A Profile of Beach Use on the East Coast of the United States with Per Trip Values and Consumer Surplus Estimates for Day, Short Overnight, and Long Overnight Trips

Abstract

We provide a statistical profile of beach use on East Coast of the United States (beaches from Massachusetts to South Carolina) using survey data from a random sample of beach goers from the twenty states nearest to these beaches. We reported details on demographics and trip taking behavior and then provide a set of per trip values for day, short overnight, and long overnight trips. We also present consumer surplus access values by state. These are done in using a random utility model with alternative-specific-constant models for day, short overnight and long overnight model separately. We also estimate a model that combines the trips and a second-stage model that allows us to explore the effect of specific attributes on beach use. And finally, we include a contingent behavior validity check. Per trip values for day, short overnight, and long overnight trips are $19, $91, and $333.

1. Introduction

The economic and cultural importance of outdoor recreation on beaches in the United States is well known. The National Oceanic and Atmospheric Administration reports that "[o]cean-based tourism and recreation contributes approximately $143 billion in gross domestic product to the national economy each year." Millions of visitors, day trippers and vacationers alike, annually indulge in a variety of activities ranging from pursuits directly tied to nature like fishing, birdwatching, and hiking to pursuits indirectly tied nature such as visiting boardwalks, shopping centers, museums, and restaurants. Among beaches in the United States, those on the East Coast stand out as one of the more common destinations. We estimate that were 79 million day trips, 24 million short overnight trips (< 4 nights), and 15 million long overnight trips (> 4 nights) taken in 2015 to East Coast beaches – this includes beaches from Massachusetts to South Carolina. Together they make up 224 million visitor days. The count is from a survey we will describe later in the article, which includes visitors from the 20 states nearest to these beaches – excluding visitors from more distant states and foreign countries. By way of comparison 5.5 million people visited the Grand Canyon National Park in 2015 and 4.1 million visited Yellowstone National Park in 2015.

The purpose of this article is to profile beach use on the East Coast and use a travel cost random utility maximization model to estimate per trip values for day, short overnight, and long overnight trips to the same beaches. These values are of use in many policy settings in coastal resource management – including impacts from climate change, damage assessment of oil spills and other hazardous episodes, managing the extent of beach nourishment projects, planning for beach retreat, documenting the effects of offshore wind farms and other infrastructure projects on beach use, and so forth. In short, there is a long list of uses for these values in benefit transfers in benefit-cost analyses, natural resource damage assessments, and other priority setting decisions. In addition, the profile may be used in impact analyses and other local planning efforts and promote sustainable coastal management generally.

We use survey data assembled in 2015 originally for the purposes of estimating the impact of offshore wind turbines on beach use in our analysis (Parsons et al. 2020 and Parsons et al. 2021). This is a follow-on analysis with the same data covers beach use at 275 ocean beaches from Massachusetts to South Carolina. We have two functional samples: (1) 2050 respondents from the general population and (2) 1725 respondents from the beach going population. Both were drawn from the households living in the 20 states nearest to the East Coast beaches and both are weighted by GfK International such that they are probabilistic or 'representative' of the underlying population. About 35% of the general population visited at least one beach during the year. We use that figure as our participation rate.

The travel cost random utility model (Haab and McConnell, 2002, Chapter 9) has been applied to ocean beaches in many areas of the world, so we have a good foundation from which to work. Since our focus is on estimating per trip values, we confine our econometric analysis largely to 1725 participants in the data set and estimate an alternative-specific-constant (ASC) model (English et al. 2018). We report models separate day, short overnight, and long overnight trips, but also present an application following a recent argument in the literature that combines trips of different length into a single model.

Our paper is structured as follows. We begin with a review of the relevant literature, followed by a detailed description of our study design and model. Then we describe the survey and present a profile of beach users from these data. Next, we present our econometric model and the results. We also include a section on hypothetical beach closures as a demonstration of the model. We conclude with a summary of our findings and implications.

Before we begin, we want to clarify how we are using the term "per trip value". There are two common usages. One is the per trip value computed from a RUM Model using the log-sum difference when one site is dropped from the choice set divided by coefficient on trip cost -- the monetized difference in the expected utility of a trip. In this article we will refer to this as a "per choice occasion value". It is the expected value of a trip to a given site. Since every beach in the choice set has a positive probability of a trip, the choice occasion value for every respondent for every beach is positive. To put the per choice occasion value in per trip terms, we divide it by the probability of visiting the site -- the log-sum difference when one site is dropped from the choice set divided by the probability of taking a trip to the dropped site. The latter is synonymous with per trip values used from single-site models where one divides total seasonal consumer surplus (choice occasion surplus here) by the number of trips for a person (probability of taking a trip here) to arrive at a per trip value. When we refer to a "per trip value" in this article, this is the variable we have in mind.

2. Literature

Economists have been estimating travel cost random utility models of beach use for 50 years. Table 1 is a compilation of data sets used for estimating such models accompanied by publications using the data. We will refer to these data sets in italics in this section. The US EPA funded two major data collection efforts early on for the purpose of measuring water quality benefits. These are the *1974 Boston Area* data and *1983 Chesapeake Bay* data (see Table 1). Binkley and Hanemann (1978), Hanemann (1978), and Feenberg and Mills (1980) use the *1974 Boston area* data, which covered 30 beaches in the Boston and surrounding areas. They focus on day trips and estimate recreational benefit of water quality improvements where water quality was based on physical properties of beaches, presence of litter and maintenance frequencies. Bockstael et al. (1989) also applied RUM Model and focused on day trips to 12 beaches using the *1983 Chesapeake Bay* data. They report choice occasion values of $1.08 per choice occasion per household for a 20% reduction in water pollution across all beaches. Water pollution was defined by a nitrogen-phosphorous index. Hick and Strand (2000) use the same data set to investigate the implication of distance- and familiarity-based choice sets in a RUM Model, and discovered that using traditional distance-based choice sets can significantly bias welfare estimates if the majority of substitutes are unknown to respondents.

Table 1: Beach Use Summary by Data Set

Survey Data Set	Published Articles	Model Type	Value in $2023
1974 Boston Area *Choice Set*: 30 beaches *Population:* Boston Area residents	Binkley and Haneman (1975)	Logit model 1 (constant, distance, phosphorus) Logit model 2 (Model 1 with coliform presence variable) Logit model 3 (Model 2 with color variable)	94* 135* 76.02*
	Haneman (1978)	Logit model (no TC variable)	N/A
	Feenberg and Mills (1980)	Logit model (no TC variable)	11.62*
	Bockstael, Haneman and Strand (1984)	N/A	N/A
	Bockstael, Haneman and Kling (1999)	First-stage GEV Model of choice among freshwater and saltwater beaches	10.75
1983 Chesapeake Bay *Choice Set*: 12 beaches *Population:* Beachgoers in Chesapeake Bay	Bockstael, Haneman and Strand (1989)	N/A	N/A
	Haab and Hicks (1997)	Mixed logit 1 (with fecal coliform variable only) Mixed logit 2 (model l with additional dummies) Endogenous choice set	169.79 113.02 83.6

	Hicks and strand (2000)	Familiar set standard RUM	44.91
		Familiar set standard RUM (4-hour distance)	30.01
		Distance based standard RUM (1 - 3.5 hours range)	[205.9; 44.67]
1987 New Bedford *Choice Set:* 5 beaches *Population:* 338 randomly selected beach users in New Bedford	McConnell (1986)	N/A	N/A
	Haab and Hicks (1997)	Mixed logit 1 (region Constants only)	7.72
		Mixed logit 2 (model 1 with Additional dummies)	38.87
		Mixed logit 3(model 2 without distance variable)	18.51
		Endogenous choice set 1 (with distance variable)	20.33
		Endogenous choice set 2 (without distance variable)	15.69
1994 Florida *Choice Set:*297 beaches *Population:* Central Florida residents	Environmental economics Research Group (1998)	Nested logit (travel time to site only)	50.43
		Nested logit (travel time and beach time)	38.04
		Nested logit (travel time, beach time and non-beach time accounting for non-beach-recreational activities)	1.5
1997 Mid-Atlantic *Choice Set:*62 NJ, DE, MD and VA beaches *Population*: Central Florida residents	Parsons, Tomasi and Massey (1999)	Standard logit all sites	54.24
		Nested logit familiar	82.54
		Nested logit unfamiliar	54.24
		Standard logit favorite	90.4
	Massey (2002)	Multinomial logit	39.64
			39.54

		Multinomial logit with interactive variables	
			17.31
		Mixed logit	
			17.79
		Mixed logit with interactive variables	
	Parsons (2003)	Three-level nested logit	47.46
	Parsons and Massey (2003)	Multinomial logit Mixed logit	40.4 21.57
	Haab and McConnell (2002)	Nested logit Conditional logit	23.73 31.51
	Von Haefen, Phaneuf, and Parsons (2004)	Monte Carlo Markov chain algorithm for Hicksian Consumer surplus estimates	N/A
	von Haefan, Massey, and Adamowicz (2005)	Hurdle model in choice experiment application	N/A

1998 Lake Eri Data *Choice Set:* 15 beaches on Lake Eri *Population:* Ohia Lake Eri beach user	Murray et al. (2001)	Multinomial Logit (MNL)	17.63
	Yeh et al. (2006)	Nested logit model (NML): Day trips Overnight Trips	 19.18 89.45*
1998 Costa Rica *Choice set*: 7 forested beaches Population: Resident of Costa Rica	Cutter et al. (2007)	Nested logit model for all Swimmer & Hiker only	142** 83.3**
1999-2000 Southern California *Choice Set*: 53 beaches *Population:* Households in Southern California	Hanemann et. Al. (2004)	Conditional logit	20.81
	Hanemann, Pendleton, and Mohn (2005)	Random parameters model	9.71
	Hilger and Hanemann (2006)	Finite mixture logit	[2.71; -84.23]
	Hilger and Hanemann (2008)	Logit model	20.81
2000-2001 San Diego *Choice Set:* 31 beaches *Population:* Randomly chosen San Diego County residents	Lew (2002)	Multinomial logit-Heckman Multinomial logit-HFS Nested multinomial logit-Heckman Nested multinomial logit-HFS	20.03 21.39 20.97 21.89
	Lew and Larson (2005a)	Full site repeated nested logit. Aggregate sites repeated nested logit	113.03 124.20
	Lew and Larson (2005b)	Two-step mixed logit Joint mixed logit	17.13 9.31
	Kuriyama, Hanemann and Hilger (2010)	Latent segmentation Kuhn Tucker model	N/A

2000 Australia Sunshine Coast *Choice set*: 5 beaches *Population:* Beachgoers of Queensland	Blackwell (2007)	Ordinary Least Square (OLS) Truncated Poisson Truncated Negative Binomial (TNB)	62.11** 49.04** 119.95**
2001 Texas Gulf of Mexico Coast *Choice Set:* 65 beaches *Population:* Residents living within 200 miles of the Gulf of Mexico	Parsons et.al. (2009)	Multinomial Logit Mixed Logit	79.7 31.76
	Parsons and Kang (2010)	Mixed Logit	43.04
2009 North Carolina *Choice set*: Beach of 16 counties Outer Banks *Population:* Household of outer banks	Lardry et al. (2012)	Random effect Poisson	132.74
2010 Delaware Bay *Choice Set:* 7 beaches *Population:* On-site survey of beach visitors	Parsons et. al. (2013)	Pooled single-site travel cost model	46.57
	Johnston et al (2015)	Used Parsons et.al. (2013)	N/A
2011 Northwest Florida *Choice set:* 7 beaches *Population:* Respondents residing in 13 US states that constitute the primary domestic market for coastal tourism to Northwest Florida	Whitehead et. al. (2016)	Random Parameter count data travel cost model. Negative binomial count data travel cost model	388.16 423.44
2011 US Coastal beach Area *Choice Set:* Shoreline counties in the Gulf of Mexico *Population.* Households who lived sufficiently far from the Gulf of Mexico that an overnight trip to the Gulf could be expected to have been planned in advance (outside of TX, LA, AR, MI, FL, GA, TN)	Glasgow and Train (2018)	Multinomial Logit	451.99
2011 Australia Gold Coast *Choice Set:* 4 Beaches *Population:* Beachgoers of selected	Blackwell et al. (2013)	Ordinary Least Square (OLS) Truncated Poisson	.57** 33.3** 47.6**

beaches		Truncated Negative Binomial (TNB)	
	Zhang et al. (2015)	Truncated Negative Binomial (TNB)	19.47**
2013 Southern California *Choice Set:* 31 Orange County beaches *Population:* adult residents of Orange County, CA	Leggett et. al. (2018)	Standard repeated nested logit with TC and Debris only	10.14
		Standard repeated nested logit with some site choice	10.31
		Standard repeated nested logit with all site choice variables	10.80
		Standard repeated nested logit with participation variables	35.71
2013 Gulf Coast	English et al. (2018)	Nested logit model	108.95
Choice set: Beaches of six state area *Population:* national sample: resident of 48 states local sample: TX, AL, FL, LA, MS, GA	English et al. (2020)	Nested logit model: Day trip	 11.78
		Overnight trip	435.95
		Combined trip	130.8

* Estimated distance to the site instead of travel cost

**TC is measured other than USD

More recent applications for valuing water quality improvements include Murray et al.'s (2001) study using the *1998 Lake Erie* data, which covers 15 beaches in Ohio. Using day trip data, they estimate the value of reducing the number of beach advisories beaches at single beaches at $1.85 per trip per person and $27.93 per season per person. Yeh et al. (2006) use the same data set to model day and overnight trips simultaneously. They find a reduction of one beach advisory across all beaches with advisories is valued at $2.10 per trip per person for day trips and $6.45 per trip per person for overnight trips. Hilger and Hannemann (2008) used the finite mixture logit model (FML), an advanced variant of the RUM model for addressing systematic preference heterogeneity, in conjunction with the traditional conditional logit model using the *2000 Southern California* data and estimate an increase in per trip beach recreation benefit of $5.71 and $1.23, respectively, for improving water quality of a letter grade grade ranged from A+ to F, where letter grades are measured by total coliform, fecal coliform, and enterococcus. Kuriyama et al. (2010) use the same data set to expand the latent segmentation technique to the Kuhn Tucker Model. They calculate the welfare loss resulting from a 20% decrease in water quality across 53 beaches to be between $1.73 and $16.77 per person per year. Lew (2002) included a water quality measure (on-site posting of water quality violations at the beach) in his RUM Model using the *2000-1 San Diego* data but find it is statistically insignificant.

In addition to these multisite models, there are a number of studies that use single site models with contingent behavior data to measure the value of improvements in water quality for beach recreation. A prominent example is McConnell (1986), who used the *1986 New Bedford, MA* data to estimate the value of a hypothetical elimination of PCB contamination from two beaches located in New Bedford Harbor. He approximates the benefit of removing PCBs to be $4.08 per year per household. Similarly, Hanely et al. (2003) evaluated the value of water quality improvements for day trips on seven Scottish beaches using the *1999 South-West Scotland* data where respondents rated water quality on a 5-point Likert Scale. They estimated the value of water quality improvement from present conditions to the index's top level worth $0.77 per person per trip and $9.37 per season.

Concerns about beach erosion have given rise another set of articles that considers the value of beach width for beach recreation. Parsons and Massey (2003) applied a travel cost model within a Random Utility Maximization framework to estimate the value of changes associated with different beach widths using the *1997 Mid-Atlantic* day-trip data, which covers 62 ocean beaches. Their findings indicate that both very narrow (less than 75 feet) and very wide (more than 200 feet) beaches are less valued compared to beaches of intermediate width. The study also measured welfare losses associated with beach width reduction, estimating that a reduction from more than 75 feet to less than 75 feet might result in welfare losses of $0.75 per person choice occasion for specific beaches and up to $5 for all beaches in Delaware. Von-Haefen et al. (2004) used a multistage Monte Carlo Markov chain approach in the RUM model to estimate the value of lost beach width across all beaches in the same data set, yielding per person per season values ranging from $50 to $139. Whitehead et al. (2010) used the *2003 North Carolina* data on 17 North Carolina beaches using three econometric models—single-site with contingent behavior, count-data system, and Kuhn Tucker—to estimate the economic impact of increasing beach width by 100 feet. Their findings varied, with estimated values ranging from $106 to $309 per person per season. A related study by Whitehead et al. (2008) focused on the single-site contingent-behavior model, estimating the value of this increase at about $7 per person per trip and between $61 to $85 per person per season using the same data set. Stefanova (2009) used the *2005 Mid-Atlantic data* in a day-trip RUM Model to evaluate the economic impact of preserving beach widths over seven continuous beach groupings, and concluded that a 150-foot width would improve visitor welfare, providing values ranging from $0.12 to $2.00 per person per choice occasion. Likewise, Parsons et al. (2013) employed a single-site contingent-behavior model using the *2010 Delaware Bay Beach* data to analyze economic outcomes of changing beach widths. Results showed a loss of $5 per person per day if beach widths were reduced to a quarter of their current size, and a gain of $2.70 per person per day if widths were doubled. These calculations included both day and overnight trips.

Beach Characteristics like parking space, vehicle access, bike paths, congestion, presence of parks play a vital role when it comes to beach recreation experience. Whitehead et al. (2008) used the *2003 North Carolina* data covering 17 beaches to estimate the value of improving nearby parking at $22 to $28 per person per trip at all beaches, using a contingent-behavior model. Beach characteristics can affect different recreational groups very differently. For example, Stefanova (2009) estimated a RUM model using the *2005 Mid-Atlantic* data to assess the impact of vehicle access on beaches. Focusing on day-trips only, she estimated a welfare loss of $0.18 per trip for surf fishers while a gain of $1.60 per trip for non-surf fishers if vehicle access was discontinued across all sites. Cutter et al. (2007) estimates a RUM model using the *1998 Costa Rica* data to analyze the benefits of various on-site activities (swimming, sunbathing, hiking) in beach recreation. They valued several different beach attributes: temperature, kilometers of hiking trails, water/toilet facilities, table and grills, and an index of beach quality based on width, sand quality and water temperature Their findings indicated significant value differences based on activity type, with clear substitution effects when resource availability changed across beaches. For instance, a 75% reduction in hiking trails resulted in a $25 loss per trip for hikers and an $8 gain for swimmers and sunbathers.

The recent focus on offshore wind projects has also led to research that focuses on the impact of offshore wind turbines on beach recreation. Landry et al. (2012) employed a single-site contingent-behavior model using the *2009 North Carolina* data to determine the impact of offshore wind turbines on beach recreation. They combined thirty-one North Carolina beaches into a single site for analysis and found that placing wind turbines one mile offshore at all 31 beaches leads to a welfare loss of $17 per person per season, equivalent to approximately 1% of the total value of a trip during that season. In a more recent study, Parsons et al. (2020) used the RUM model with contingent-behavior data based on responses to visual simulations of wind power projects at seven different distances offshore (2.5-20 miles) in 275 east coast ocean beaches and discovered that the closer the projects are to shore, the greater their negative impact. For example, at 2.5 miles offshore, 29% of the sample said they would not go to the beach, compared to 5% at 20 miles offshore. These are the same data used in the present analysis. Fooks et al. (2017), Voltaire et al. (2017), and other studies also attempt different variants of travel cost model to estimate welfare change due to changes in beach characteristics in case of offshore wind turbine installation.

Dundas et al. (2020) studied effect of weather on recreational fishing in the Atlantic and Gulf Coast regions – from 2004-2009 using two level nested logit model with the 2004-2009 NOAA National Marine Fisheries Service (NMFS) angler intercept data and found declines in participation (up to 15 percent) and aggregate welfare loss (up to $312 million annually) over a range of predicted climate futures. Similarly, Toimil et al. (2018) analyzed travel cost data for 57 Northern Spanish beaches to estimate the per square meter welfare loss in beach recreation by 2100 under the RCP8.5 scenario-a high-emissions scenario for global warming, commonly referred to as "business as usual," which assumes continued increases in greenhouse gas emissions. They projected that the cumulative losses in beach recreation value by the end of the century would reach approximately €4752.54 million (97.5th percentile), representing 6.5% of the Asturian capital stock. Leggett et al. (2018) also used a travel cost RUM model in *2013 Southern California* data to estimate the welfare loss of beach recreation associated with marine debris at 31 beaches in Orange County, California. They reported that a 25% reduction in marine debris at all beaches could lead to a per capita seasonal benefit of $12.91. Wang et al. (2020) applied the Kuhn–Tucker model to estimate the welfare loss for surf and marsh fishing trips due to the closure of the three most frequented recreational sites in Louisiana. They calculated annual welfare losses ranging from $592 to $2,101 per traveler.

Like our study, many analysts have focused their welfare analyses on simple per trip access values. Access value represents the consumer surplus that individuals gain from accessing and enjoying beach amenities. It provides a comprehensive estimate of the total recreational benefits associated with a specific beach or a collection of beaches within a region. In an early application of the travel cost model to measure beach access value, Haab and Hick (1997) estimated the mean access value of $43 using multinomial logit model in RUM framework using the *1983 Chesapeake Bay* data. In a more advanced application Blackwell (2007) study stands out as the first Australian beach recreation study using the *2000 Australia Sunshine Coast* dataset. The research examined five beaches on Queensland's Sunshine Coast and Cottesloe Beach in Western Australia. Blackwell developed separate econometric models for residents and visitors, distinguishing primary trips from side trips and travel cost is calculated from the place where the side trip began for the latter case. The five beaches were treated as a single beach (stacked regression) and focused on the beach access value. Blackwell estimated access value for residents (day trips) at $17.41 per person per trip and for visitors at $107.75 per person per trip. Bin et al. (2005) used a similar single-site trip cost approach to determine the value of beach access for seven North Carolina beaches using *2003 North Carolina* data. They also used a stacked regression model with distinct models for day and overnight trips, allowing variation in constants and travel cost coefficients across beaches. The resulting beach access values per person per trip varied from $11 to $80 for day trips and $11 to $41 for overnight trips. Landry and Liu (2009) employed a variant of the single-site travel cost model known as the discrete factor method (DFM), which accounts for correlation across demand equations and incorporates unobserved heterogeneity. They estimated the per trip benefit to be between $164 and $167 using *2003 North Carolina* data. In contrast, Whitehead et al. (2008) used a simpler count data model based on the single-site travel cost approach, estimating the per person per trip value at $94 with same data. Blackwell et al. (2013) and Zhang et al. (2015) applied a similar approach to estimate the recreational value of Gold Coast beaches at $10.44 and $19.47 per person per trip, respectively, for single beach visits and per visitors. Additionally, several studies have explored measuring access value using various adaptations of the travel cost model, including works by Windle et al. (2017) and Roca et al. (2009).

Study Design & Model Specification

Travel Cost Random Utility Model

We consider separate models for day, short overnight, and long overnight trips. Again, a day trip is one where a person visits a site and returns home on the same day. A short overnight trip is a trip between 1 and 3 nights away (commonly a weekend) and a long overnight trip is more than 3 nights away. In so doing we are assuming these decisions are separable in the usual sense in consumer theory, which we think is reasonable give the different time constraints and features of these trips. Later we consider a theoretical set up where the three trip types are treated as equivalents in a unified model – the so called optimized out model (English et al. 2020).

The three models all have the same form, so we will layout one generic set up. We use a simple Random Utility Maximization model wherein an individual is choosing one beach from a set of 275 beaches on each choice occasion. Let beaches be indexed by i where there are I beaches ($i = 1, \ldots, I$) and let individuals be indexed by n where there are N people ($n = 1, \ldots, N$). We do not consider the participation decision in our model. The choice model is conditioned on knowing a person is making a beach trip on a given choice occasion (Train 1998).

Each beach j is assumed to give a person n an indirect utility V_{ni}. With a choice set of 275 beaches there are 275 utility possibilities of $\{V_{n1}, \dots, V_{nj}, \dots V_{n275}\}$. Following random utility theory, we assume the indirect utility is composed of an observable and an unobservable part. This gives $V_{ni} = U_{ni} + \varepsilon_{ni}$, where U_{ni} is the observable part, which is parameterized for estimation, and ε_{ni} is the unobservable and random part. Then, in random utility theory, we assume an individual n on a given choice occasion chooses the beach giving the highest utility. Under this theory an individual's utility on a given choice occasion is $Max\{U_{n1} + \varepsilon_{n1}, \dots, U_{ni} + \varepsilon_{ni}, \dots, U_{n275} + \varepsilon_{n275}\}$.

In its empirical form our model is $U_{ni} = \alpha_i + \beta_{ni} \cdot tc_{ni}$, where α_i is the alternative specific constant for beach i and tc_{ni} is the trip cost for person n to reach beach i. This is sometimes referred to as an alternative-specific constant (ASC) model. In an ASC model each alternative in the choice set is parameterized by a lone constant (α_i), which picks up the full effect of each beach (i.e., embodies all its salient attributes) relative to other beaches. An ASC model will in estimation perfectly rank order the beach in terms of visitation – the most visited site attaining the highest parameter and so forth. The model also includes a trip cost variable (tc_{ni}), which includes the travel and time cost of reaching of the beach and, in the overnight models, the cost of staying at the beach. We choose the ASC model, because our interest is estimating per trip access values and not attributes of the beach. Others have done the same (English, et al., 2018 and Parsons et al. 2021) Each beach utility now has the form $V_{ni} = \alpha_i + \beta_{tc} \cdot tc_{ni} + \varepsilon_{ni}$ and the value of a trip is $Max\{\alpha_1 + \beta_{tc} \cdot tc_{n1} + \varepsilon_{n1}, \dots, \alpha_i + \beta_{tc} \cdot tc_{ni} + \varepsilon_{ni}, \dots, \alpha_{275} + \beta_{tc} \cdot tc_{n275} + \varepsilon_{n275}\}$.

The error terms $\{\varepsilon_{n1,\dots,}\varepsilon_{ni,\dots,}\varepsilon_{n275}\}$ in this behavioral model make it stochastic, which gives rise to a probabilistic choice model and an expected utility for use in the welfare analysis. As is well documented in the discrete choice literature, assuming the error terms are independent and identically distributed type

I extreme value random variables the probability of person n choosing beach k is

$$(1) \qquad pr_{nk} = \frac{\exp\left(\alpha_k + \beta_{tc} \cdot tc_{nk}\right)}{\sum_{i=1}^{275} \exp\left(\alpha_i + \beta_{tc} \cdot tc_{ni}\right)},$$

which is the standard logit form. The type I extreme value distribution also gives an expected utility of trip of

$$(2) \qquad EU_n = ln \sum_{i=1}^{275} \exp\left(\alpha_i + \beta_{tc} \cdot tc_{ni}\right),$$

Which is often called simply the "log-sum". Using different assumptions about error term distribution one can arrive at different forms for the probability and expected utility with different properties (e.g., nested logit and mixed logit). We use the standard logit in our application. For more on the development and nuisances of random utility theory and discrete choice econometrics see Train (2009).

Equations (1) and (2) then are the building blocks for our analysis. We estimate the parameters in equation (1), 274 ASCs and one on travel cost, using maximum likelihood. (One ASC is dropped to normalize the model.) The likelihood function in log from is $\sum_{n=1}^{N} \sum_{i=1}^{275} y_{nk} \cdot \ln\left[pr_{nk}\right]$, where $y_{nk} = 1$ if person n visits beach k, and $= 0$ otherwise. The parameters α_i and β_{tc} are chosen to maximize the likelihood function – the set of parameters most likely to generate the set of outcomes realized in the data.

The per choice occasion value for any given site i then is the change in expected utility with the site in the choice set versus out of the choice set and then monetized by dividing by the coefficient on travel cost. Using equation (2) the per choice occasion access value for site 1 is

(3) $\Delta W_1 = \left\{ln \sum_{i=2}^{275} \exp(\alpha_i + \beta_{tc} \cdot tc_{ni}) - ln \sum_{i=1}^{275} \exp(\alpha_i + \beta_{tc} \cdot tc_{ni},)\right\}/-\beta_{tc}.$

Dividing by the travel cost coefficient monetizes the change in expected utility, because $-\beta_{tc}$ is the marginal utility of income in the model. As shown by Bockstael and McConnell (2007) and Haab and McConnell (2002), equation (3) can be expressed as

(3') $\Delta W_1 = \ln(1 - pr_{n1})\,/-\beta_{tc}$

In this form it is easy to see that the larger the probability of visiting a site (pr_{n1}), the larger the choice occasion value. As the probability approaches 0, the choice occasion value goes to 0. The per trip value for site 1 then is

(4) $\Delta w_{n1} = \{\ln(1 - pr_{n1})\,/-\beta_{tc}\}/pr_{n1}.$

This follows since $\ln(1 - pr_{n1})\,/-\beta_{tc}$ is the choice occasion value and pr_{nk} is the expected "quantity" of trips taken during the choice occasion. Each site has some non-zero probability of being visited. For small values of pr_{n1}, $\ln(1 - pr_{n1}) \approx pr_{n1}$ (Haab and McConnell 2002, p.229 and MacNair 2022). In this case, the per trip value is

(4') $\Delta w_{n1} = \{\ln(1 - pr_{n1})\,/-\beta_{tc}\}/pr_{n1} \approx \{pr_{n1}/-\beta_{tc}\}/pr_{n1} \approx 1/-\beta_{tc}$

The same calculation can be made for choice occasion access value to multiple sites. So, for example if sites 1, 2, and 3 were closed equation (3') becomes $\Delta W_{1,2,3} = \ln(1 - pr_{n1} - pr_{n2} - pr_{n3})\,/{-\beta_{tc}}$ and for per trip values one divides by $pr_{n1} - pr_{n2} - pr_{n3}$.

This result should look familiar to practitioners of single site recreation demand models where the common seasonal consumer surplus has the form $\frac{x_n}{-\beta_{tc}}$, where $x_n$is the predicted number of trips during the season and β_{tc} is the coefficient on trip cost. In that model the per trip value for the site under study is $\frac{\frac{x_n}{-\beta_{tc}}}{x_n} = \frac{1}{-\beta_{tc}}$. By analogy and using site 1, the "occasion" surplus (numerator) in a RUM Model is $\ln(1 - pr_{n1})\,/{-\beta_{tc}}$ and the "expected number of trips to the site" (denominator) is pr_{n1}.

In our application, we estimate separate models for day, short overnight, and long overnight trips. As noted earlier these are treated as separable commodities and so are estimated as three separate models giving us three sets of ASCs and three β_{tc} coefficients. We will discuss the details of each data set in a later section. We will also consider a model where the three trip types are analyzed in a single unified model following the logic of English et al. (2020). And finally, to understand the importance of various beach attributes on choice we estimate a second-stage model with our estimated ASCs. This follows the work of Murdock and Timmons (2006) and Melstrom and Jayasekera (2017). This formulation controls for the unobservables in choice and gives us additional policy-relevant findings over variables such as beach width and vehicle access.

3. Beach and Respondent Data

The Beaches

Our analysis covers the beaches shown in Figure 1. These range from Massachusetts to South Carolina and include 275 beaches. The beaches were defined largely "as they are recognized by beach goers", usually the coastal community neighboring the beach (e.g., Rehoboth Beach, Wrightsville Beach, Ocean City, etc.). The beaches under consideration extend nearly 995 miles along the coast and cover nine states. North Carolina comprises nearly one third of this length. The beach count by state is reported in Table 2. The median beach length is 4,000 meters and the median width is 50 meters. The distribution of lengths and widths are shown in Tables 3 and 4. The widest beaches are in New Jersey (e.g., Wildwood (523 meters) and Wildwood Crest (284 meters)). The minimum beach width is zero due to some rocky shoreline. All the smaller beaches are in Rhode Island (e.g., Point Judith, Deep Hole Beach).

Figure 1: Beach Area Included in the Analysis

Table 2: Count of Beaches by State

State	Number of Beaches	Percent
New Jersey	51	19%
Massachusetts	49	18%
Rhode Island	49	18%
South Carolina	42	15%
North Carolina	40	15%
New York	23	8%
Delaware	14	5%
Virginia	5	2%
Maryland	2	1%
Total	**275**	**100%**

Table 3: Count of Beaches by Length

Beach Length (meters)	Number of Beaches	Percent

0-1600	54	20%
1601-3200	60	22%
3201-4800	44	16%
4801-6400	37	13%
6401-8000	24	9%
8001-9600	56	20%
Total	**275**	**100.00%**

Table 4: Count of Beaches by Width

Beach Width (meters)	Number of Beaches	Percent
0-40	99	36%
41-80	136	49%
81-120	29	11%
121-160	11	4%
Total	**275**	**100.00%**

The beaches vary in character from small local natural beaches (e.g., West Chatham, MA) to large, developed beaches with a tourist focus (Myrtle Beach, SC, Atlantic City, NJ, and Ocean Beach, MD). Table 5 is a frequency distribution of beaches by degree of development. Since most beaches have diversified in their development, we have classified them as primary and secondary, where primary is the predominate type of development and secondary is the second most common. The beaches in the region are mostly developed but the development is usually characterized by low lying development with at most some higher rise buildings. A few beaches, of course, have taller structures, usually hotels, casinos and other amusement facilities. Finally, Table 6 shows some of the salient beach characteristics of our 275 beaches. Nearly 40% of the beaches feature some type of natural or green space as a park or park within the beach area. Almost one in four are exclusively parks (e.g., Delaware Seashore, Cape Hatteras National Seashore, NC, and Assateague Island National Seashore, MD, VA). Others, like Cape May, NJ have notable parks as part of their beach areas. There are many well know boardwalk beaches including Rehoboth, DE, Myrtle Beach, SC, and Wildwood, NJ. About 17% of the beaches are boardwalk beaches and only 4% have amusement facilities. Some of the latter beaches are Seaside Heights, NJ, Coney Island, NY, and Carolina Beach, NC. Shore fishing is common on many of the beaches and many have 4-wheel-drive vehicle access (14%) and/or a fishing piers (14%). In some cases, the fishing pier(s) is a dominate feature on shore such as on Virginia Beach, VA. Several of the beaches (8%) require boat to access the beach.

Table 5: Count of Beaches by Level of Development

	Primary Development		**Secondary Development**	
	Number of Beaches	Percent	Number of Beaches	Percent
No or very sparse fixed building	111	40%	110	40%
Development consisting exclusively of low lying (< 4-5 stories) structures	107	39%	122	44%
Dominated by low lying structures with some taller structures present	50	18%	39	14%
Predominantly structures taller than 4-5 stories	7	3%	4	1%
Total	**275**	**100%**	**275**	**100%**

Table 6: Beach Characteristics (yes = 1, no = 0)

	Number of Beaches	Percent
Federal, State, or Local Park	64	23%
Green Area or Park Within	40	15%
Boardwalk	46	17%
Fishing Pier	38	14%
Vehicle Access	39	14%
Seawall	11	4%

Amusements	12	4%
Ferry or boat access only	22	8%

Respondents

We sampled households from the 20 states nearest the beaches on the East Coast just described and asked about their recreation/vacation trips to the 275 beaches in past year. Figure 2 shows the states sampled. We used GfKs Knowledge Panel, which is a probabilistic-based panel of survey respondents and widely accepted as a gold-standard among survey researchers. The survey was done in 2015 asking respondents about beach trips in 2014. The survey was primarily designed to analyze the effect of offshore wind power projects on beach visitation and so included a large contingent behavior section on the reaction of beachgoers to possible wind projects. These data have been analyzed elsewhere (Parsons et al. (2020) and Parsons and Yan (2021). In this study we focus on the beach visitation data.

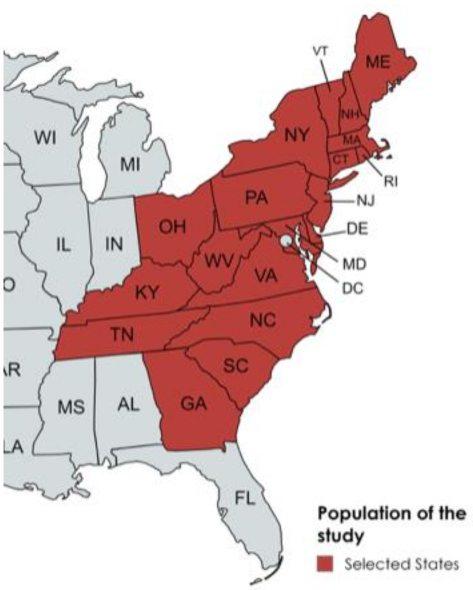

Figure 2: States Sample for Beachgoers

The survey was done in two phases. The first phase was a general population survey in which we sampled 500 people to learn about participation (beach going) rates and how the general population might differ from the beach goer population. Respondents were drawn randomly but drawn so that the share of people from each state matched the proportions from the actual population. The participation rate (share who visited one of 275 beaches) was 35% --174 of the 500 respondents. The second survey was an oversample survey where respondents were screened for participation – only respondents who had visited an East Coast beach in 2014 were included. The oversample sample size is 1,551. The two surveys together provided a total of 2,051 completed interviews with 1725 beachgoers. Two sets of survey sample weights were developed by GfK. One set is for the full sample of 2,051 and weights observations such that it is reportative of the general population – heavily weighting the non-participants who were heavily under sampled. The other set of is for the beachgoer sample of 1,725. It weights observation such that beachgoers from the general population and oversample samples can be combined and mimic a random draw from the beachgoers in our 20 states.

Table 7 shows the basic demographics of the beachgoer and the general population. Both columns here and in the upcoming tables are weighted such the sample mimics the beach goer and general population. So, for example, the general population numbers are weight to reflect the 35% participation rate from the population. The general population demographics align well with U.S. Census data 2014 after weighting, as they should be by construction. Notice in the table that beachgoers are slightly younger, more educated, more likely to work full time, and have higher income. Table 8 shows the frequency of beach trips by beachgoers and the general population. So, 57% of the beach goer population takes between 1 to 5 trips in a year, and 21% takes more than 5 trips in a typical year. The remaining 22% go less often than once a year. In the general population 39% report never or almost never taking beach trips and among those taking a trip most (25%) take between 1 and 5 trips. Finally, we asked people to report the way they most frequently use the beach while on trip. The results are show in Table 9: 37% reported activities in the sand, such as sunbathing, walking, reading, playing etc., 28% reported activities in the water like swimming, surfing, wading, etc., and 25% reported activities on the nearby boardwalk such as shopping, site seeing. Only 4% reported surf fishing. Table 10 shows the number of different beaches visited by respondents. About half visited only one beach and 85% visited three or fewer.

Table 7: Sample Demographics: Beachgoers and General Population

	Beachgoers (n=1725) Percent	General Population (n=2050) Percent
Age		
18-24 years	11.9%	9.6%
25-34 years	19.7%	18.0%
35-44 years	19.6%	17.9%
45-54 years	15.6%	16.0%
55-64 years	18.6%	20.7%
65-74 years	11.3%	12.0%
75+ years	3.3%	5.9%
Education		
Less than High School or GED	6.9%	11.8%
High School or GED	25.8%	31.4%
Some College or Assoc. Degree	26.9%	25.6%
College or Higher	40.4%	31.3%
Employment Status		
Full time	47.0%	40.0%
Part time	8.0%	8.0%
Retired	19.0%	23.0%
Other	21.0%	22.0%
Unemployed	5.0%	7.0%
Household Income (per year in 2015 USD)		
$0 – $24.9K	10.08 %	17.87 %
$25K – $49.9K	17.78 %	21.7 %
$50K – $74.9K	15.04 %	18.22 %
$75K – $99.9K	20.04 %	14.88 %
$100K – $149.9K	24.8 %	18.67 %
$150K + per year	12.26 %	8.65 %

Table 8: Frequency of Beach Visits by Sample in a Typical Year

	Beachgoers (n=1725) Percent		General Population (n=2050) Percent	
Frequency of Beach Visits	Number of Respondents	Percent	Number of Respondents	Percent
More than 5 times per year	366	21%	162	8%
Between 1 to 5 times per year	988	57%	510	25%
Once every 2 years	206	12%	224	11%
Once every 3 to 5 years	73	4%	181	9%
Less than once every 5 years	57	3%	164	8%
Never or almost never	35	2%	809	39%
	1725	**100%**	**2050**	**100%**

Table 9: Most Important Activities During Beach Visits

Most Important Activities	**Beachgoers**	**Percent of the Sample**
Activities on the Sand	632	37%
Activities on the Water	480	28%
Activities on the Boardwalk/Nearby	433	25%
Shore Fishing	62	4%
Others	114	6%
Total	**1721**	**100%**

Table 10: Number of Beach Visited by Beachgoers

Number of Visited Beaches	**Frequency**	**Percent**
1	855	49.6%

2	368	21.3
3	231	13.4
4	94	5.4
5	63	3.7
6 to 10	99	5.7
More than 10	15	0.9
Total	**1725**	100%

The models discussed in the next section are developed using a series of questions on the number of day, short overnight, and long overnight trips taken over previous year (2014). A short overnight trip is any overnight trip with four nights or less away from home (usually weekend trips). The average length of the short overnight trip in the sample is 2.1 nights. A long overnight trip is any trip more than 4 nights away (usually week-long vacations). Its average length is 6.1 nights away. Finally, 26.3% of the respondents took only day trips, 20.6% took only short overnight trips, 22.5% took only long overnight trips, and 30.7% took some combination of the three trip types.

Table 11 shows the distribution of trips by destination state. Table 12 shows the absolute count of trips when inflated to the population using a simple population-size/sample-size weight. The count of trips to beaches on the East Coast is estimated at 118 million. Our data excludes people from states and countries outside of the study area we discussed earlier, so it is an understatement. We see in Table 11 that the New Jersey has the most trips with over 31 million in 2015. This is followed by South Carolina with 17 million trips, and then North Carolina and Massachusetts 14.5 million each. The composition of trip types varies considerably across the states. New Jersey and New York have the largest share of day trips, and the Carolinas have the largest share of overnight trips. This is consistent with South and North Carolina's reputation as tourist destination and having smaller nearby population centers relative to the northern states. When we look at the numbers in terms of beach days in Table 13 the Carolinas rise in the ranking due their number of overnight trips. The total number of beach days in 2015 is 224 million. Although long overnight trips account for the fewest trips in the year, they account for most of the beach days (nearly 100 million) due to length of stay.

Table 11: Distribution Trips by Destination State

State	Day Trips (Percent)	Short overnight Trips (Percent)	Long Overnight Trips (Percent)
New Jersey	31%	23%	10%
New York	16%	16%	6%
South Carolina	10%	16%	32%
North Carolina	11%	13%	19%
Massachusetts	13%	11%	10%
Rhode Island	9%	3%	2%
Delaware	4%	8%	5%
Virginia	3%	6%	9%
Maryland	4%	5%	7%
Total	**100%**	**100%**	**100%**
Number of trips	**4,096**	**1,229**	**800**
Number of days on beach	**4,096**	**2,581**	**5,040**

Table 12: Trips by Destination State and Percent from Out of State (Millions, Percent)

State	Day Trip	Out of State	Short Overnight Trips	Out of State	Long Overnight Trips	Out of State	Combined Trips
New Jersey	24.11	22%	5.45	56%	1.52	75%	31.08
New York	12.74	4%	3.79	6%	0.94	24%	17.47
Soth Carolina	8.25	19%	3.70	64%	4.95	95%	16.90
Massachusetts	10.48	9%	2.59	41%	1.56	59%	14.63
North Carolina	8.52	16%	3.06	37%	2.93	66%	14.51
Rhode Island	7.11	21%	0.79	82%	0.34	72%	8.24
Delaware	2.79	76%	1.85	84%	0.73	82%	5.38
Maryland	2.79	13%	1.13	60%	1.09	72%	5.01
Virginia	2.23	19%	1.34	59%	1.36	76%	4.93
Total	**79.02**		**23.71**		**15.43**		**118.16**
Beach days	**79.02**		**49.79**		**97.20**		**226.02**

Finally, the trip cost calculation is a key component in modeling recreational behavior. It is, in effect the price of trip to each site in a respondent's choice set. Given that our model accounts for three types of trips—day, short overnight, and long overnight—the calculation of travel costs varies accordingly. For day trips, only transportation and related expenses are considered. However, for short and long overnight stays, additional costs for lodging, meals, and incidental expenses are incorporated to accurately reflect the increased expenditures associated with extended stays. Time cost is a critical component of total travel cost, representing the opportunity cost of time spent on trips. Commonly, travel cost models value time at one-third of an individual's potential earnings, based on a standard approach initiated by Cesario (1976) and derived from Beesley's (1973) study on commuter choices. We use one-third of wage and use reported yearly income divided by 2080 (days worked in a year) as a proxy for wage. This is standard in the literature (Parsons 2017). Trip cost for individual n visting beach i in our model is

$$Trip\ Cost_{ni} = Transit\ Cost_{\ ni} + Time\ Cost_{ni} + Overnight\ Cost_{ni},$$

where,

$$Transit\ Cost_{ni} = \{\tau_{ni} dist_{ni} + toll_{ni} + fees_{ni} + ferry_{ni}\} \cdot share_n$$

$$Time\ Cost_{ni} = .33 \left\{\frac{Income_i}{2080}\right\} \cdot time_{ni}.$$

τ_{ni} is the cost per mile cost for individual n to reach beach i, $dist_{ni}$ is round trip distance, $toll_{ni}$ is the cost of highway tolls, $fees_{ni}$ is the cost beach access on some of the beaches, $ferry_{ni}$ is the cost of the ferry beaches with boat access only or if taking a ferry is cheapest route (e.g. Cape May Ferry), and $share_n$ the self-reported share of expenses paid on a typical trip (reported separately for day, short overnight, and long overnight trips). $Income_i$ is the respondent annual income provided by GfK and $time_{ni}$ is the round-trip time to reach the site. $Overnight\ Cost_{ni}$ include lodging and meal expense and is computed using by per diem rates for lodging, meals, and incidental expenses, sourced from the General Services Administration (GSA) for each zip code area. We assume an average duration of short overnight trips (2.1 days) and long overnight trips (6.3 days). No such cost is included for day trips.

Travel distances to 275 beach destinations were computed for each respondent using PC*Miler Spreadsheets software, based on round-trip calculations from their residential addresses (specified by 5-digit zip codes) to the geographical midpoint of each beach. The route type was set to "practical" in the PC*Miler software. Driving cost for each beach trip was determined by multiplying the calculated distance by the per-mile operating cost of vehicles, as reported in the 2015 AAA Driving Costs Report. Additionally, tolls, ferry fees, and driving times were also calculated using PC*Miler, employing the same origin and destination parameters as the distance calculations. Table 13 breaks the costs down by component for the chosen beach for an all beaches in the choice set for each trip type and includes a simple distance variable as well. For example, the average distance to chosen beaches in the day trip data set is 89 miles and for all beaches in the choice set is 815 miles. For short overnight trips these numbers are 410 miles and 854 miles, and for long overnight trips are 752 miles and 937 miles.

Table 13: Mean Trip Cost to Chosen Site and All Sites

	Day Trip		Short Overnight Trips		Long Overnight Trips	
	Chosen Site	All Sites	Chosen Site	All Sites	Chosen Site	All Sites
Total Trip Cost	**$39.8**	**$304.4**	**$540.4**	**$724.7**	**$1468.1**	**$1578.0**
Transit Cost	$25.0	$178.3	$80.9	$182.8	$141.7	$200.9
Time Cost	$14.7	$126.0	$69.9	$140.9	$106.5	$128.4
Distance	89 mi	815 mi	410 mi	854 mi	752 mi	937 mi

Note: Lodging and Meal cost not included here.

Results

The regression results are shown in Tables 14 through 16 separated by trip-length type. In each case we report the trip cost coefficient and the ASCs for the 15 beaches with the largest ASCs. The last line shows the ASC range for the remaining beaches. We have excluded Bethany Beach Delaware for normalization purpose. So the results will be relative to it. The results are as expected. The shorter the trip length, the greater the trip cost coefficient. The day trip coefficient is .052, the short overnight coefficient is .011, and long overnight coefficient is .003. So, day trippers are the most sensitive to trip cost and the vacationers are least sensitive. This implies a lower marginal utility of incomes for the longer trips and hence higher per trip and access values as we will see shortly.

The top 15 ASCs for day trips are all from Massachusetts and Rhode Island beaches. So, after controlling for trip cost these are most popular beaches for day trips. The top ASCs for the Short Overnight Model are Long Beach, NY, Myrtle Beach, SC, Ocean City, MD, and Virginia Beach, VA – four well-known beaches geared toward overnight trips with lodging/accommodations. Hilton Head and Atlantic City also rank high as do, again, several beaches on Martha's Vineyard. In the Long Overnight Model, Myrtle Beach, SC, Ocean City, MD, and Virginia Beach, VA again show up among the top four and then many other beaches in the Carolinas such as Duck and Kitty Hawk, NC.

Table 14: Day Trip RUM Model

Variables		Coef	Std Err
Trip Cost		-0.052	0.006
asc17	Abnecotants Isand – Nuntucket, MA	9.705	1.436
asc204	Aquinnah – Martha's Vineyard, MA	8.978	0.984
asc232	Siasconset – Nuntucket, MA	8.508	1.368
asc241	Block Island, RI	8.333	0.883
asc238	Tom Nevers/New South Rd – Nuntucket, MA	8.216	1.368
asc214	Esther Island, MA	8.134	1.376
asc218	Katama – Martha's Vineyard, MA	8.112	1.159
asc219	Madaket – Nuntucket, MA	7.791	1.368
asc237	Surfside Beach/Fisherman's Beach – Nuntucket, MA	7.715	1.201
asc28	West Chatham, MA	7.298	1.483
asc220	Miacomet – Nuntucket, MA	7.220	1.400
asc233	South Beach – Martha's Vineyard, MA	7.171	0.987
asc205	Chilmark – Martha's Vineyard, MA	6.689	0.996
asc265	Cape Cod National Seashore – Eastham, MA	6.330	1.138
asc268	Cape Cod National Seashore – Provincetown, MA	6.049	1.064
Range of other ascs		[5.506 :-0.596]	[1.131:1.313]
Observations (Trips)		9976	

Table 15: Short Overnight Trip RUM Model

Variables		Coef	Std Err
Trip Cost		-0.011	0.001
asc89	Long Beach, NY	6.748	1.028
asc183	Myrtle Beach, SC	6.326	0.471
asc16	Ocean City, MD	6.245	0.358
asc203	Virginia Beach, VA	5.979	0.379
asc232	Siasconset – Nuntucket, MA	5.624	0.922
asc173	Hilton Head Island, SC	5.620	0.436
asc33	Atlantic City, NJ	5.579	0.321
asc218	Katama – Martha's Vineyard, MA	5.575	0.634
asc205	Chilmark – Martha's Vineyard, MA	5.562	0.698
asc204	Aquinnah – Martha's Vineyard, MA	5.560	0.591
asc237	Surfside Beach – Nuntucket, MA	5.559	0.898
asc120	Nags Head, NC	5.418	0.529
asc233	South Beach – Martha's Vineyard, MA	5.416	0.613
asc116	Kill Devil Hills, NC	5.157	0.595
Range of other ascs		[5.079 : -1.5]	[0.0461 : 1.029]
Observations (Trips)		2967	

Table 16: Long Overnight Trip RUM Model

Variables		Coef	Std Err
Trip Cost		-0.003	0.000
asc183	Myrtle Beach, SC	7.263	0.595
asc16	Ocean City, MD	6.994	0.510
asc203	Virginia Beach, VA	6.797	0.496
asc171	Fripp Island, SC	6.108	0.865
asc204	Aquinnah – Martha's Vineyard, MA	5.941	1.059
asc116	Kill Devil Hills, NC	5.839	0.677
asc173	Hilton Head Island, SC	5.664	0.490
asc107	Duck, NC	5.545	0.546
asc117	Kitty Hawk, NC	5.456	0.933
asc186	North Myrtle Beach, SC	5.451	0.500
asc89	Long Beach, NY	5.378	1.095
asc106	Corolla, NC	5.318	0.557
asc169	Edisto Island, SC	5.137	0.854

asc182	Murrels Inlet, SC	5.115	0.680
asc265	Cape Cod National Seashore – Eastham, MA	5.016	0.588
Other asc		[5.003 :-0.017]	[0.500 : 1.087]
Observations (Trips)		1975	

Next, we simulated the welfare loss for closing all beaches in each state for one year. Since there is no temporal substation in our model this can be scaled up or down factionally to get losses for a closure for months or even weeks. While this is not ideal, it is common in most RUM Models used in damage assessments. The results are shown in Table 17. The choice occasion values are per person are calculated using equation (3) or (3'). The time period for each is the relevant period for the trip length – day, short overnight, and long overnight. Since in a RUM Model ever respondent has a positive probability, these values average over all respondents in the analysis. No doubt, many live far from the beaches in the state in question and so have near zero values. The average values as shown tract the popular beach reasonably closely as we would expect. The choice occasion values are largest for New Jersey, New York, and the Carolina, for example. Day trip choice occasion values range from $0.50 to $7. Short and long overnight range from $2 to $34 and $8 to $123. When these values are scaled up the population and all choice occasions over a year, we get the aggregate welfare losses shown in the last column. These can be thought of extreme cases where all beaches in each state are closed for one year. And, as mentioned above may be scaled – divide by 12 to arrive at the loss for one month, which will be averaged over the months in a year. The aggregate losses, surplus measures, range from $216 million to over $3 billion depending on the state.

Table 17: Mean Per Occasion and Aggregate Welfare Loss of Closing All Beaches by State

Closing State	**Day Trip** (2015 USD)	**Short Overnight Trip** (2015 USD)	**Long Overnight Trip** (2015 USD)	**Aggregate Loss** (million USD)
New Jersey	$7.34	$33.97	$123.84	$3,296.37
New York	$3.35	$15.50	$56.51	$1,504.25
South Carolina	$2.94	$13.63	$49.67	$1,322.05
North Carolina	$2.64	$12.20	$44.48	$1,183.95
Massachusetts	$1.89	$8.75	$31.88	$848.58

Rhode Island	$1.47	$6.78	$24.73	$658.29
Maryland	$0.57	$2.66	$9.69	$258.00
Virginia	$0.52	$2.39	$8.70	$231.49
Delaware	$0.48	$2.23	$8.13	$216.51

Values from Table 17 can be turned into per trip values by using equation (4), which divides the choice occasion values by the probability of taking a trip. Per occasion values are used for estimating total welfare loss in presence of beach closures policy though out the a state. These are unit values that are widely used in benefit transfer and damage assessment cases where the parties agree to the number of lost trips due to a spill and unit surplus value to monetize that loss. These per trip values are, as expected, stable over the sample. Table 1 shows per trip value estimates from several other studies. There is a broad range of estimates there, but the estimates here seem more or less in line with recent results. For example, in a Gulf Coast study English et al. (2020) have per trip values for day trips at $12 (ours is $19) and for overnight trips, without distinguishing weekend and longer trip, has $435 (ours are $91 and $333). And, in a California study Leggett et al. (2018) have day trip values around $10 but getting as high as $35 under different specifications.

English et al. (2020) and Lupi et al. (2020) argue that trip of different length should not be treated as different "commodities" as we have thus far. Instead, they argue that trips of longer length are merely repacking of the recreation experience to make the trip possible. In their model each person "optimizations out" all the on-site activities like sunbathing, visiting restaurants etc. and how long they stay. After optimizing all these features, a site utility is rendered and the person decides whether or not to take a trip and how many to take. In this way trips are customized by each person, choose the optimal "bundle" for them. It also implies that the cost or price of the trip includes only travel and time cost required to reach the site. Any other cost (lodging etc.) is net of any utility the site provides and so will be embodied in the site constant. Another argument for combining trips is the practical matter that overnight trips do not naturally "fit" the travel cost model, in that trips are intended to be "get-aways" and so near sites may be undesirable. Hence, these sites, which have low travel cost will contaminate the results by signaling that low cost are not a good think and bias the trip cost coefficient. Figure 3 shows this effect, where long overnight trips and to limited extent short overnight trips avoid near sites – the density of trips over short distances is lower. When the trips are combined the down slope on distance emerges.

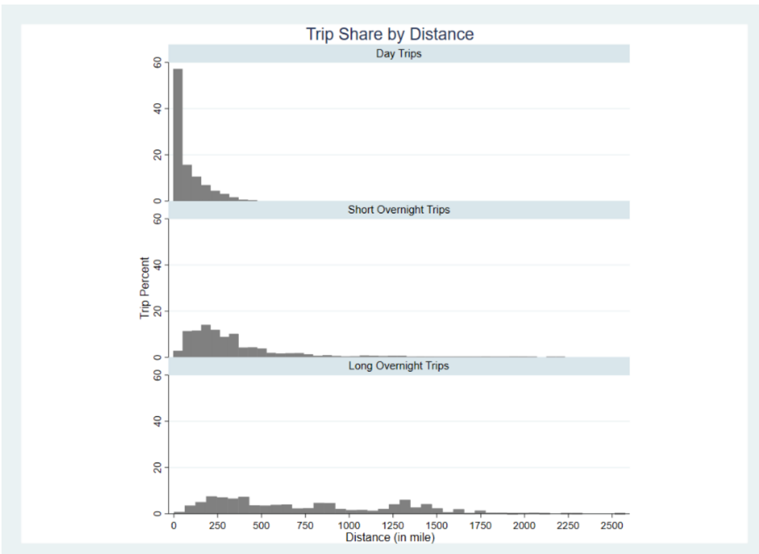

Figure 3: Trip Density by Distance

English et al. (2020) goes on to consider models for separate day and overnight trips like ours, which are conventional, with models that combine trips and then compare results. We do the same. Our results are shown in Table 18. The per trip value is about $76 so, close to but less than the short overnight trip and significantly greater than the day trip value of $19, which make up the lion's share of the trips. Table 19 reports the aggregate values. In our case aggregate values are lower when the unified trip theory is applied. We have presented two sets of values for the separated models – one that includes on-site costs and one that does not. In both cases, the combined models give lower estimates. Interestingly, English find the reverse. There is no clear a priori reason to believe one or the other outcome. It will depend on the count on nature of trip profiles.

Table 18: Combined Trip RUM Model

Variables	Beach, State	Coef	Std Err
Trip Cost		-0.013	0.001
asc17	Abnecotants Isand - Nuntucket, MA	6.432	0.793
asc183	Myrtle Beach, SC	6.333	0.569
asc16	Ocean City, MD	6.041	0.463
asc203	Virginia Beach, VA	6.020	0.527
asc173	Hilton Head Island, SC	5.876	0.547
asc28	West Chatham, MA	5.845	0.982
asc170	Folly Beach/Folly Island - Charleston, SC	5.431	0.561
asc89	Long Beach, NY	5.419	0.763
asc232	Siasconset - Nuntucket, MA	5.366	0.898
asc162	Capers Island, SC	5.354	1.064
asc116	Kill Devil Hills, NC	5.347	0.720
asc204	Aquinnah - Martha's Vineyard, MA	5.317	0.583
asc236	Squibnocket - Martha's Vineyard, MA	5.313	1.123
asc33	Atlantic City, NJ	5.309	0.451
asc176	Isle of Palms, SC	5.223	0.700
Range of other ascs		[5.218 : 0.000]	[0.926 : 0.844]
Observations (Trips)		14918	

Table 19: Aggregate Welfare Loss Comparison of Closing All Beaches in a State keeping other open from different models (in million 2015 USD)

Closing State	Total Loss from Separate Trip Models	Total Loss from Separate Trip Models (without meal & lodging cost)	Total Loss from Combine Trip Model
New Jersey	3296.37	1380.33	1980.85
New York	1504.25	1010.46	903.93
South Carolina	1322.05	718.15	794.44
North Carolina	1183.95	639.79	711.46
Massachusetts	848.58	439.76	509.93
Rhode Island	658.29	262.67	395.58
Maryland	258.00	546.98	155.04
Virginia	231.49	394.55	139.11
Delaware	216.51	247.07	130.11

Finally, we consider a second-stage model following Murdock (2006) wherein we regressed our ASC estimates on beach characteristics. This allows us to consider the relative importance of the attributes and give us parameters that may be of policy relevance. The results are shown in Table 20 and variables are defined in Table 21. Beach length is good predictor of beach visitation. The larger beaches have more space and in many cases are nearly a collection of smaller beaches, so this is no surprise. Width also works as expected. Respondents prefer wider beaches – 50 to 150 meters is strongly preferred to < 50 meters but > 150 is at best only weakly preferred to 50 to 150. So there appears to be an optimum. Also, while the signs make sense the statistical significance is not always there. Amusements is a good predictor for all trip types and boardwalk appears to matter for day trips but no overnight trips. This is perhaps explained by many of the overnight beaches being more of the cottage-style.

Table 20: Second Stage OLS Murdoch Regression

Variables	**Day Trip ASCs**		**Short Overnight Trip ASCs**		**Long Overnight Trip ASCs**		**Combine Trip ASCs**	
	Coef	Std Err	Coef	Std Err	Coef	Std Err	Coef	Std Err
Log Length	0.54***	0.17	0.46***	0.13	0.41***	0.15	0.49***	0.14
Width 50 - 149	0.66	0.57	1.23***	0.44	1.00	0.78	0.75	0.47
Width 150 - 249	0.71	0.63	1.16**	0.49	0.82	0.82	0.76	0.51
Width over 250	0.54	0.67	1.80***	0.53	1.12	0.84	0.68	0.55
Amusements	1.32**	0.61	1.31***	0.44	1.50***	0.47	1.34***	0.51
Boardwalk	0.72*	0.44	-0.01	0.35	-0.57	0.39	0.34	0.37
Development 1	0.11	0.26	0.26	0.20	0.60***	0.22	0.26	0.21
Development 2	0.42*	0.25	0.49**	0.19	0.06	0.21	0.35*	0.20
Fishing Pier	0.48	0.38	0.67**	0.27	0.67***	0.30	0.52*	0.31
Park	0.52	0.35	-0.07	0.28	0.28	0.32	0.07	0.28
Park Within	0.76*	0.41	0.33	0.34	-0.04	0.37	0.31	0.34
Remote Beach	1.32***	0.42	0.86***	0.32	0.22	0.38	0.45	0.33
Vehicle Access	0.64*	0.39	0.40	0.30	0.33	0.34	0.68**	0.32
MA	3.68***	1.34	0.78	0.96	-0.08	1.00	1.17	1.13
RI	2.43*	1.40	-0.26	1.03	-1.64	1.10	0.12	1.18
NY	0.10	1.36	-0.20	0.99	-0.25	1.03	-0.75	1.15
NJ	0.95	1.30	-1.70*	0.94	-2.35***	0.97	-0.57	1.10
DE	0.18	1.41	-0.79	1.01	-1.70	1.05	-0.05	1.18
VA	0.09	1.48	0.09	1.06	-1.18	1.13	0.41	1.25
NC	-0.32	1.30	-0.56	0.94	-1.33	0.96	0.62	1.10
SC	1.07	1.32	-0.19	0.95	-0.53	0.98	1.47	1.11

Constant	-4.87**	2.16	-3.17**	1.60	-1.27	1.86	-3.09*	1.77
n	220		190		161		236	
R-squared	0.42		0.52		0.50		0.42	

Standard errors in parentheses

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

Table 21: Variable Definition of Beach Characteristics Effect

Variable	Definition
Log Length	Natural logarithm of beach length
Width 50 - 149	=1, if beach width is more than 50 feet and less than 149 feet
Width 150 - 249	=1, if beach width is more than 150 feet and less than 249 feet
Width over 250	=1, if beach width is greater than 250 feet
Amusements	=1, if amusements are present at the beach
Boardwalk	=1, if boardwalk is present at the beach
Development[6]	0 – Areas that have no or very sparse fixed buildings, 1 – Areas that have development consisting exclusively of low lying (<4-5 stories) structures, 2 – Areas that are dominated by low lying structures with some taller structures present, 3 – Areas that are predominantly structures taller than 4-5 stories. The average development is 0.77, and 146 out of 275 beaches are above average
Fishing Pier	=1, if a fishing pier is present at the beach
Park	=1, if beach is a state park
Park Within	=1, if part of the beach is a state park
Remote Beach	=1, if a beach can be accessed only by a boat
Vehicle Access	=1, if driving on the sand is permitted
MA, RI, NY, NJ, DE, MD, VA, NC, SC	=1 if the beach is in the state

Conclusion:

Our findings suggest that the recreational value assigned to different beaches varies according to the duration of the visit. Specifically, as recreationalists plan to extend their stays from a single day to several nights, their willingness to incur higher travel costs increases, ranging from approximately $19 to $333. This trend is also reflected in the average distances to the selected beaches: while the average distance for day trips is 89 miles, this extends significantly to 752 miles for longer overnight stays. This indicates that overnight trips, even excluding meal and lodging expenses, tend to generate greater value compared to day trips. The rationale behind this trend is that visitors are more inclined to travel further as the duration of their stay increases.

Furthermore, our analysis using a separate trip model reveals distinct beach preferences based on the intended length of stay. For day trips, beaches in Massachusetts are predominantly chosen, likely due to their proximity and accessibility. In contrast, for short overnight stays, typically lasting a few nights over a weekend, beaches in well-known locations such as Ocean City, Atlantic City, and Virginia Beach are preferred, which offer extensive amusement facilities. For longer stays, spanning a week or more, the quieter beaches of North Carolina and South Carolina emerge as preferred destinations, underscoring a distinct shift in visitor preferences towards more tranquil environments for extended vacations.

Through the application of various models within the same analytical framework, our research demonstrates that the estimated welfare derived from beach recreation can significantly vary based on the modeling assumptions employed, particularly those regarding the length of trips. By modeling trips ranging from a single day to multiple days, allowing for increased trip length enhances the ability of recreationists to choose an optimal bundle of different length trips. This integration of multiple trip lengths into a combined trip model probably facilitates greater substitution opportunities, which tends to lower the overall welfare estimates compared to models that estimate different trip lengths separately and then aggregate the welfare outcomes. Conversely, employing separate trip models somehow imposes certain restrictions on site choice preferences, as indicated by our findings reveal a distinct set of beaches preferred for varying trip lengths. As they limit the substitution possibilities between different trip types and consequently reflect a higher valuation for specific site attributes tailored to the trip's duration.

Excluding the meal and lodging expenses from the travel cost components for overnight trips, as commonly recommended in conventional literature—under the assumption that these costs are optimized out during the trip selection process—results in a higher welfare estimate compared to that derived from the combined model. We observe that the estimated travel costs estimate to decrease when trips are modeled separately but exclude meal and lodging expenses. This suggests that meal and lodging costs should not be treated merely as constant additions to travel costs that do not alter the travelling decision of individuals. These findings indicate a need for further investigation to understand how separate models yield different welfare estimates compared to the conventionally accepted approach of modeling trip lengths separately. Further research is required to determine which modeling approach provides estimates that are closer to reality. This will enhance our understanding of the economic implications of travel behavior and the validity of commonly used economic models in recreation studies.

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