}}{\lambda})} \dfrac{(\sum_{k=1}^{J}\sum_{n\in\mathcal{M}}\exp(\frac{V_{iknt}}{\lambda}))^{\lambda}}{\exp(V_{0t}) + (\sum_{k=1}^{J}\sum_{n\in\mathcal{M}}\exp(\frac{V_{iknt}}{\lambda}))^{\lambda}} & \text{if} \quad j \in \{1, ...j-1\} \\ \dfrac{\exp(\frac{V_{iJt}}{\lambda})}{\sum_{k=1}^{J}\sum_{n\in\mathcal{M}}\exp(\frac{V_{iknt}}{\lambda})} \dfrac{(\sum_{k=1}^{J}\sum_{n\in\mathcal{M}}\exp(\frac{V_{iknt}}{\lambda}))^{\lambda}}{\exp(V_{0t}) + (\sum_{k=1}^{J}\sum_{n\in\mathcal{M}}\exp(\frac{V_{iknt}}{\lambda}))^{\lambda}} & \text{if} \quad j = J \end{cases} \tag{4}$$

The probabilities are decomposed into two terms. The first, absent from the no visit alternative, indicates the probability of visiting a specific national park using a specific travel mode, conditional on visiting some park. The second term indicates the probability of visiting or not visiting any of the parks. The literature often refers to the parameter, λ, as the dissimilarity coefficient. For consistency with random utility maximization, λ is bounded between zero and one. Higher values of λ indicate more dissimilar alternatives in the visit nest, and λ equal to one simplifies the choice probabilities to the conditional logit probabilities.

5 A Two-Step Approach to Estimate Demand

This section describes the procedure used estimate demand for national park visitation. This approach shares similarities with the maximum likelihood estimator proposed by Berry, Levinsohn, and Pakes (2004) which combines micro and macro level data to estimate a demand system, and with Murdock (2006), which also uses a two-step approach to estimate demand for recreation. However, the particular features of the survey and visitor count data motivate a distinct procedure.

5.1 Step 1a: Maximum Likelihood with a Contraction Mapping

To begin, I estimate the parameters in equation (1). These include the marginal disutility of travel costs, the premium for flying relative to driving, and observable heterogenity in preferences for park attributes. The individual-level survey data do not include the date of respondents' visits, so I estimate a constant park-month effect in this step. I recover the panel of park-month effects in Step 1b.

I specify a three part likelihood function to fully incorporate the visitation information contained in the survey data. Using the choice probabilities from equation (4), the likelihood of observing individual i's visitation history is:

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

The first term represents the contribution of individual i's most recent visit. For this visit, I observe which park the individual visited. The second term represents the likelihood for all other visits in the two years prior to the interview, where v_i indicates the number of visits in the past two years in addition to the most recent visit. The third term represents the likelihood from all non-visits in the two years prior to the interview. If an individual never visits a national park in the two years prior to their interview, then the model interprets this as choosing the no visit alternative for each of the 24 months prior to their interview. Because I do not observe when these visits occurred, I drop the t subscript.

When maximizing the log likelihood function, I constrain the visitation shares predicted by the model to match the visitation shares observed in the visitor count data. I impose the constraint by applying the contraction mapping introduced by Berry (1994):

$$\delta^{n+1} = \delta^n + ln(s) - ln(\hat{s}(\delta^n,\beta)) \tag{6}$$

As the optimization routine iterates over values of β, the contraction mapping solves for the unique vector of park fixed effects, δ, that matches observed and predicted visitation shares for each β attempt. Leveraging the contraction mapping has several practical benefits. First, it allows me to simultaneously incorporate visitation information from individual-level surveys and park-level visitor counts. Second, the contraction mapping pins-down δ, so the optimizer must search only over β. This reduces the estimation time. Finally, many parks are never chosen in the survey data, so their park fixed effects cannot be identified from the survey data alone.

5.2 Step 1b: Calibrating Park-Month Effects Over 15 Years

In this step, I recover a monthly panel of park-month effects. I recover the panel by applying the contraction mapping month-by-month, from January 2005 through December 2019. With an estimate of β from Step 1a, estimation proceeds as follows.

I first calculate the individual choice probabilities for each month, P_{ijmt}, and then compute the predicted visitation shares for each month by summing choice probabilities across individuals and travel modes. This provides a predicted visitation share for each park in each month. This mirrors the structure of the visitor count data. Beginning with January 2005, I apply the contraction mapping to find the unique δ that matches the predicted and observed visitation shares, given $\hat{\beta}$. Repeatedly applying the contraction mapping across months produces a full panel of δ estimates.

The key insight is that the predicted visitation shares, which are necessary to apply the contraction mapping, depend on individual choice probabilities but not observed choices. Thus, they can be calculated outside the survey period when individual choices are not observed.

Calibration outside the survey period raises several important concerns. First, the geographic distribution of population may change significantly over the 15-year calibration period. To account for this, I calibrate the model using predicted choice probabilities from American Community Survey microdata (Ruggles et al. 2021). These microdata capture changes in the geographic distribution of population at the annual level. They also represent the national population,like the telephone survey data.

Calibration outside the survey period also requires assumptions on the stability of β across time. In this paper, I assume β is constant across the entire 15-year calibration period. While this is not necessary, the assumption is grounded in empirical results. In a preliminary robustness check, I allow β to vary in the 2008 and 2018 individual-level survey periods and obtain similar estimates across years. Dundas and von Haefen (2020) also provide evidence supporting this assumption. They allow travel cost coefficients to vary annually and obtain fairly stable estimates from 2004 through 2009.

5.3 Step 2: Estimating Preferences for Park Attributes

In Step 2, I estimate equation (3), which explains park-month effects as a function of park attributes. In section 7, I use a flexible set of fixed effects to identify the impact of temperature on demand. Common causal inference approaches, like difference-in-differences, event study, or regression discontinuity can also be implemented at this step.

6 Results: Preferences for U.S. National Parks

Table 3 reports estimates of the coefficients for travel cost, travel mode, and observable heterogeneity terms, β from equation (1). Potential visitors are willing to pay a $376 per trip premium to drive rather than fly. This premium may result from the flexibility driving provides, in terms of both scheduling and the ability to add side trips. It also reflects costs I do not include in travel costs, such as airport parking fees and the risk of flight cancellations. The dissimilarity coefficient is significantly different from one, which indicates the national park visit alternatives differ meaningfully from the no visit alternative.

Figure 2 shows the estimated park-month effects for two parks: Glacier NP and Great Smoky Mountains NP. These represent the mean utility provided by each park throughout 2018. They should be interpreted relative to the no visit option, which is normalized to provide a zero mean utility.[3] Thus, the consistently negative park-month effects indicate potential visitors, on average, prefer the no visit alternative to visiting a specific park, even if that park had zero travel costs. While this seems unlikely, the result is sensitive to the market definition and the number of choice occasions, assumptions I explore in preliminary robustness checks.

[3] To change the interpretation, regress park-month effects on month-of-sample or park fixed effects and take the residual as the new park-month effect. This makes interpretation relative to the average of other parks in a given month or relative to the specific-park average.

Table 3: Model Estimates 2008 and 2018 Survey Periods

	(1)
Fly	-0.945
	(0.087)
Travel Cost ($100)	-0.251
	(0.016)
TC x Income < $25,000	-0.277
	(0.022)
TC x Income > $100,000	0.127
	(0.009)
Disimilarity Coefficient	0.657
	(0.042)

Note: The table shows estimates of the travel mode, travel cost, and heterogeneity coefficients in equation 1. All coefficients are significant at the 95% level. Dividing the flying coefficient by the travel cost coefficient reveals potential visitors are willing to pay $376 more per trip to drive rather than flying.

Glacier's park-month effects exhibit dramatic seasonal variation, peaking in the summer and falling in the winter. Converting the seasonal difference to dollar terms, potential visitors are willing to pay $1032 more, on average, to visit in July of 2018 rather than January. Great Smoky Mountains displays a flatter peak period and less extreme winter decline. Similar patterns at other parks suggest that temperature and climate drive seasonal variation in park-month effects. I explore this finding further in section 7.

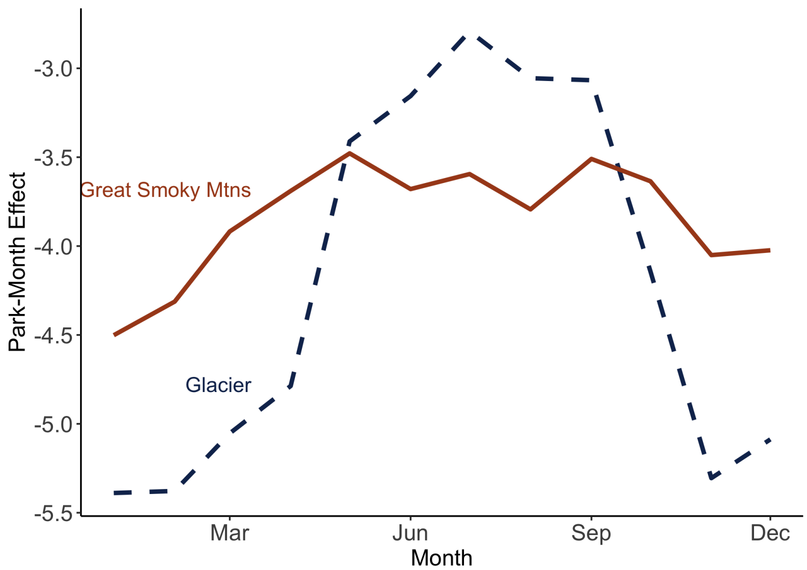

Figure 2: The graph plots estimated park-month effects for Great Smoky Mountains NP (solid-brown) and Glacier NP (dashed-blue) for each month in 2018. Both exhibit seasonal variation that has been largely overlooked in the recreation demand literature.

Next, I explore preferences for park attributes in equation (3) using a correlated random effects model (Table 4). Due to data availability and limited variation in some park attributes, coefficient estimates for unshaded variables are identified with cross-sectional, between park, variation. Elevation, for example, does not change meaningfully within parks over a fifteen year period. For shaded variables, the data capture meaningful variation across parks and time, and I control for time-constant omitted attributes when estimating willingness to pay.

This collection of observable park attributes explains 46 percent of the variation in park-month effects. Potential visitors tend to prefer parks with bison and redwood forests and avoid parks with grizzly bears. Coastal parks also tend to attract more visitors, while there is no preference for ruggedness. Even with this broad array of park attributes, over half the variation in park-month effects remains unexplained. Given the unique resources the parks protect, this 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 nearly constant across time.

The national park coefficient reflects the impact of an official national park designation rather than one of the various other unit designations. The coefficient is identified from three parks (Pinnacles, Gateway Arch, and Indiana Dunes) that became national parks between 2005 and 2019. Redesignating units to have the official national park designation has been proposed as a possible solution to limit crowding at existing parks. Based on this limited evidence, redesignation seems unlikely to cause substitution away from other parks. Although, preliminary evidence from a broader set of redesignations suggests an official national park designation increases visitation at the redesignated park (Szabó and Ujhelyi 2021), and redesignation likely exhibits practically significant heterogeneity.

By capturing mean utilities after controlling for travel costs, park-month effects provide a national park *awesomeness* index. Table 5 shows the implied ranking for 2018 based on parks' maximum park-month effect throughout the year. I also convert the park-month effects to a 100-point scale, providing a "Rating" for each park. The maximum park-month effect between 2005 and 2019 scores 100 and the minimum scores 0. This ranking method offers an attractive alternative to rankings from the popular media that are typically based on travel bloggers' personal experiences or raw visitation counts. Unlike experience-based rankings, it is systematic and incorporates the visitation history of the entire U.S. population. Unlike raw visitation rankings, it controls for the travel costs of reaching a park, isolating the appeal of the park itself.

The top ten ranking includes many of the most famous national parks, like Glacier, Yellowstone, and Grand Canyon. One surprising result is that Golden Gate National Recreation

Table 4: Preferences for Park Attributes

	Coefficient	WTP
Redwoods Present	0.600	239
	(0.569)	
Bison Present	0.524*	209
	(0.281)	
Coastal	0.432	172
	(0.300)	
Nearby Pop. Density	0.079**	32
	(0.018)	
Mean Elevation	0.051	20
	(0.038)	
Road Miles	0.010*	4
	(0.006)	
Miles of Trail	0.006	2
	(0.009)	
Ruggedness	0.000	0
	(0.000)	
Shoreline x Ruggedness	0.000	0
	(0.000)	
Lake Acreage	0.000	0
	(0.000)	
Land Cover Diversity	0.000**	0
	(0.000)	
Miles of Road x Ruggedness	0.000	0
	(0.000)	
Swamp Acreage	0.000	0
	(0.000)	
Acreage (10k)	0.001	0
	(0.002)	
Miles of Trail x Ruggedness	0.000	0
	(0.000)	
Rainy Days	-0.009**	-4
	(0.002)	
Avg Rainy Days	-0.018*	-7
	(0.011)	
National Park	-0.034*	-14
	(0.020)	
Grizzly Bears Present	-0.854	-340
	(0.522)	
R-squared:	0.459	

* - Significant at 90% Level, ** - Significant at 95% Level. The table shows estimates from a correlated random effects regression of park-month effects on park attributes. Estimates for shaded variables control for time-constant omitted park attributes. Unshaded variables use only between park variation. Flexible temperature controls are also included in the regression model. Willingness to pay (WTP) is calculated by dividing each attribute coefficient by the travel cost coefficient and multiplying by 100.

Table 5: Most Awesome National Parks (2018)

Rank	Park	Rating
1	Golden Gate RA	97.4
2	Glacier	93.9
3	Yellowstone	92.9
4	Grand Canyon	92.5
5	Grand Teton	91.9
6	Mount Rainier	91.4
7	Acadia	91.0
8	Rocky Mountain	90.9
9	Olympic	90.6
10	Zion	90.5

Note: The National Park awesomeness index combines visitation and travel cost data to rank parks by the mean utility they provide visitors. The ranking reflects each parks maximum park-month effect throughout 2018.

Area tops the list. Golden Gate provides views of the famous Golden Gate Bridge, beaches, hiking trails, and popular attractions like Alcatraz Island, but for several reasons, its ranking is likely inflated. 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 may make it part of a larger trip to the Bay Area. Furthermore, local residents may visit Golden Gate several times per month, or even several times per week. The model's assumption of one choice occasion per month seems appropriate most people and most parks, but it is likely too coarse for local residents. This biases Golden Gate's park-month effect upward.

7 How does Temperature Impact Demand?

In this section, I apply the framework to study how temperature impacts demand. This provides insights for understanding how climate change will impact visitation patterns. It also provides a blueprint for applying the the framework to study other challenges facing the National Park System.

To begin, I filter the visitation data through the demand system, as described in sections 5.1 and 5.2. Then, I specify a particular functional form of equation (3). Motivated by Bento et al. (2020), I decompose climate impacts into long-run changes in average temperatures and short-run deviations from averages. I bin average temperatures to flexibly capture non-linearity, and I estimate separate deviation impacts for each average temperature bin.

$$\delta_{jt} = \sum_{b} \alpha_{avg}^{b} \mathbb{1}(\overline{temp}_{jt} \in b) + \sum_{b} \alpha_{dev}^{b} (temp_{jt} - \overline{temp}_{jt}) \mathbb{1}(\overline{temp}_{jt} \in b) + \gamma_{js} + \phi_t + \nu_{jt} \quad (7)$$

$\overline{temp}_{jt}$ represents the ten-year moving average temperature at park j in the month-of-year of month t. It is, roughly, the anticipated or expected temperature, if a potential visitor were planning a trip more than a few weeks in advance. $temp_{jt}$ represents the (average high) temperature at park j in month t. It measures the actual, experienced temperature in month t. Taking the difference, $(temp_{jt} - \overline{temp}_{jt})$ represents the realized deviation from the moving average temperature in month t, or the short-run temperature shock.

Equation (7) also includes a flexible set of fixed effects to identify the causal impact of temperature. γ_{js} is a park-by-season fixed effect that isolates variation within a park-season. Here, I specify three-month seasons. ϕ_t further controls for system-wide factors affecting demand, such as the number of weekend days in a month.

Potential visitors prefer to visit in months with long-run average temperatures between 70°F and 85°F (Figure 3). The ideal temperature premium is \$503 relative to visits with long-run average temperatures of 30°F, and \$107 relative to visits with long-run average temperatures of 95°F. Abstracting from impacts to park resources, this suggests potential welfare benefits from increasing average temperatures.

Preferences for short-run temperature shocks vary intuitively across long-run average temperatures (Figure 4). Willingness to pay for a one degree temperature increase peaks at \$6 between 40°F and 55°F. Impacts at high temperatures are indistinguishable from zero.

Changes in long-run average temperatures impact demand more than short-run shocks (Figure 5). When temperature changes impact willingness to pay most, at 50°F, the impact

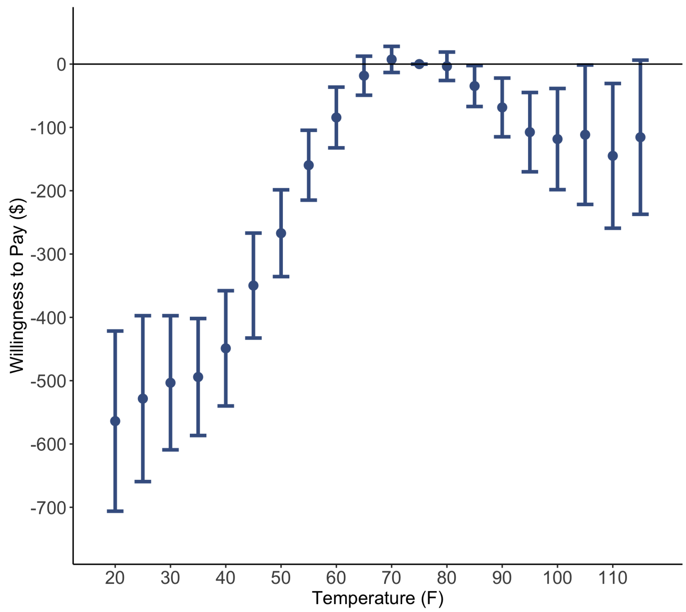

Figure 3: The figure shows potential visitors' willingness to pay for a park visit across long-run average temperatures. All estimates are relative to the 75°F bin.

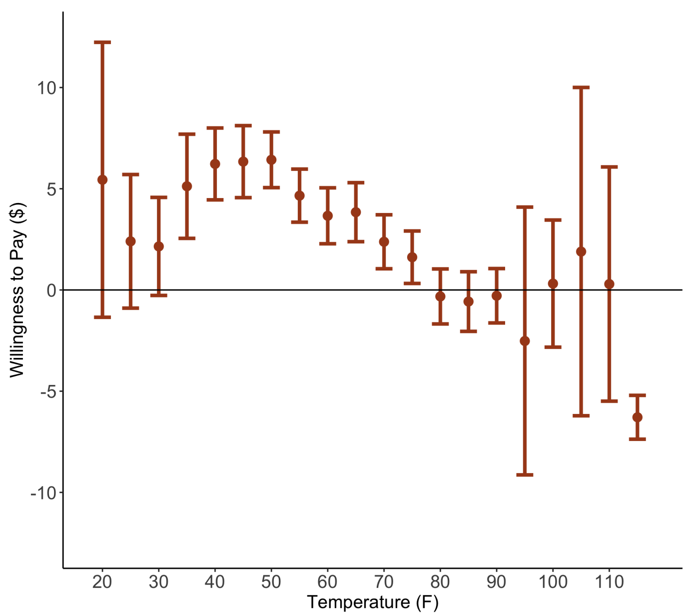

Figure 4: The figure shows potential visitors' willingness to pay for a one degree Farenheit positive temperature shock.

of a long-run average temperature change is over three times larger than an equivalent short-run temperature shock, .

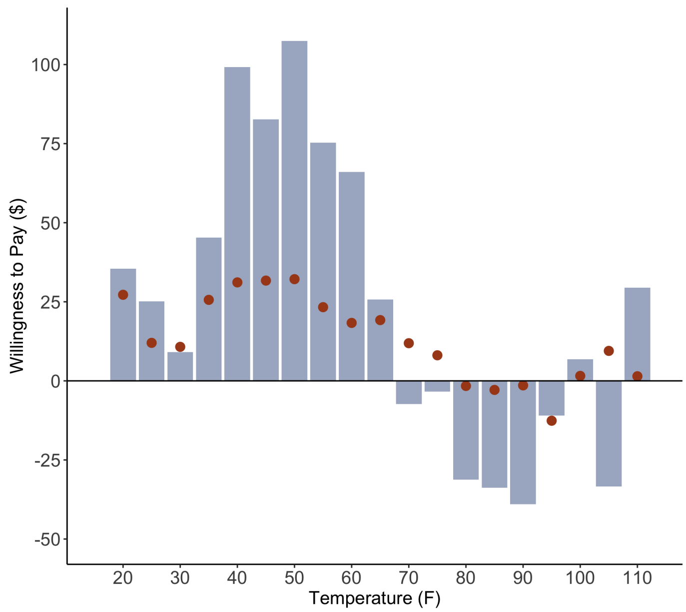

Figure 5: The graph shows the willingness to pay for a five degree increase in long-run average temperature (blue bars) and short-run temperature shocks (brown dots) by long-run average temperature. It provides a uniform change in temperature for comparing estimates displayed in 3 and 4.

8 Conclusion

This paper creates a versatile framework to study demand for U.S. national parks. I apply the framework to estimate the willingness to pay for changes to long-run average temperatures and for short-run temperature shocks. Potential visitors prefer temperatures between 70°F to 85°F and respond to long-run average temperatures more than short-run shocks. Long-run average temperatures of 95°F are preferred to 30°F by roughly $400. This suggests warming temperatures due to climate change may increase the welfare generated by national parks; although it does not account for impacts to park resources. Preferences for deviations from average temperatures are more muted, particularly at high temperatures.

The results also provide general evidence describing preferences for national parks. Potential visitors are willing to pay $376 more to drive rather than fly to a park, conditional on travel costs. The mean utility provided by a park visit varies dramatically across seasons, especially for parks with harsh winters. The national park *awesomeness* index provides a systematic alternative to existing rankings that controls for travel costs. Observable park attributes explain 46 percent of variation in the index, meaning idiosyncratic, unobservable, or difficult to quantify attributes play an important role in driving visitation patterns.

The framework and estimation procedure have the potential to generate future research on national parks and recreation demand more broadly. The estimation procedure provides a method to control for changing travel costs and demand system spillovers when conducting causal inference. It filters visitor count data through a structural model, allowing for welfare analysis and counterfactual simulations, and it bridges gaps between individual-survey efforts. The framework is relevant for many of the challenges facing the national park system, such as crowding, the dynamic effects of wildfires, and infrastructure investments. This is particularly important given recent legislative actions, which provide new resources for the continued conservation of the country's most treasured resources.

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