THESIS

THE RECREATIONAL VALUE AND SOCIAL COST OF NATIONAL PARKS: AN APPLICATION OF THE TRAVEL COST METHOD

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Luc Lallement

Department of Agricultural and Resource Economics

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Master's Committee:

Advisor: Jesse Burkhardt

Leslie Richardson
Jude Bayham
Terry Iverson

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ABSTRACT

THE RECREATIONAL VALUE AND SOCIAL COST OF NATIONAL PARKS:
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Studies that value the natural resources and recreational opportunities of a National Park have been explored for some time. Of the myriad techniques used to determine these values, our study uses the Travel Cost Method (TCM) to estimate the consumer surplus (CS) value per-visit for several National Parks surveyed in 2022. Previous studies have typically been conducted for one site or region at a time. Our data is novel in that it contains survey results from five different National Parks as part of the first year of the Socioeconomic Monitoring Survey conducted by the National Park Service (NPS). The parks range in size, purpose, and popularity, and we examine heterogeneity in CS estimates across these differences. Many of our CS estimates are new to the TCM literature, and some provide an update to existing estimates. In addition, we use the Social Cost of Carbon (SCC) to calculate the social cost of trips to the surveyed parks. These results are used to determine the total social cost of visitation, how costs would change if social costs were incorporated into the travel cost, and finally how visitation would change in this scenario. Our methodology builds on previous literature in the TCM space by incorporating econometric techniques to address multi-purpose visitors and on-site data collection. We find that our CS estimates are in line with previous TCM estimates. When social costs are incorporated, we estimate that there would be fewer visitors to the parks when social costs exceed an individual’s estimated willingness to pay, if social costs were hypothetically incorporated via a carbon tax. Our study contributes to both the methodology of TCM studies

and CS estimates of use-value for natural resources and can inform future authors on how to incorporate outside data (such as the SCC) to a well-established field. In addition, our estimates can be used by the NPS to inform policy decisions and benefit-cost analysis.

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1 Introduction

In the United States (US), National Parks are designated areas to be protected for conservation purposes. The US government has set aside these places to preserve wilderness flora and fauna. In addition, these natural spaces are used as recreational sites. The National Park Service (NPS), the agency that oversees US National Parks, also oversees national monuments and various historical, recreational, and natural properties. Many of these public lands have an access fee that helps offset the operating costs of the park and is used to enhance the visitor experience via reinvestment to the park.

The mission of the NPS is to "preserve…the natural and cultural resources and values of the National Park System for enjoyment, education, and inspiration" (NPS 2022). Non-market valuation studies are used to further these goals. Travel Cost Method (TCM) studies can be used to estimate consumer surplus per visit to various parks using data from visitor surveys. Through its Socioeconomic Monitoring (SEM) Program, the NPS deploys visitor Surveys at 24 parks each year to capture regional trends in visitor experience (National Park Service 2023). Parks are divided by high- and low-visitation, and further by four classifications: natural, recreation, and urban and non-urban historical. These consumer surplus estimates are used in many ways: to evaluate the level of access fee, to demonstrate the value to visitors, for cost-benefit analysis, natural resource damage assessment, and more.

We have created travel cost models for representative parks from each SEM classification. The parks are as follows: Arches National Park (NP), Cape Hatteras National Seashore (NS), Cumberland Gap National Historical Park (NHP), Gateway Arch NP, and Rocky Mountain NP. In this paper, we examine differences in consumer surplus (CS) across these parks. While previous literature using the TCM to examine these measures at national parks, both domestic and otherwise, has been explored, many studies are conducted on only one park[1]. Our study has the unique advantage of evaluating data across a diverse range of national parks and sites, all from the same time period. We estimate consumer surplus per-person per-trip ranging from $91 to $1,683[2] and $12 to $217 per-person per-day. In addition, annual visitation is used to extend this estimate across the year. The park that gives that highest CS per visit and per day is Arches, and Rocky Mountain NP gives the greatest annual CS in part due to its large visitation. We also compare our estimates of CS to Bin et al. (2005), who conducted a travel cost study for beaches in North Carolina. We find our CS per day estimate for Cape Hatteras to be lower in magnitude, but similar to CS per day estimates the authors calculated for other beaches in their survey. Finally, we compare our CS estimates to a recent paper from Landry et al. (2021) in which they estimate CS per day for outdoor recreation. Due to the specificity of our study, we find our CS per day estimates to be smaller in magnitude. The details of the differences in our study compared to the aforementioned studies are described in the Results and Discussion section.

A key assumption of the TCM is that visitors to a site only traveled there and back to their home. This piggybacks from demand theory: this assumption must be made if one is to assume that the cost of traveling to a site can be attributed to that particular site alone.[3] There have many studies that address when this assumption is too strong (Loomis 2006; Martínez-Espiñeira and Amoako-Tuffour 2009). In our model we incorporate the method proposed by Loomis et al. (2000) to contribute to a growing body of knowledge that is addressing this issue. We find results consistent to those from Loomis et al. (2000) in sign and magnitude.

[1] See Mazumder 2012; Heberling and Templeton 2009; Lee and Han 2002; Fix and Loomis 2017; Neher, Duffield, and Patterson 2013; Landry et al. 2021.
[2] The range given for these per-visit estimates are across primary and non-primary visitors.
[3] In other words, travel and time costs in the travel cost model is equivalent to price in classic demand theory.

With the data available to us through the SEM survey, we impute driving distance in miles for respondents to the surveyed national parks, as well as the opportunity cost of time spent traveling. Using estimates of the social cost of carbon (SCC) from the EPA (2022) and Interagency Working Group on Social Cost of Greenhouse Gases (IWG) (2021), we estimate the social cost of traveling to a given national park. Our analysis shows that the average social cost per trip range from $3 to $43.65[4] per visitor per trip, with Arches NP having the highest average social cost per trip and Rocky Mountain NP having the highest annual social cost. The inclusion of the SCC in our analysis is not to signal that trips made to national parks are more costly to the environment than we currently realize. Instead, we choose to include these estimates and analysis so that future authors may examine our results and compare the social costs of visiting a national park to the social cost of other activities. It can be argued that consumers who visit national parks are choosing an activity that has lower social costs than alternatives: an example of which could be flying to an international destination. The Results and Discussion section examines the implication of realizing these external costs to the consumer. We find that consumers would take approximately 0.1 less trips on average.

The remaining structure of the paper is as follows: first the Background and Literature reviews the current progress of the field and how the work contributes to it, next the Data and Methods section presents both our data and our techniques of analysis, the Results and Discussion section presents the results of the models and interpretations, and finally the Conclusion section closes by summarizing and discussing limitations and extensions.

[4] The range given for average social cost per trip is across two estimates of the SCC.

2 Background and Literature Review

The background and literature review provides context on the current progress of the travel cost model within the field of environmental economics, other non-market valuation studies completed for national parks and their related findings, and finally a brief overview of the social cost of carbon: its creation and current use in studies and policy. In addition, we show how our research fits within this context.

2.1 Current Progress of the Travel Cost Model

The travel cost method (TCM) is a technique used within the larger context of non-market valuation. The aim of the field is to provide valuation for goods that are not traded in a market setting. The definition of "valuation" in the economic sense relates to how people and firms assess trade-offs (Segerson 2017). Goods, services, and resources are all limited in their quantity, while people and firms are unlimited in their wants, desires, and goals. Thus, for every transaction that these groups consider, they think about what choice they implicitly are not making in addition to the chosen path. So while one cannot go to a store to "buy" a hike, the choice to go hiking is made in parallel with the choice not to do another given activity (Segerson 2017). Traveling to natural spaces takes both time and money, and the travel cost method uses these operating costs and opportunity costs to determine an individual's value for the site (Parsons 2003).

The TCM resides within the greater context of non-market valuation that is largely comprised of two categories of approaches: stated preference and revealed preference methods (Atkinson and Mourato 2008). Stated preference methods refer to those that use surveys to elicit preferences from respondents concerning hypothetical changes in policy. The two most common techniques used are contingent valuation (CV) and choice experiments. Stated preference methods are powerful in their flexibility of analyzing policy related questions and their ability to value environmental goods. In its most simple form, respondents are asked to indicate their preference for a change in the provision of an environmental good via their maximum willingness to pay (WTP) for an "improvement" or a minimum willingness to accept (WTA) for a "deterioration" for the given environmental good. The good itself can be something simple like the construction of a public park or something abstract like risk due to erosion or wildfire.

Revealed preference methods "infer preferences for nonmarket goods as implied by past behavior in an associated market" (Atkinson and Mourato 2008). In typical markets, consumers reveal their preferences for a good by how much of it they purchase at a given price. Nonmarket goods do not have this luxury, so revealed preference methods use consumer behavior in a typical market to create a "surrogate market." The advantage these methods have over stated preference is that they reflect real consumer behavior rather than hypothetical behavior, which may be subject to bias (whether conscious or not). Two main techniques are popular for revealed preference methods: the hedonic price method and the travel cost method. The latter is frequently used to value recreational use for natural sites (Parsons 2003), which is why it is appropriate for our study.

The TCM has been applied to both single and multi-site models, with the former being the relevant model for our data. Our aim is to estimate consumer surplus per visit at the surveyed national parks. Previous studies have addressed this question for different natural sites with success. Bin et al. (2005) estimated consumer surplus for visits to various North Carolina beaches, allowing for the slopes and intercepts of their demand equations to vary. An example of the zonal travel cost model comes from Fleming and Cook (2008), who surveyed Lake McKenzie and Fraser Island in Australia. This model groups visitors by region and creates visitation rates by their “zone’s” proportion of the total visits of the survey. This method has been phased out over time as econometric techniques have advanced, however it has similar foundations as our study. Both studies estimate per-visit value for the surveyed sites, and additionally infer that value over an entire season by multiplying by the total annual visitation. We apply the same method to our novel dataset to contribute to consumer surplus estimates in the larger TCM literature.

The nature of our survey data is that it was collected on-site, which can introduce some biases if unaddressed. The benefit of on-site sampling is found in its practicality: many observations can be collected over a short period of time for low cost compared to alternatives. Studies that involve cold calling to collect survey data are more timely and thus more costly. However, our recorded observations for the number of trips taken are truncated at zero. In other words, on-site sampling necessitates that the respondent has taken at least one trip to the site. This can fail to account for individuals whose willingness to pay is lower than the travel cost to the site, thus biasing the imputed demand curve. In addition, on-site sampling may unintentionally survey individuals who visit the site more frequently than average. This can bias the trip count variable to be overstated and thus bias estimated average willingness to pay.

Fortunately, scholars have explored this bias issue in count-models in the past. The names given to the two problems are truncation and endogenous stratification, respectively. This was first pointed out by Shaw (1988) who demonstrated the inconsistency and bias mathematically. The solution to the problem is to alter the underlying distribution when conducting a count regression, either through ordinary least squares (OLS) regression or maximum likelihood (ML) regression. Count data models transform the count data variable to a specified distribution, and the most common choices are the Poisson and Negative Binomial distribution. Authors choose which distribution fits their data best when modeling. Some examples of the use of truncated and endogenously stratified corrected count data TCM models include Creel and Loomis (1990) and Grogger and Carson (1991). These authors show differences in OLS and ML regression techniques, and empirical differences in WTP estimates without correction. The choice to use either Poisson (or a variant of the Poisson distribution) or Negative Binomial distributions depends largely on the presence of over-dispersion in the data (Gurmu 1991). In the Methods section we outline our process and choices to use either the Endogenously Stratified and Truncated Poisson distribution or the Endogenously Stratified and Truncated Negative Binomial distribution for each model of each park. Our model uses a package created for the statistical programming language STATA by Nakatani and Sato (2005) which corrects the Negative Binomial distribution for truncation and endogenous stratification. Specifics on the correction are outlined in the Methods section.

One of the assumptions of a TCM model is that respondents do not travel to different destinations on their trip from home (Haspel and Johnson 1982). This assumption presents itself as especially problematic for national parks, as they are often national recreation destinations. Many studies have considered how to address the issue.[5] Various techniques have been used, such as attributing a portion of the travel cost to the site for incidental visits. We take the approach of coding our respondents as "primary" visitors if they indicated that their primary purpose for their trip from home was to travel to the site.

This method is exemplified by Loomis, Yorizane, and Larson (2000), in which the authors model demand for whale watching in California. They find a difference in consumer surplus values between primary and non-primary visitors ranging from 20% to as much as 70%.

[5] See Loomis 2006; Martínez-Espiñeira and Amoako-Tuffour 2009; Parsons and Wilson 1997.

In their study they do not find statistical significance between consumer surplus estimates with and without their primary purpose dummy variable, however the authors note that "omission of these multi-destination trip users will result in an underestimate of total site benefits.". We find (as well as Loomis, Yorizane, and Larson 2000; Loomis 2006; Martínez-Espiñeira and Amoako-Tuffour 2009) that non-primary purpose visitors have higher CS values and are less sensitive to changes in travel cost, and primary purpose visitors have lower WTP and are more sensitive to changes in price.

Many economic studies have been conducted to estimate various forms of valuation (per visit, per season, etc.) for national parks, both domestic and otherwise. The next section describes the progress of these studies and compares published WTP estimates for national parks with our own.

2.2 Applied Valuation Studies to National Parks

Economic valuation of US National Parks has been explored by numerous researchers, and various methods have been used. Haefele et. al. (2016) conducted a nation-wide survey of the American public to determine the total economic value that the National Parks Service provides, including all sites that are managed under the NPS. This study was conducted using a choice experiment method, which asked respondents whether they are willing to pay for an increase in taxes to prevent cuts to National Park lands. After controlling for preferences about the NPS and natural resources, the authors use estimated per household value to expand to nationwide value by multiplying by the total number of households. A similar study was conducted for Korean national parks by Lee and Han (2002). The authors note one of the main advantages to a CV study is estimating use and non-use value and they apply their estimated values to justify a fee increase to access the parks. While a TCM study can only estimate use-value for the surveyed area, similar policy implications can be drawn. This is especially true for recreational and historical parks, which our data provides.

The TCM has been used to value National parks in India, Pakistan, and Australia, just to name a few (Mazumder 2012; Khan 2006; Fleming and Cook 2008). Heberling and Templeton (2009) also completed a noteworthy study for Great Sand Dunes National Park in Colorado, USA. Combination revealed- and stated-preference analyses have been explored by economists in the past[6] and have proved a powerful tool in estimating values for non-market goods, such as recreation areas. A very recent and informative study from Landry et al. (2021) uses the TCM to estimate how consumer WTP has changed due to the COVID-19 pandemic. The authors have the advantage of data from a nationwide random survey, which they argue captures an accurate view of the population. They do not face the truncation and endogenous stratification issues we do. The authors estimate that consumer surplus declines post-COVID by an average of 18.6%. In addition, their per visit per household consumer surplus estimates range from $625 to $833, which is in line with our estimates in magnitude.

An advantage of our novel data set is in its specificity. With the SEM Visitor Survey combined with an Arches 2022 visitor survey, we can estimate CS measures for our surveyed parks of Arches National Park, Rocky Mountain National Park, Cape Hatteras National Seashore (NS), Gateway Arch National Park, and finally Cumberland Gap National Historical Park, which have not been previously published save for Cape Hatteras NS. Landry et al. (2016) completed a TCM study for Cape Hatteras in which they estimate per household CS at $403 per trip. It is noteworthy that the authors also correct for on-site sampling, which they note lowers their CS estimation. While these measures are important on their own, they will also be able to be

[6] See Whitehead et. al. (2008)

analyzed and built upon with respect to future TCM surveys for natural recreational sites of diverse sizes, type, and location. This is especially important as land and natural resource managers move forward to handle consumer demand in a post-COVID society.

2.3 The Social Cost of Carbon

The Social Cost of Carbon (SCC) is "an estimate, in dollars, of the economic damages that would results from emitting on additional ton of carbon dioxide into the atmosphere" (Rennert and Kingdom 2022). It is used by governments to inform policy and investment decisions in the United States (US) and beyond. Recent literature has examined the current SCC set by the US Federal Government and its appropriateness. Setting aside socio-economic debates concerning discount rates and the like, we use the EPA's most recent SCC estimate of $190 per ton (EPA 2022). This is in line with a similar estimate of $185 per ton published by Resources for the Future (Rennert et al. 2022).

SCC is typically used in benefit-cost analysis or benchmark-setting by federal agencies (Medicine et al. 2017) by economically valuing the damages caused by increased emissions due to production or a similar activity. Additionally, the SCC has been used in studies and taught in environmental economics classrooms as a "Pigouvian Tax" on carbon (Tol 2008). In simple terms, this is the tax producers or consumers would have to face if they were to internalize the external cost of emitting carbon dioxide. We use our estimates of travel distance to create a social cost in addition to the typical travel cost, and thus relate the average social costs in several ways: first, we estimate seasonal social cost of visiting the surveyed parks by imputing our estimated per visit social cost of a season's worth of visits. Second, we compare the average social cost of trips taken to our estimated consumer surplus. From here, we examine how consumer surplus would be impacted if visitors had to internalize the social cost of their trip, say through fees or higher gas prices. Our study is novel in incorporating social costs into the TCM framework. And while consumers may never consider the social cost of any trip they take, our estimates present an interesting result of the flexibility of using the SCC to impact consumer demand in a natural resource market.

3 Data and Methods

Our data comes from the Socioeconomic Monitoring (SEM) Program under the NPS (National Park Service 2023). Specifically, the SEM Visitor Survey samples twenty-four randomly selected parks each year to help the NPS understand socioeconomic trends over time. 2022 was the first year of this program. The NPS sorts parks into four types: natural, recreational, historic urban, and historic non-urban, seen in Figure 1. From here, the parks are divided by high and low visitation and randomly selected by each of the eight total categories. The four parks analyzed are all high visitation parks, and each one is a different type. Visitors at these parks are asked questions relating to “trip characteristics, experiences, spending, perceptions, demographics, and more”(National Park Service 2023). Questions in this survey ask respondents to provide both subjective and objective measures on several topics. We additionally combine survey data from Arches National Park, who conducted their own survey in 2022. The survey is nearly identical to the surveys in the SEM program.

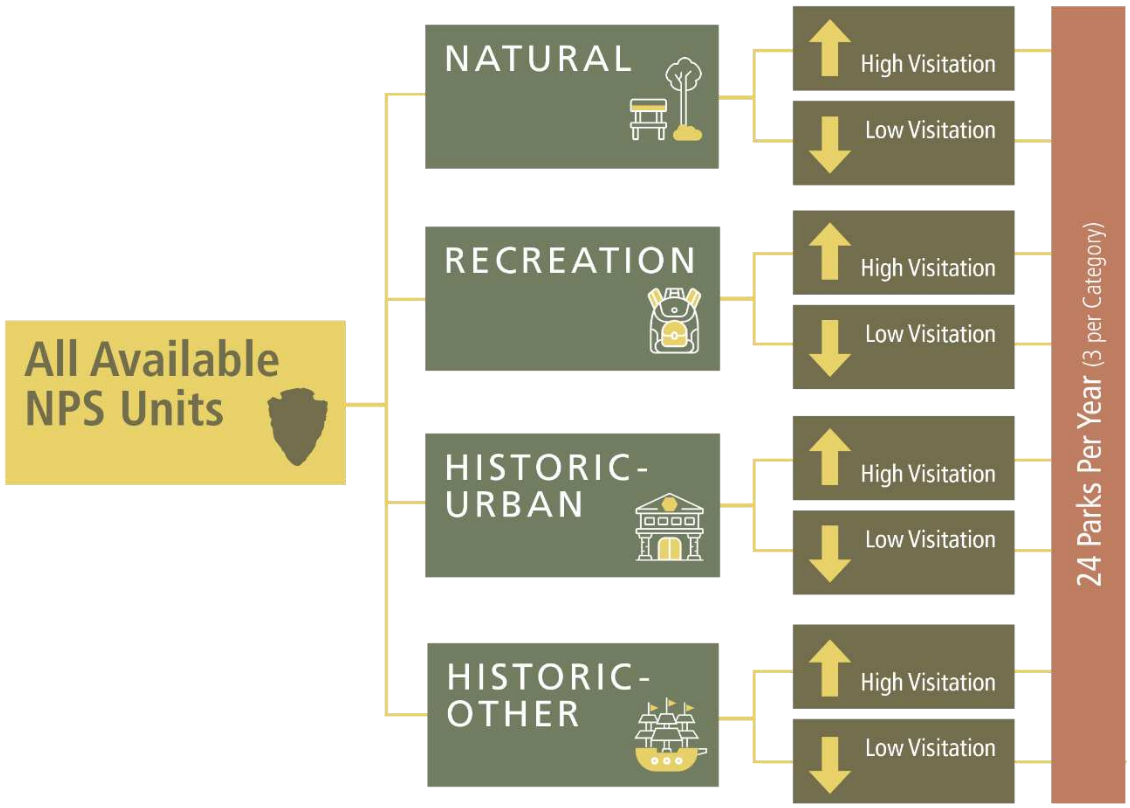

Figure 1: Flow chart of park selection for SEM Visitor Surveys[7]

3.1 Collection, Sorting, and Cleaning

We use data for four parks from the SEM study: Rocky Mountain National Park (RMNP), Gateway Arch National Park (GANP), Cape Hatteras National Seashore (CHNS), and Cumberland Gap National Historical Park (CGNHP). We additionally incorporate data from the second year of an ongoing survey being conducted at Arches National Park (ANP). The goals of the two surveys are similar, thus the questions across the two are comparable. The data was collected through a third-party contractor under the NPS and was collected on site for each park.

[7] National Park Service. *Flow Chart of Park Selection for Socioeconomic Monitoring Visitor Surveys*. June 27, 2022. https://home.nps.gov/subjects/socialscience/sem-park-selection.htm.

The surveys were conducted at a variety of sites around each park. The surveyors recorded the respondent's (only park visitors) verbal responses on an iPad. Although the surveys were conducted in person, the surveyors ensured a random sample of respondents. At the end of the survey, respondents were asked to voluntarily provide their address to be mailed a "mail-back" survey that asked more specific questions. Among other questions, respondents indicated their education level, household income, and primary activity done in the park on the mail-back survey and not on the in-person survey. About 70% of respondents on average did not complete a mail-back survey. Consequently, we do not observe income, education, and primary activity for a subset of the original respondents. Due to the issue of non-response of the mail-back survey, we choose to exclude some variables from our "ideal" TCM models, such as education and primary activity done in the park. For a summary of missing variables across the five surveys, see Table 1.

Table 1: Summary Statistics for Variables

	Variable	*Observations*	*Missing*	*Mean*	*SD*	*Max*	*Min*
ANP	Visits	780	1	1.28	0.53	7	1
	Travel Cost		9	779.62	538.69	3224.05	23.38
	HH Income		403	129456	56104.5	200000	12500
	Age		377	49.57	15.77	89	18
	Group Size		0	3.11	2.47	45	1
CHNS	Visits	1567	28	3.76	10.39	150	1
	Travel Cost		91	287.58	288.25	3519.48	1.99
	HH Income		1288	121102	55355.5	200000	12500
	Age		108	48.14	15.11	88	18
	Group Size		3	5.11	4.15	38	1
CGNHP	Visits	1211	0	2.37	1.81	7	1
	Travel Cost		18	187.39	282.75	2537.55	2.44
	HH Income		912	97199	52636	200000	12500
	Age		19	50.36	16.6	94	18
	Group Size		0	2.11	0.93	5	1
GANP	Visits	1234	11	1.97	6.37	104	1
	Travel Cost		102	310.62	299.69	2256.28	1.53
	HH Income		1089	109741	49355	200000	12500
	Age		781	44.51	15.52	90	18
	Group Size		61	4.09	10.76	300	1
RMNP	Visits	1271	17	2.82	5.55	55	1
	Travel Cost		137	462.1	342.16	2597.74	5.36
	HH Income		975	132137	53858.1	200000	12500
	Age		31	46.58	16.6	87	18
	Group Size		0	4.62	5.26	87	1

The income question was formatted categorically, which is common in TCM surveys (Landry et al. 2021). Respondents were asked to indicate in which of the provided ranges of incomes did their household income fall. Like previous authors, we transform household income to the mid-point of the provided income range. For example, for a respondent who indicated their household income is between $50,000 and $74,999, their household income was transformed to $62,500. This was done for all ranges of income except for the highest range ($200,000 or more) in which the input household income was transformed to $200,000. Finally, we divide by the number of individuals in the household who contribute to that income. Our goal is to estimate per person per visit CS when creating the model. In addition, to complete our survey responses we replace the missing values for income with the median income per household by zip code. This data is acquired from the 2021 American Community Survey (United States Census Bureau 2021), a branch of the United States Census survey. In previous TCM studies, where individual income information is not available, authors have used zip-code specific median income as a proxy (Heberling and Templeton 2009; Neher, Duffield, and Patterson 2013; Bowker et al. 2009). We use these studies as a guide on how to handle missing household income as a supplement to our collected data.

To solicit a visitation rate for each respondent, individuals were asked how many times they have visited the park they are currently visiting within the past year. We needed to sort responses to these questions for three locations: Rocky Mountain, Gateway Arch, and Cape Hatteras. These locations had unreasonable outliers at the high end such as 365 and 1000. These likely are errors in the recording of the data in that either commuters were surveyed, or an employee was accidentally surveyed. It is reasonable to assume that a visitor would not visit a park every day of the year, let alone multiple times a day every day of the year. Thus, we remove responses that are greater than three standard deviations from the average number of visits for that park. We can see from Figure 2 that trips follow a non-normal distribution, i.e., they are highly skewed. As detailed in the Empirical Specification section, both the distribution of trips and the fact that it is a non-negative integer variable requires count data models to be properly estimated.

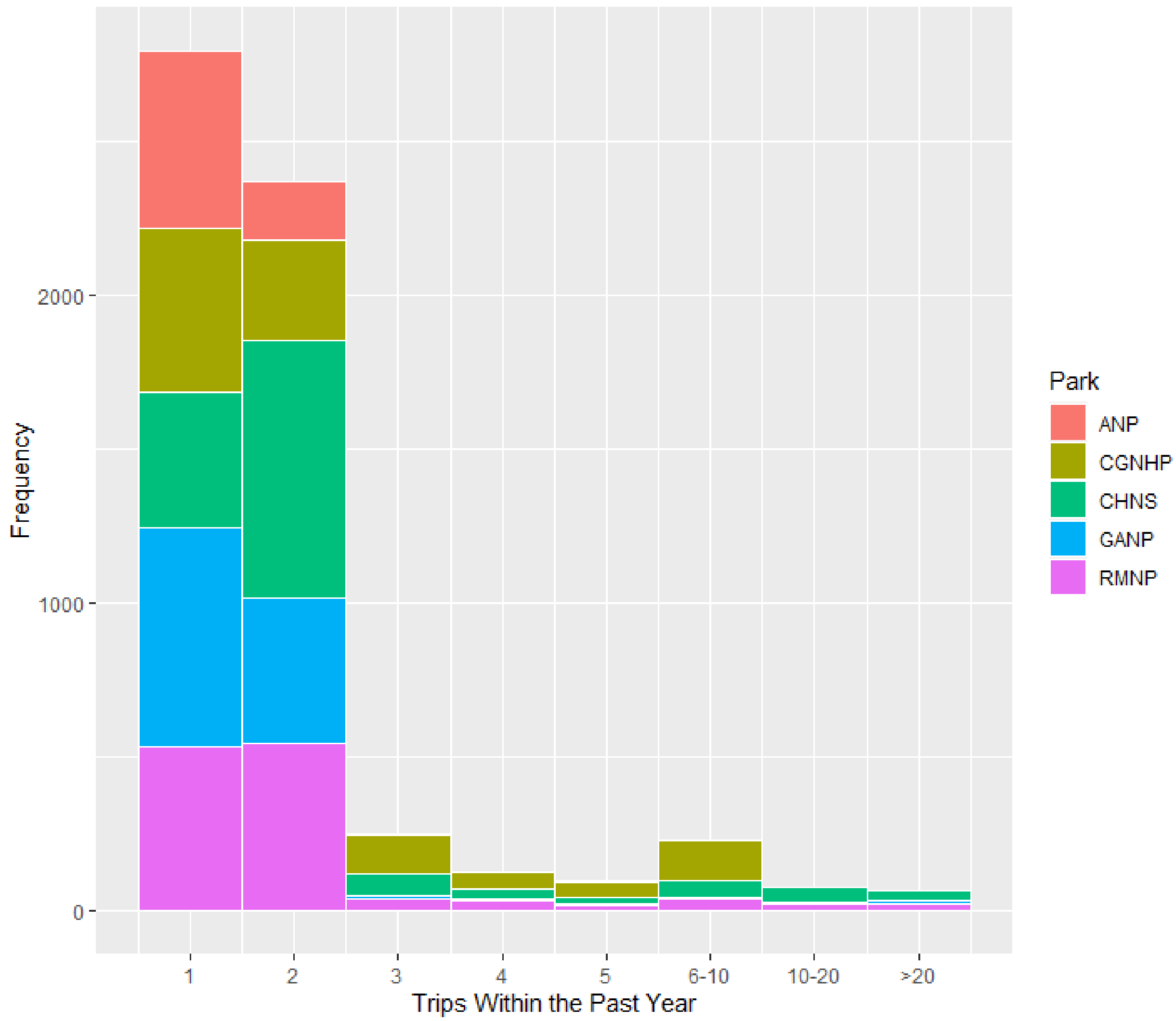

Figure 2: Frequency Chart of Trips for Cape Hatteras NS

Respondents to the survey were asked if they are a permanent or seasonal/second home resident of the local area around the park. From here, if a respondent indicated that they were *not* a permanent or seasonal resident, they were asked a follow up question concerning the primary reason for leaving home: “Was your visit to (e.g.) Gateway Arch the primary purpose for your overall trip away from home?” The purpose of this question is to divide respondents into two groups: primary purpose visitors and incidental visitors. When calculating travel cost, which is described below, we can assume that all calculated travel costs for a primary purpose visitor can be attributed to traveling to that site alone. This dummy variable was cleaned to include local residents into the primary visitor group. Even though they were not asked the follow up "primary purpose" question, due to their locality to the region we assume that they are primary visitors.

3.2 Travel Cost Calculation

The travel cost calculation has three steps: cleaning the reported home zip code, running code to determine driving distance and time, and finally converting that time and distance into a travel cost. Firstly, some respondents did not indicate a zip code, and were thus dropped from the analysis. Additionally, international respondents were also dropped. Four-digit home zip codes in the United States needed a zero added as the first digit to allow them to be transformed to coordinates. Zip codes were mapped to their corresponding city and coordinates were created as the center of the given city. Next, using an Application Programming Interface (API) developed by Esri (2023) within R, we are able to calculate driving time and distance between two coordinates – the respondent's home zip code and the park

The coordinates for the destination varied for each park. The destinations and their corresponding coordinates can be found in Table 2. Destinations were chosen based on their appropriateness for each location. For example, for Rocky Mountain NP, there are multiple ways to enter the park, with some being over 40 miles from each other. We chose the most popular entrance to the park, Fall River Road Toll Station ("Rocky Mountain National Park Guide | Fall River Village Resort" n.d.), as this is the most common way an average visitor will enter the park.

Table 2: Destinations used for Travel Cost Calculation

Park	*Destination*	*Address*
RMNP	Fall River Visitor Center	US-34, Estes Park, CO 80517
GANP	Gateway Arch Park	200 Washington Ave, St. Louis, MO 63102
CGNHP	Cumberland Gap Visitor Center	521 Colwyn St, Cumberland Gap, TN 37724
CHNS	Cape Hatteras Lighthouse	46379 Lighthouse Rd, Buxton, NC 27920
ANP	Arches Visitor Center	Moab, UT 84532

We assume that all respondents face the same cost per mile for their trips. We use the weighted average cost of $0.2767 per mile, as reported by AAA for the year 2022 (AAA 2022). We make this assumption for two reasons. First, longer distance trips are more likely to be multi-purpose trips (Landry et al. 2016). If one assumes a uniform cost across all respondents, regardless of whether they are single- or multi-site visitors, one may overestimate consumer surplus for multi-site visitors since they cannot attribute all their travel cost to traveling to the site. However, we include a primary purpose dummy variable in our model that accounts for differences in WTP across primary purpose and multi-purpose visitors. Details on the specification of the model can be found below. Second, we argue that using AAA's operating cost per mile is a lower bound for travel cost. Meaning, flying to a destination likely incurs a greater cost to a household, especially when one considers additional transportation to and from the airport (both from home, and to the site). From this logic, we conclude that CS estimates for our models are conservative. We prefer this direction of potential bias to overestimation, as we would prefer the significance of our estimates to be under rather than overstated.

After determining travel distance in miles, multiplied by cost per mile, we then double it to account for the return trip. Additionally, we divide the calculated operating costs by the number of people in the group who split expenses, as reported by the respondent. We transform the respondent's yearly household income to hourly individual income by dividing it by the number of people who contribute to household income and assume full-time employment of 2,000 hours worked per year. This is used to determine the opportunity cost of time, which is proxied by one third of the respondent's hourly income multiplied by the travel time (Parsons 2003). If there is a fee to access the park, this is added to the travel cost as well. See Eq. 1 for a summary of travel cost calculation:

$$TC_i = \frac{\left((\$0.2767 * dist_i * 2) + (entrance\ fee)\right)}{expenses\ split_i} + \left(\left(\frac{salary_i}{contributers_i} * \frac{1}{2000} * \frac{1}{3}\right) * (2 * driving\ time_i)\right) \quad \text{Eq. 1}$$

3.3 Social Cost Calculation

Next, we estimate the social cost of each trip. First, we transform distance in miles to gallons of fuel burned over the trip. We multiply the round trip distance by the inverse of the national average fuel efficiency of 25.4 miles per gallon (EPA 2016) to give us gallons per trip. From here, the relationship of gallons of fuel burned to weight of carbon emitted is a well-documented scientific process. A gallon of gasoline emits approximately 20 pounds of carbon dioxide (EIA 2022), and there are 2,000 pounds in one ton. Finally, we multiply by two estimates of the SCC as reported by the EPA of \$185 and \$55 per ton of carbon dioxide to get the social cost of an individual's trip (Interagency Working Group on Social Cost of Greenhouse Gases (IWG) 2021). We include two estimates of the SCC as a sensitivity analysis. See Eq. 2 for a summary of the social cost calculation:

$$SC_i = (dist_i * 2) * \frac{gal}{25.4\ miles} * \frac{20\ lbs\ CO_2}{gal} * \frac{ton}{2{,}000\ lbs} * \frac{\$SCC}{ton} \qquad \textit{Eq. 2}$$

3.4 Empirical Specification

In simple terms, the TCM is built upon the idea that visitors who live far from desirable sites will visit them less frequently (quantity) than visitors who live closer because they face higher transportation costs and a higher opportunity cost of time to travel there (price), ceteris paribus. To set up a model of trips taken as a function of travel cost, we must establish the consumer's utility maximization function. Suppose that a consumer's utility is derived from trips taken to a site y with price p, and the quantity consumed of a composite good x[8]. The consumer has income m which they choose to allocate to each good. If we normalize the price of x to one, we can write the consumer's budget constraint as $py + x = m$. Thus, the consumer will maximize their utility subject to their budget constraint:

$$V(v, x, y) = \max_{v,x}(U(y, x): py + x = m) \qquad \textit{Eq. 3}$$

If we assume an internal solution to the above maximization problem, then the indirect utility function for trips chosen by the consumer at their utility maximizing level is:

$$v = f(p, m) \qquad \textit{Eq. 4}$$

This indirect demand function is what we seek to estimate using the TCM. For this, alternative regression techniques need to be utilized for trip data as it behaves differently than continuous data[9]. From Figure 2, one can see that trips do not follow a Normal Distribution but rather a Poisson or Negative Binomial distribution. The choice of which distribution to use in a model

[8] x represents a linear combination of all private goods the consumer consumes.

[9] I.e., trips are a non-negative integer variable.

depends on whether overdispersion is present. The assumptions and models for both distributions are detailed in the following sections.

3.4.1 Poisson Model

We denote the realized number of trips taken by a given consumer as Y, a count variable (i.e., a non-negative integer). Using the Poisson distribution to model trips, we can look to Haab and McConnell (2002) to express the probability function for Y:

$$\Pr(Y = y) = \frac{e^{-\lambda}\lambda^{y}}{y!} \qquad \text{Eq. 5}$$

Here λ is the expected value of trips and is a function of the independent variables specified in the model. In Poisson distribution, the expected value and variance of Y are equal to λ. Since trips are a non-negative integer, λ usually takes a log linear form:

$$\lambda_i = \exp\left(\boldsymbol{x_i\beta_1} + p_i\beta_2\right) \qquad \text{Eq. 6}$$

Here x_i is a vector of socio-economic variables and other variables that are used to estimate expected trips, and p_i is the travel cost for the respondent $(i = 1,2, \ldots, n)$. β_1 and β_2 are unknown parameters. The parameters in Eq. 5 and Eq. 6 are estimated using the maximum likelihood method. From here, we can construct the likelihood function by multiplying likelihoods across individuals:

$$L = \prod_{n=1}^{n} \frac{\left(e^{-\lambda_n}\lambda_n^{y_n}\right)}{y_n!} \qquad \text{Eq. 7}$$

Finally, the on-site sample for each of the parks is truncated at zero to one trip and more frequent users appear in our samples due to on-site sampling (endogenous stratification). To correct the probability function for truncation, we replace y_n with $y_n - 1$ in the basic Poisson function Eq. 5. The function now takes the form (Shaw 1988):

$$\Pr(y_n \mid y_n > 0) = \frac{e^{-\lambda_n}\lambda^{y_n - 1}}{(y-1)!} \qquad \textit{Eq. 8}$$

And thus, Eq. 8 enters the likelihood function for each individual instead of Eq. 5. The above Poisson model can be estimated using standard regression packages by regressing $trips^* = trips - 1$ on the specified covariates. If the equi-dispersion assumption holds (i.e., there is no overdispersion present), then the truncated Poisson model is robust to endogenous stratification as well[10]. This is shown by Shaw (1988).

3.4.2 Negative Binomial Model

In the Poisson model, we assume that the expected value and variance of Y are both equal to λ. For recreational trip data, the variance is generally higher than the conditional mean, and this causes overdispersion in the data. If overdispersion is significant, then the estimated standard errors for the Poisson model are underestimated. The Negative Binomial distribution addresses overdispersion by adding a parameter, α, that represents unobserved heterogeneity in the observations. From Haab and McConnell (2002), the Negative Binomial distribution assumes the following form:

$$\Pr(y \mid x) = \frac{\Gamma(y + \alpha^{-1})}{y!\,\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda}\right)^{\alpha^{-1}}\left(\frac{\lambda}{\alpha^{-1} + \lambda}\right)^{y} \qquad \textit{Eq. 9}$$

Where $\Gamma()$ is the gamma function. Here the expected value of the Negative Binomial distribution is the same as Poisson, λ. However, the variance of the dependent variable is $V = \lambda(1 + \alpha\lambda)$. If overdispersion is significant via the likelihood ratio test, (i.e., if $\alpha > 0$) then the Poisson model is rejected in favor of the Negative Binomial distribution. Finally, if we add in

[10] See Martínez-Espiñeira and Amoako-Tuffour 2008.

corrections for truncation and endogenous stratification of Y, the probability function derived by Englin and Shonkwiler (1995) is:

$$\Pr(y_i \mid y_i > 0) = \frac{y_i \Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})} \alpha^{y_i} \lambda_i^{y_i - 1} (1 + \alpha\lambda_i)^{-(y_i + \alpha^{-1})} \qquad \textit{Eq. 10}$$

3.5 Model Specification

Within the framework of the individual TCM, our single site demand function for visits V is:

$$V = \beta_0 + \beta_1 Travel\ Cost + \beta_2 Primary\ Purpose + \beta_3 Primary\ Purpose * Travel\ Cost + \beta_4 Income + \beta_5 Group\ Size + \beta_6 Age + e \qquad \textit{Eq. 11}$$

Where β_3 is the estimated coefficient on the interaction between travel cost and primary purpose visitors, as specified by Loomis et al. (2000). Both Poisson and negative binomial models are estimated, and results of both distributions as well as a Likelihood Ratio test for overdispersion are described in the next section. The models are estimated using the statistical analysis software STATA. As described above, the endogenously stratified and truncated Poisson model is estimated with conventional regression techniques by differencing the dependent variable, trips, by one. The truncated and endogenously stratified negative binomial distribution from Eq. 10 is estimated using the function "nbstrat" (Hilbe and Martinez-Espineira 2005).

4 Results and Discussion

4.1 Travel Cost Models

The results are presented first for the Poisson models, and then for the Negative Binomial models as specified above. For some cases, the “age” variable is dropped from analysis due to sample truncation. In these scenarios, when age is included, the maximum likelihood estimator does not converge. Therefore, age is dropped to allow us to estimate CS. The estimated results using the truncated Poisson distribution are presented in Table 3. In addition, estimated results using the truncated and endogenously stratified negative binomial distribution are presented in Table 4.

Table 3: Model Results using the Truncated Poisson distribution.

VARIABLES	(1) ANP	(2) CHNS	(3) CGNHS	(4) GANP	(5) RMNP
Travel Cost (TC)	-0.000594***	-0.00105***	-0.00359***	-0.00126***	-0.000774***
	(0.000144)	(0.000265)	(0.000423)	(0.000247)	(0.000171)
Primary Purpose Dummy (PP)	0.934***	2.200***	0.986***	1.937***	1.982***
	(0.195)	(0.122)	(0.0935)	(0.130)	(0.154)
TC x PP	-0.00135***	-0.00565***	-0.00858***	-0.00862***	-0.00271***
	(0.000372)	(0.000316)	(0.00101)	(0.000930)	(0.000215)
Individual Income	1.00e-05***	1.15e-06	-3.12e-07	-2.83e-06*	3.26e-06***
	(1.52e-06)	(7.15e-07)	(1.41e-06)	(1.54e-06)	(7.20e-07)
Group Size	0.0180	-0.0841***	-0.105***	-0.454***	-0.101***
	(0.0137)	(0.00669)	(0.0174)	(0.0340)	(0.0105)
Age	-	0.00848***	0.00156	-	0.0136***
	-	(0.00125)	(0.00150)	-	(0.00121)
Constant	-1.499***	0.0788	0.439***	1.210***	-0.616***
	(0.172)	(0.142)	(0.143)	(0.161)	(0.171)
Observations	762	1,225	1,152	647	1,162
Log-likelihood	-678.74453	-3762.5038	-1560.1021	-1135.8776	-2592.8722
χ^2	116.11	3041.37	1163.67	1286.15	2868.01
Pseudo-R^2	0.0788	0.2878	0.2716	0.3615	0.3561

Note: The park names are abbreviated as follows: Arches National Park (ANP), Cape Hatteras National Seashore (CHNS), Cumberland Gap National Historical Park (CGNHS), Gateway Arch National Park (GANP), Rocky Mountain National Park (RMNP).

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Model Results using the Endogenously Stratified Negative Binomial distribution.

VARIABLES	(1) ANP	(2) CHNS	(3) CGNHS	(4) GANP	(5) RMNP
Travel Cost (TC)	-0.000493***	-0.000675**	-0.00350***	-0.00100***	-0.000925***
	(0.000155)	(0.000266)	(0.000431)	(0.000276)	(0.000211)
Primary Purpose Dummy (PP)	0.840***	1.626***	0.957***	1.765***	1.591***
	(0.231)	(0.154)	(0.0987)	(0.190)	(0.201)
TC x PP	-0.00110***	-0.00293***	-0.00744***	-0.00645***	-0.00168***
	(0.000381)	(0.000340)	(0.00104)	(0.00103)	(0.000256)
Individual Income	9.36e-06***	-1.47e-06	-5.51e-07	-2.56e-06	7.33e-06***
	(1.97e-06)	(1.32e-06)	(1.53e-06)	(2.62e-06)	(1.58e-06)
Group Size	0.0306	-0.0599***	-0.0976***	-0.174***	-0.0622***
	(0.0260)	(0.0100)	(0.0189)	(0.0374)	(0.0135)
Age	-	0.00847***	0.00159	-	0.0119***
	-	(0.00259)	(0.00169)	-	(0.00252)
Constant	-16.07	-19.51	0.284*	-3.307	-14.31
	(212.1)	(589.7)	(0.164)	(4.476)	(152.1)
ln (α)	14.51	19.57	-1.966***	3.640	13.45
	(212.1)	(589.7)	(0.367)	(4.559)	(152.1)
Observations	762	1,225	1,152	647	1,162
Log-likelihood	-616.66805	-2110.5152	-1553.3366	-694.32405	-1685.9339
χ^2	66.09	495.96	598.96	295.24	673.51
AIC	1.634	3.457	2.709	2.165	2.914
BIC	-5016.776	-8660.828	-8071.397	-4148.774	-8151.872

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The first thing to note in the results table is that the coefficient on travel cost, which is used to calculate consumer surplus below, is significant and of the expected sign for all parks and with both distributions. Our results are consistent with previous studies in magnitude and sign for estimated travel cost coefficients. Similarly, the estimates for the primary purpose dummy variable are consistent with those by Loomis (2006). It should be noted that our dummy variable is coded opposite of the previous author: for our model, "primary purpose" is one for primary purpose visitors and zero otherwise. We can interpret the positive coefficients to mean that at an equilibrium price (i.e., travel cost), primary purpose visitors demand more trips than non-primary visitors[11]. Furthermore, the interaction term on travel cost and primary purpose is negative, which is also consistent with previous findings. Primary purpose visitors face a flatter demand curve, or in other words, a more elastic demand curve. They are more sensitive to changes in their travel cost than non-primary visitors. They also have commensurately lower CS estimates, which is consistent with previous findings (Loomis 2006).

We can see that the estimated α for the truncated and endogenously stratified Negative Binomial models is significant for Arches NP and Cumberland Gap NHS. Therefore, our models show that there is significant overdispersion in these data and thus the endogenously stratified Negative Binomial models are better suited for them. It is also noted that the other parks have a non-zero estimated α, however, they are not significantly different from zero due to their respective estimated standard errors.

The estimated coefficient on income is significant for Arches NP and Rocky Mountain NP for their respective models. Although the magnitude for each of the models is small, our models show that income is a significant predictor of trips taken to these two parks. Other

[11] These visitors are also called "incidental," "multi-destination," or "multi-purpose" in previous literature, all of which refer to the same thing.

authors have found mixed results in similar TCM studies: income is an insignificant (sometimes negative) predictor of trips taken (Heberling and Templeton 2009; Neher, Duffield, and Patterson 2013; Bowker et al. 2009). However, we note that we have used zip code level median income for missing observations. While previous authors have taken this route in the past, we acknowledge that the respondents for our surveys may not be "median" earners within their respective zip codes. It can be argued that visitors to national parks are likely relatively wealthy compared to the average person, as they have sufficient funds to allocate to leisure time for a trip as expensive and time consuming as visiting a national park. However, using zip code level median income may be a better substitute than sample level median income. Although we can never know the true value of missing entries, we find it more useful and statistically robust to have variation in the income variable via zip code level medians rather than assigning the same value (sample median) for all missing entries. This is in addition to the aforementioned use of income in determining travel cost.

4.2 Welfare Estimates

In Table 5 consumer surplus estimates are presented for the truncated and endogenously stratified models. For each dataset we calculate CS using the appropriate model with respect to overdispersion. For non primary-purpose visitors, we calculate consumer surplus with the following equation:

$$CS = -\frac{1}{\hat{\beta}_{TC}} \qquad \textit{Eq. 12}$$

Table 5: Welfare Estimates for the Surveyed Parks

Park	$\hat{\beta}_{TC}$	*CS per trip (Non-Primary)*	$\hat{\beta}_{PP*TC}$	*CS per trip (Primary)*	$\overline{D}$	*CS per day*	*Visitation*	*Annual Value*
ANP	-0.00059	$1,683.50	-0.00135	$514.40	2.37	$217.32	1,460,652	$317.43 M
CHNS	-0.00105	$952.38	-0.00565	$149.25	9.26	$16.12	2,862,844	$46.16 M
CGNHS	-0.0035	$285.71	-0.00744	$91.41	7.35	$12.43	732,916	$9.112 M
GANP	-0.00126	$793.65	-0.00862	$101.21	2.62	$38.60	1,618,774	$62.49 M
RMNP	-0.00077	$1,291.99	-0.00271	$287.03	3.54	$80.97	4,300,424	$348.22 M

Note: $\overline{D}$ refers to the surveyed average number of days spent in the park per visitor. Visitation is annual from 2022, as reported by the NPS.

It should be noted that the CS estimate of interest is for primary-purpose visitors. This is found by adding the coefficient estimate for travel cost together with the coefficient estimate for the interaction of travel cost and the primary-purpose dummy variable. Consumer surplus per year is found by dividing Eq. 12 by the surveyed average number of days in the park per visitor (to determine CS *per day*) and then multiplying by yearly visitation as reported by the NPS (NPS n.d.). Visitation is reported as "recreation visits," i.e., how many entrances to the park there were over the past year. We multiply visitation by CS per day as opposed to CS per visit for the following reason: if an individual takes a trip to the park and stays outside of the park during their trip but enters the park on four different days, the visitation records that as four visits, however, it was only one trip that the individual took from home. Thus, dividing by the average number of days spent in the park per trip provides a more conservative estimate of annual CS value. We prefer this to a potential overstatement of CS per year. In addition, since CS estimates are lower for primary-purpose visitors, we note that in this way annual CS estimate is further conservative.

Arches NP has the largest CS per trip estimate by far, being $514.40. This is an interesting result as Arches has relatively lower annual visitation than the other surveyed parks (save for Cumberland Gap NHP) and, generally speaking, is a smaller park by acreage. Its large CS estimates (per day and annual) could come from two effects: first, its days visited per trip and per year are comparatively lower than the other parks and second, it has greater average travel costs compared to the others[12]. In simple terms these two measures tell us that individuals travel greater distances to visit Arches and stay for a shorter time when there. The reasons for both are likely due to the remoteness of the park, with the closest major city of Grand Junction, Colorado,

[12] See Table 1 for a reference on the spread of visits and travel costs across the parks.

being over one hundred miles away; and the availability of a second national park nearby: Canyonlands NP. This is similar for Rocky Mountain NP, as it is over an hour's drive from Denver, Colorado, although it has more visits per trip than Arches NP. It is one of the most popular parks under the NPS' jurisdiction and thus produces the largest annual CS. For context, we can compare this to the park's 2023 enacted budget of $14.8M, a fraction of the estimated CS the park produces (US Department of the Interior 2023).

We can see that CS per visit estimates are lower for primary purpose visitors than for non-primary purpose visitors (or "incidental visitors"). To discover the explanation behind this finding, we need to consider the indirect demand curve we have estimated. The "equilibrium price" used to determine CS in the TCM is the average travel cost. This doesn't change for each type of visitor. Thus, as primary-purpose visitors face a *flatter* demand curve, their CS estimate is smaller. See Figure 3 for a visual reference on consumer surplus calculation. Our model estimates that primary-purpose visitors take more trips at the equilibrium travel cost, as indicated by the estimated coefficient on the primary-purpose dummy variable being positive. This,

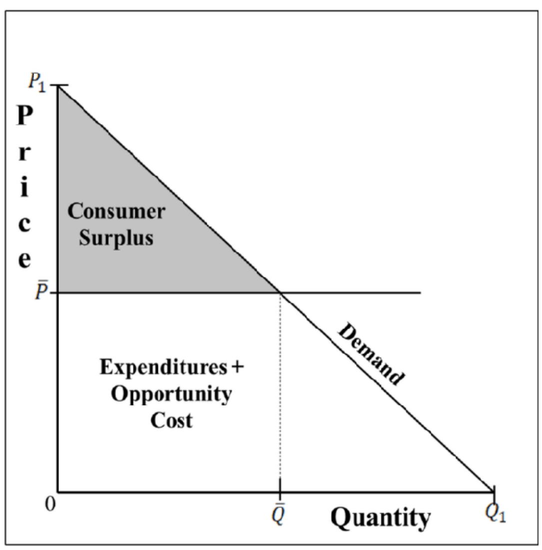

Figure 3: Demand graph depicting Consumer Surplus

although primary purpose visitors get less CS per visit, they take *more* trips on average and thus acquire higher value overall, *ceteris paribus*.

We can compare our CS per day estimate for Cape Hatteras to Bin et al. (2005), who estimated consumer surplus for several beach sites in North Carolina. The authors restrict travel cost by distance, excluding those visitors that were over 1,000 miles away from the sites. Their decision is informed by the choice to use a fixed cost per mile for their respondents: they only wanted to calculate travel cost by driving. In this way, their dataset reflects marginal WTP of local visitors. They estimate CS for a visitor-day at Cape Hatteras to be \$60.37, or \$98.45 in 2022 dollars. This estimate is larger in magnitude to our CS per day estimate of \$16.12 for primary visitors and smaller for CS per day estimate of \$102.85 for non-primary visitors. It should be noted that while they include a multi-destination dummy variable in their model, they do not interact the dummy variable with travel cost as we do. So, we can draw two comparisons: our non-primary CS per day estimate is in line with their estimation when one considers inflation and second, our primary CS per day estimate is smaller but closer in magnitude to the author's CS per day estimates for the other beaches they surveyed, which range from \$11 - \$80. Finally, we note that we are comparing the authors estimates for *day trips* to these sites, as they stratify by this and *overnight* trips. Their sample size for day trips to Cape Hatteras NS is much smaller than ours, which is to say that our estimates reside in a different statistical context than theirs.

In addition, the study conducted by Landry et al. (2021) has CS estimates that are comparable in magnitude to ours. In their study, they ask participants whether they are single-site visitors or multi-site visitors. For multi-site visitors, they simply ask what the last site was they visited and calculate travel cost to that site. Next, they ask how many trips the respondent took pre- and post-COVID. They pool responses to these questions and estimate models with a post-COVID demand shift dummy variable. Their CS estimates are per visit and multiplied by a scaled version of mean trips taken within their sample to acquire per household per year consumer surplus. If we compare their post-COVID CS estimate per visit by applying the same CS equation to their travel cost coefficients, we can see their estimates are $625 - $714.29 depending on the distribution used. Our CS estimates per visit are $91.41 - $514.40 for primary purpose visitors. The disparity between our estimates and theirs may come down to specificity in the data or different sample populations. Their survey was randomly distributed while ours was collected on site. Furthermore, their study asked respondents to list visits to any outdoor recreation site: national parks, state parks, national and state forests, any public lands (such as Bureau of Land Management lands), etc. The pooling of these outdoor recreation sites likely yielded a higher CS estimate overall.

4.3 Social Cost Analysis

After calculating social cost per visitor, we then take the average over the sample for each park and multiply by annual visitation. From here, we estimate total annual external damages due to carbon dioxide pollution from visitation for each park. The results are presented in Table 6.

Table 6: Social Costs

Park	*Mean SC ($185/ton)*	*Mean SC ($55/ton)*	*Mean TC*	*Annual SC ($185/ton)*	*Annual SC ($55/ton)*	*% of Annual CS ($185/ton)*	*% of Annual CS ($55/ton)*
ANP	$43.65	$12.98	$813.21	$63,755,850.28	$18,954,441.98	20%	6%
CHNS	$13.91	$4.13	$382.55	$39,811,088.15	$11,835,728.91	86%	26%
CGNHS	$10.58	$3.15	$203.14	$7,755,906.33	$2,305,809.99	85%	25%
GANP	$15.31	$4.55	$429.02	$24,777,993.94	$7,366,430.63	40%	12%
RMNP	$21.18	$6.30	$646.24	$91,079,505.19	$27,077,690.73	26%	8%

As social cost is a function of distance, as is travel cost, the two are commensurate in magnitude across the parks. For both estimates of the SCC, we can see that Arches NP has the highest average social cost among the parks. Rocky Mountain NP produces the highest amount of damage due to CO_2 pollution from its visitors, due to its very high visitation. We assume that the individuals face a consistent social cost per mile traveled. This may not be the case, as some travelers may fly to the destination, take public transit, or use a guide service to travel by bus. We also note that the social cost of carbon, as applied here, is estimating the social cost of traveling itself, not the damages from the entire trip. This social cost measure does not capture the entire carbon footprint of a visitor's trip: for example, visitors may travel by plane, which emits more CO_2 than driving. Thus, we can think of our estimated social cost as being a lower bound on the true social cost of visits.

One can also think of the average social cost as a tax if visitors were to pay, i.e., internalize, the external costs of their emissions when visiting these parks. Costs would increase, on average, by the mean SC calculated in Table 6 per person per trip for each park. In this sense, due to the downward sloping demand curve for trips, higher costs would result in fewer trips and thus lower emissions at the equilibrium. As an extension of our models, we can use our estimates of elasticity of price to determine the change in visits if consumers were to pay their social costs in the form of a Pigouvian tax. These results are presented in Table 7.

Table 7: Estimated Change in Visits due to a Pigouvian Tax

Park	*Predicted Avg. Trips*	*Δ Trips ($185/ton)*	*Δ Trips ($55/ton)*	*New Predicted Trips ($185)*	*New Predicted Trips ($55)*
ANP	1.415	-0.085	-0.025	**1.330**	**1.390**
CHNS	3.324	-0.093	-0.028	**3.231**	**3.296**
CGNHP	0.568	-0.116	-0.034	**0.452**	**0.533**
GANP	2.080	-0.151	-0.045	**1.928**	**2.035**
RMNP	2.850	-0.074	-0.022	**2.776**	**2.828**

We can see that consumers would take about 0.1 less trips on average across the samples. As described in the introduction, the inclusion of the SCC analysis is not to describe in detail a facet of national parks that is costly and to justify less visits to one. Visits to a national park have a social cost of emissions like all activities do, however their distinction is twofold: national parks *produce* consumer surplus, and alternative activities to visitation may be more socially costly. As described in Table 6, for the two most socially costly national parks, Arches NP and Rocky Mountain NP, their annual social costs are only about a fourth of their annual CS estimates. Comparing the two directly, we can see that the overall benefits outweigh the costs. In addition, we note that alternative activities could have higher social costs. People who do not visit a national park likely do not choose to do “nothing” and emit zero CO_2 as an alternative. Looking at the social cost of visits as a negative implies this assumption. Although we would never observe the perfect counter-factual, we hope our study encourages scholars to compare our estimates of the social costs of visiting a national park to other activities. From this extension, future policies could be enacted to give national parks greater resources to maintain themselves as they could be potentially less socially costly than other leisure activities.

5 Conclusions

This study provides consumer surplus estimates for five National Parks in the United States for the year 2022. We use the travel cost method to estimate these values and correct our models for biases introduced in on-site sampling. We estimate consumer surplus per-person per-visit ranging from \$91 to \$1,683[13] and \$12 to \$217 per-person per-day. In addition, annual visitation is used to extend this estimate across the year. The park that gives the highest CS per visit and per day is Arches, and Rocky Mountain NP gives the greatest annual CS in part due to its large visitation. We also compare our estimates of CS to Bin et al. (2005), who conducted a travel cost study for beaches in North Carolina. We find our CS per day estimate for Cape Hatteras to be lower in magnitude, but similar to CS per day estimates the authors calculated for other beaches in their survey. Finally, we compare our CS estimates to a recent paper from Landry et al. (2021) in which they estimate CS per day for outdoor recreation. Due to the specificity of our study, we find our CS per day estimates to be smaller in magnitude.

As this is the first year of the SEM Visitor Survey program, future studies will be able to add CS estimates for more parks and can potentially create a library of CS estimates for many parks across the country. We hope that these CS estimates can be used in policy decisions and benefit cost analysis for parks of similar scale, both domestic and abroad. We also note that we are one of the first studies to incorporate the Social Cost of Carbon with the TCM. We hope to inspire future economists to integrate similar social measures into future studies. In closing, the continuing contribution of non-market valuation studies is important for the country to update consumer's values for natural resources so that they may be protected for future and current generations.

[13] The range given for these per-visit estimates are across primary and non-primary visitors.

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