Marine Resource Economics, Volume 20, pp. 145–161
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0738-1360/00 $3.00 + .00

Some Consumer Surplus Estimates for North Carolina Beaches

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Abstract *We estimate consumer surplus of a beach day using the single-site travel cost method. Onsite visitation data for seven North Carolina beaches were collected between July and November of 2003. Two pooled count data models, corrected for endogenous stratification and truncation, are estimated to account for bias stemming from onsite sampling. One model pertains to beach visitors that make single day trips to the beach, while the other is for visitors that stay onsite overnight. In each model, we allow for heterogeneity across sites through intercept-shifting and demand slope-shifting dummy variables. Depending upon the site, the estimated net benefits of a day at a beach in North Carolina range between $11 and $80 for those users making day trips and between $11 and $41 for those users that stay onsite overnight. These estimates are of the same order of magnitude as the results from earlier studies using travel cost methods but are considerably larger than the previous findings based upon stated preference methods.*

Key words Travel cost, consumer surplus, beach access.

JEL Classification Codes D12, D63, H31, Q26.

Introduction

Ocean beaches are threatened resources. Erosion is actively occurring along 80-90% of the eastern U.S. coastline, with estimates at approximately one meter of beach width lost, on average, on developed shorelines each year (Galgano and Douglas 2000). North Carolina's coast has experienced beach erosion due to both sea level rise and coastal storms. Ironically, it is coastal development that disrupts the fragile balance of nature; static land use configurations do not allow sufficient flexibility within the dynamic coastal zone. The Cape Hatteras Lighthouse provides evidence

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We thank three anonymous reviewers for their helpful comments and Todd Hales for his research assistance.

of the dynamics of the North Carolina coast. The lighthouse stood about 1,500 feet back from the waves when it was erected in 1870, but by 1999 that distance had been reduced to less than 200 feet (http://whyfiles.org/091beach/index.html). The lighthouse was subsequently moved a quarter mile back from the ocean, a response that was enabled by the lack of development on Cape Hatteras National Seashore. Due to the density of development, this type of response is not available in the typical beachfront community.

Many coastal communities in North Carolina, such as Wrightsville, Carolina, and Kure beaches, have implemented beach nourishment projects in order to preserve beaches and coastal development. According to a recent report by North Carolina Sea Grant, from 1965 to 1998 the Carolina Beach program has cost $26.3 million and the Wrightsville program has cost $16.7 million (NC Sea Grant 2000). While the costs of such projects are substantial, with millions of dollars from public funds, there is a dearth of scientific research on the value of beach resources. Freeman (1995) notes: (*i*) the lack of studies which provide estimates of the value of access to beach resources and (*ii*) a paucity of information on how values change with site quality. In light of the potential for sea level rise, the former values appear fundamental in devising an optimal long-run policy response. How much money should be spent on preserving beaches depends upon their value as recreational resources, what people are willing to pay to preserve beaches for future generations, as well as any non-use values related to ecosystem integrity or habitat preservation. It is difficult to justify the use of scarce public resources in protecting beaches without some knowledge of the value such beaches provide.

This study provides some empirical estimates of the value of a beach day for the average visitor within a travel cost method framework. Ocean beaches are unique resources found on the coastal fringe. The Atlantic and Gulf regions of the U.S. have approximately 4,300 miles of ocean coastline, most of which exhibits sandy beaches. The wide appeal of coastal beaches is made apparent when one considers how far many households will travel to spend time at the beach. Beaches are the leading tourist destination, with historic sites and state and national parks a distant second. Approximately 180 million Americans visit the beach each year, making about 2 billion visits, almost double the trips to national and state parks and other wilderness areas (Houston 1996). The time and money that households expend in traveling to beaches are a signal of the value of these resources. The travel cost model (TCM) makes use of this basic idea, applying the basics of demand theory to recreational resources; distance from the resource provides (presumably) exogenous variation in price that allows for the demand relationship to be identified. Such models can be used to estimate the value of a beach day, as well as to value changes in exogenous factors that affect the recreational experience, such as site quality and congestion.

Data were gathered onsite at seven ocean beaches in North Carolina. In order to obtain a stronger representation of beach visitation, including both peak and non-peak beach seasons, the survey was administered from July to November of 2003. While onsite sampling is a cost-effective sampling strategy, especially when a small percentage of the population may visit the particular site of interest, avid users are more likely to be included in the sample than occasional users; this is the problem of endogenous stratification. In addition, non-users of the resources are not sampled; this is the problem of truncation. We estimate two pooled count data models—one for daily users and one for those that stay overnight—each of which is corrected for endogenous stratification and truncation (Shaw 1988). Our results indicate that net benefits per person per beach day range between $11 and $80 for daily users and between $11 and $41 for overnighters, depending upon the site. These estimates are comparable to the results of a previous study that examined the value of a beach day in Florida, but somewhat higher than results for New Jersey beaches derived from a stated preference approach.

On the Value of Beaches

While earlier studies have focused on estimating the value of a change in beach quality, such as beach width or water quality, less attention in the literature has been given to examining the value of access to beaches. In this paper, we provide some consumer surplus estimates for access to seven North Carolina beaches utilizing pooled travel cost data. We estimate two models—one for daily users and one for users that spend at least one night onsite—primarily because we do not observe onsite costs, an element of expenditures that is likely to vary dramatically between these two user groups. We also expect that demand may be divergent across these two groups. For each model, we use the framework of the single-site model, but pool data for seven different sites allowing for heterogeneity in the intercept and slope of the demand curve. Consumer surplus is offered as an approximation of willingness to pay for access. The single-site TCM requires relatively little in terms of data and is easy to estimate, which is why we are surprised that, to our knowledge, there is only one other paper in the literature that utilizes the single-site TCM to value a beach day. Using the single-site model, Bell and Leeworthy (1990) estimate the value of a beach day in Florida at $34 (1984 U.S. dollars (USD)) for those households traveling great distances.[1]

An alternative approach is to consider household site selection via the random utility model (RUM). The RUM allows for a consideration of multiple recreation sites in a single model, which offers advantages over the single-site model, but requires more information on the choice set of visitors and, in some cases, attributes of the various sites. The RUM is often used to estimate the value of quality changes across different sites. Feenberg and Mills (1980) and Bockstael, Hanneman, and Kling (1987) use a RUM to estimate the value of decreasing water pollutants at Boston-area beaches. Feenberg and Mills estimate that a 10% decrease in oil, color, and bacteria produce benefits of $1.17 per person per year (1974 USD). Bockstael, Hanneman, and Kling find that the compensating variation estimate of a 30% reduction in oil, turbidity, chemical oxygen demand, and fecal coliform is $12.04 per season for all Boston beach areas and $6.13 per season for downtown Boston beaches (both values in 1974 USD). Parsons, Massey, and Tomasi (1999) use a RUM to model beach visitation decisions in the Northeast U.S. They estimate value of lost beach width at $5.78 – $10.94 per person, per trip (1997 USD). McConnell and Tseng (2000) use a random parameters logit model to estimate the value of increased fecal coliform counts at Chesapeake Bay beaches. Doubling fecal coliform counts engendered losses of $1.12 per individual per trip for one site and $8.79 per individual per trip for all 10 sites in their model (1984 USD). Murray, Sohngen, and Pendleton (2001) use a RUM to estimate the value of reducing water quality advisories at Lake Erie beaches in Ohio. They find that the benefit of reducing one advisory is about $28 per person per year (1998 USD).

While the RUM is most often used to estimate the value of changes in site quality, it can also be used to estimate the monetary value that would compensate the average household for elimination of a site from their choice set—this is roughly equivalent to the value of access derived from the single-site TCM. Parsons,

[1] In their sample, the typical air traveler came from 1,300 miles away, while the typical auto traveler drove 900 miles.

Massey, and Tomasi (1999) estimate the impact of beach closures ranges from $0.00 – $16.85 per person per trip across six sites (1997 USD). McConnell and Tseng (2000) estimate the value of lost beach sites at $1.94 and $3.55 per individual per trip, depending upon the site (1984 USD).

Other researchers have used the stated preference approach to value some aspect of beaches. This method utilizes hypothetical market data to estimate benefits. For example, McConnell (1977) uses the stated preference approach to examine how recreational benefits vary with beach congestion and applies his results in an estimation of optimal crowding at five Rhode Island beaches. Bell (1986) conducts a telephone survey of Florida households asking respondents to state their willingness to pay for the right to use Florida beaches. His results suggest the average Florida resident is willing to pay $1.41 – $1.71 (1984 USD), depending upon congestion.[2] Smith, Zhang, and Palmquist (1997) estimate willingness to pay (WTP) to cleanup marine debris on beaches in North Carolina.

The stated preference method has been used to estimate the value of improved beach width. Landry, Keeler, and Kriesel (2003) estimate WTP for improved beach width at $6.75 – $9.92 (1996 USD) per household per day on Tybee Island, Georgia. They find WTP increases with beach width and varies with the policy implemented to increase it. Similar results are found in Kriesel, Keeler, and Landry (2004): $6.06 – $7.71 (1998 USD) per household per day for improved beach width on Jekyll Island, Georgia.[3] Shivlani, Letson, and Theis (2003) estimate mean WTP for increases in beach width at $1.69 (1999 USD) per household per visit in Florida; willingness to pay increases to $2.12 per household per visit (1999 USD) when sea turtles are identified as additional beneficiaries of the beach nourishment project. Silberman and Klock (1988) estimate WTP for a day at the beach before and after a beach nourishment project in New Jersey. Mean daily WTP before nourishment is $3.60; mean daily WTP afterward is $3.90 (1985 USD). They find a larger effect on visitation rather than benefits per day, suggesting that travel costs could play a central role in benefit estimation. Building upon this idea, Hanley, Bell, and Alvarez-Farizo (2003) use a random-effect negative binomial model with revealed and stated trips to British beaches under different water quality conditions to estimate the value of improvements. Consumer surplus per individual per year after improvements was £5.81 (year not specified).

While the literature on the value of beach resources has grown since Freeman (1995), the growth has been rather modest. Most of the recent additions to the literature value changes in site quality. Given the interest in hypothetical site quality changes, most of the recent literature utilizes stated preference methods. The rationale for this focus is clear—site quality can be controlled through policy measures. Thus, valuation of changes in site quality is directly applicable to policy analysis. While certainly useful, care must be taken with this method, as it is prone to some noted sources of bias (Mitchell and Carson 1989).

Estimates of the value of access to beach sites are important for planning a long-term response to the threat of sea level rise. At the aggregate, the benefits of beach access represent the value of beach recreation as an economic "sector"—part of our natural capital. This measure is perhaps a more fundamental concept that will provide evidence of the economic vulnerability of coastal resources engendered by the threat of sea level rise. Such information should provide guidance in long-term

[2] The first measure is associated with average congestion (66.3 sq. ft./person); the latter associated with "optimal" congestion (115 sq. ft./person).

[3] Both sets of estimates varied across type of policy used to improve beaches. Interestingly, beach nourishment engendered greater benefits on Tybee Island, while a policy of shoreline retreat (moving buildings to allow for coastal recession) exhibited a higher value on Jekyll Island.

planning decisions regarding beach management under sea level rise. Existing estimates for Florida beaches relate to residents (Bell 1986) or visitors (Bell and Leeworthy 1990), but are somewhat outdated. The stated preference estimates for New Jersey beaches from Silberman and Klock (1988) are also rather old. Parsons, Massey, and Tomasi (1999) and McConnell and Tseng (2000) provide estimates of the losses engendered by eliminating beach sites for the Northeast U.S. and Chesapeake Bay, respectively. This is a small set of results for an apparently valuable resource that is likely to become threatened in the future. Our objective is to provide more evidence on the value of beaches, and to do so in a geographic region for which the value of access has not been estimated.

Data

This study uses visitation data from seven North Carolina beaches collected onsite between July 2, 2003 and November 2, 2003. The survey was performed at Cape Lookout National Seashore, Hatteras Island, Fort Macon State Park, Pea Island National Wildlife Refuge, the Rachel Carson National Estuarine Research Reserve, Topsail Island, and Wrightsville Beach. These locations were selected because they represent a cross-section of North Carolina beaches, with variation in geographical distribution and beach characteristics, including the number of visitors present during peak beach season, beach congestion, level of development/commercialization, presence of lifeguards, wave energy, presence of visible wildlife, accessibility, and onsite facilities. Figure 1 shows the geographical distribution of these seven beach areas.

The data were collected onsite via a self-reported survey questionnaire. Efforts were made to sample at different times and on different days of the week to acquire the most representative sample possible. During the sampling period, each beach was surveyed at least once every third week on alternating days of the week. Data were collected approximately 10 days per month. The questionnaire addressed several questions relating to point of origin, the number of trips to the particular site in the past twelve months, number of days spent onsite during the current trip, as well as demographic information such as race, marital status, and income. Table 1 provides the definition and description of the variables used in this study.

Item-nonresponse to the income question was somewhat high, about 11%. A regression equation was used to predict the logarithm of household income as a function of education, race, marital status, age, and region. The predicted value was used for those households that did not report income, and the dummy variable MISSINC was set to one. The results are given below, with standard errors in parentheses.

$$\begin{aligned}
\ln(\text{INCOME}) = \underset{(0.305)}{7.802} &+ \underset{(0.214)}{0.210}\ \text{HSCHOOL} + \underset{(0.214)}{0.520}\ \text{BACHELOR} \qquad (1)\\
&+ \underset{(0.217)}{0.528}\ \text{POSTBAC} - \underset{(0.091)}{0.206}\ \text{NONWHITE} + \underset{(0.059)}{0.594}\ \text{MARRIED} + \underset{(0.012)}{0.103}\ \text{AGE}\\
&- \underset{(0.0001)}{0.001}\ \text{AGE}^2 + \underset{(0.094)}{0.058}\ \text{NORTH} + \underset{(0.064)}{0.195}\ \text{MIDATL} + \underset{(0.108)}{0.009}\ \text{MIDWEST}
\end{aligned}$$

$R^2 = 0.4383$; F-stat = 41.66; P-value for F-stat < 0.0001.

The baseline region is the southeast U.S.

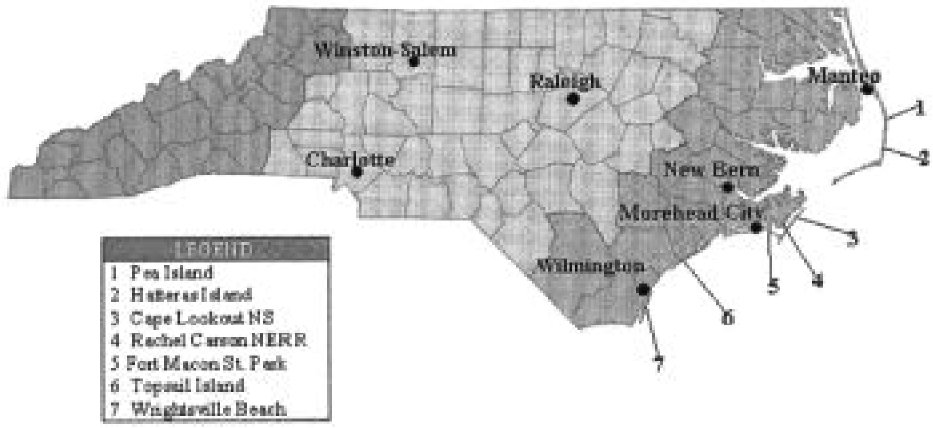

Figure 1. Map of the Seven Beach Areas in North Carolina

Table 1
Definition and Description of the Variables

Variable	Definition
TRIP	Number of beach site visits in the past twelve months
DAYS	Number of days onsite per trip
GROUP	Number of people in the group
TCOST	Travel cost to the site
SUBCOST1	Travel cost to the substitute site 1
SUBCOST2	Travel cost to the substitute site 2
INCOME	Annual household income
HIGHINC	Dummy variable: 1 if annual household income is greater than $100,000; 0 otherwise
MISSINC	Dummy variable: 1 if annual household income is missing; 0 otherwise
BACHELOR	Dummy variable: 1 if the highest level of education is a college degree; 0 otherwise
POSTBAC	Dummy variable: 1 if the highest level of education is a post college degree; 0 otherwise
MALE	Dummy variable: 1 if male; 0 otherwise
NONWHITE	Dummy variable: 1 if racial background is not white or Anglo-American; 0 otherwise
ENVMEM	Dummy variable: 1 if a member of environmental or conservation groups; 0 otherwise
AGE	Age of the survey respondent
MULTI	Dummy variable: 1 if a multiple purpose trip; 0 otherwise
CARSON	Dummy variable: 1 if Rachel Carson National Estuarine Research Reserve; 0 otherwise
HATTERAS	Dummy variable: 1 if Hatteras Island; 0 otherwise
LOOKOUT	Dummy variable: 1 if Cape Lookout National Seashore; 0 otherwise
MACON	Dummy variable: 1 if Fort Macon State Park; 0 otherwise
PEA	Dummy variable: 1 if Pea Island National Wildlife Refuge; 0 otherwise
TOPSAIL	Dummy variable: 1 if Topsail Island; 0 otherwise
WRIGHTS	Dummy variable: 1 if Wrightsville Beach; 0 otherwise

While most variables were based on what beach visitors reported, we estimated the trip costs based on an objective measurement of distance from the respondent's home to the beach site. Distance to the site is calculated using the visitor's hometown zip code and each beach's zip code. We use 35 cents times the round trip distance to the site as an estimate of travel costs, which reflects fuel and vehicle maintenance costs. Opportunity costs of travel time are estimated as a fraction of the household's hourly wage—annual income divided by 2,080, the number of hours worked in a year. We conduct sensitivity analysis for the value of travel time, varying the fraction of the wage between ¼ and 1.

Mode of transport was not elicited in the survey. It is possible that some visitors traveled to the site by plane, but the only site with a fairly large airport close by is Wrightsville Beach. Given the limited number of airports in eastern North Carolina and their diminutive size, we feel that air travel is probably not all that common among users in our dataset. In addition, it is not very likely that users making single day visits would utilize commercial aviation in travel, though some may utilize a private plane. The assumption of travel by car is more likely to cause problems in the overnight model, thus further moderating our confidence in these results. Assuming the average travel speed of 55 miles per hour, we divide the round-trip distance by 55 and multiply it with the opportunity cost of time to measure the value of travel time. There are no access fees to any of the beach areas that were included in this study. Average distance traveled was 419 miles; average estimated round-trip cost for the baseline model (valuing travel time at ⅓ the wage) was $455. Travel costs to the substitute sites were measured in a similar way. Substitute sites were identified in the survey data. However, not all respondents indicated a substitute site. These households were assigned a substitute site based on their city/state cohort. We restrict our analysis to those households traveling less than 1,000 miles, respondents with a group size less than ten, and those households that do not own property onsite.

Methods

This study estimates the consumer surplus of seven beach sites in North Carolina for two different user groups using the travel cost method (TCM). TCM is based on the simple idea that visitors who live far away from desirable sites pay high travel costs (price) and take fewer trips (quantity) than visitors who live closer, *ceteris paribus*. Combining the travel costs and the number of trips enables researchers to estimate the demand function for recreational use of the sites.

Suppose that the consumer's utility function depends on the number of visits to a recreational site, x, and the quantity of composite good, q. The round-trip travel cost associated with a visit to the site is given as p. With the price of the composite good normalized to equal one, the consumer's budget constraint is given by $px + q \leq y$, where y is income. The consumer's optimization problem is to maximize her utility function, $U(x, q)$, subject to the budget constraint. Utility maximization with interior solutions leads to the standard Marshallian demand function for recreational use of the site: $x = f(p, y)$. Often this demand function is estimated with the travel costs to substitute sites and other demographic factors that shift the demand curve, as well as the travel costs to own site and income.

Importantly, we do not observe onsite costs, an element of the price of a visit. If consumers take predominantly day trips to the beach, we might expect that onsite costs are a small portion of the price of a visit and that they do not vary much across consumers. If onsite costs are a small portion of price, we might expect only slight mis-measurement of the price variable and slight bias in estimation. If onsite costs are constant across consumers, they can be safely ignored—subsumed into the constant term. For those households that stay onsite overnight, onsite cost becomes a potentially bigger problem. Onsite expenditures can be a much larger portion of the price of a visit for these visitors and will vary with the number of days spent onsite and other consumption choices made onsite. We expect much greater mis-measurement of the price variable for these consumers, and more variation in that mis-measurement. This can cause unknown bias in estimation. Lastly, we might expect different demand for these two groups. Recognizing these limitations, we estimate separate demand equations for day trips and trips that involve overnight stay.[4] A likelihood ratio test supports this specification; we reject equivalent coefficients across these two groups.[5] We express more confidence in the results for day trips.

The dependent variable in travel cost models is associated with a data generating process for non-negative integers, known as count data process. A simple count data model that satisfies the discrete probability density function and non-negative integers is the Poisson model. The Poisson probability density function is given by:

$$f(X = x) = \frac{e^{-\lambda}\lambda^{x}}{x!}, \quad x = 0, 1, 2, \cdots, \tag{2}$$

where the parameter λ is both the mean and the variance of the random variable X, trips to the site, and takes strictly positive values. Because $\lambda > 0$, it is common to model the conditional mean as an exponential function: $\lambda = \exp(\boldsymbol{z}\beta)$, where $\boldsymbol{z}$ is the vector of demand arguments and β is the vector of parameters. These parameters are estimated by the method of maximum likelihood.

In estimating the Poisson model, we correct for selection bias resulting from onsite sampling. When the sample is drawn from an onsite survey, more frequent users are more likely to be drawn. This problem is known as endogenous stratification and causes bias and inconsistency in the estimates of β (Shaw 1988). To correct for endogenous stratification, one must weight each observation by the expected value of trips. For the Poisson model, however, this correction procedure simplifies within the likelihood function—one simply runs the standard Poisson regression utilizing $x - 1$ instead of x as the dependent variable. To correct for endogenous stratification, the means in table 2 are corrected for endogenous stratification by weighting by the inverse of actual trips taken.

Onsite sampling also leads to truncation of non-users. The procedure recommended by Shaw corrects for truncation as well. We cannot, however, claim that our model reflects the preferences of all non-users because we have no data on this segment of the population, and it is highly unlikely that the preferences of true non-users of beach resources (*i.e.*, those that rarely or never go to the beach) follow the same distribution as more-or-less frequent users. We consider our population of interest the “potential” beach visitors living within 1,000 miles of the site and claim our results as representative for that population. An anonymous reviewer offered the following intuitive definition for this population: “individuals who would answer ‘yes’ to the question, Have you in the past, or will you in the future visit one of these seven beaches in North Carolina?” Thus, the non-users that our modeling strategy corrects for non-representation of are those users that did not take a trip to one of the seven sites during our sampling period, but are likely to take at least one trip over multiple years.[6]

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[4] We thank an anonymous reviewer for making this suggestion.
[5] Chi-square statistic is 266.0997 with 28 degrees of freedom.
[6] We thank an anonymous reviewer for clarifying this interpretation of the model results.

Table 2
Summary Statistics of the Variables

	Day Trip		Overnight	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
TRIP	2.06	3.31	1.37	1.38
DAYS	1.00	0.00	5.09	3.30
GROUP	3.42	1.85	3.71	2.01
TCOST	204.50	207.85	463.69	265.37
SUBCOST1	218.22	239.86	389.82	330.76
SUBCOST2	196.61	177.19	343.95	263.21
INCOME	61,554.76	30,187.59	68,721.21	29,534.93
HIGHINC	0.14	0.35	0.25	0.44
MISSINC	0.19	0.40	0.09	0.28
BACHELOR	0.47	0.50	0.36	0.48
POSTBAC	0.17	0.38	0.29	0.46
MALE	0.44	0.50	0.50	0.50
NONWHITE	0.06	0.25	0.08	0.27
ENVMEM	0.13	0.34	0.17	0.38
AGE	39.82	11.83	41.93	12.02
MULTI	0.39	0.49	0.30	0.46
CARSON	0.14	0.34	0.06	0.23
HATTERAS	0.12	0.33	0.25	0.43
LOOKOUT	0.27	0.45	0.04	0.20
MACON	0.05	0.22	0.20	0.40
PEA	0.12	0.33	0.14	0.34
TOPSAIL	0.21	0.41	0.12	0.32
WRIGHTS	0.09	0.28	0.21	0.41

Notes: Number of observations for day trips is 130, and number of observations for overnight trips is 274. Means are weighted by the inverse of actual trips to control for endogenous stratification.

The Poisson model assumes that the conditional mean and the variance are equal, which can be a strong assumption and a potential source of misspecification for many recreational demand datasets. The variance is often larger than the conditional mean in these data sets (*i.e.*, overdispersion). The negative binomial model is an alternative to Poisson that allows for overdispersion of the conditional mean. Englin and Shonkwiler (1995) provide the likelihood function for this model. To allow for overdispersion, we also estimated the negative binomial model, but fail to reject the null hypothesis that the coefficient for the overdispersion parameter is equal to zero for each model. Thus, our results suggest that the Poisson model is the preferred specification.

Given the limited data, we pool across all seven sites in each model. We account for site heterogeneity through intercept-shifting dummy variables and slope-shifting dummy variables (for own travel cost coefficients only). The baseline case in each model is Cape Lookout National Seashore. We assume all other covariate effects are equal across sites—an assumption that cannot be tested with the data. To test for sensitivity to the valuation of time, we estimate two additional sets of models, valuing time at the full wage and $\frac{1}{4}$ the wage. Given model estimates, consumer surplus for access to the site *i* is:

$$CS_i = -\frac{\bar{\lambda}_i}{\beta_i}, \tag{3}$$

where CS_i denotes the estimated consumer surplus for site i, $\bar{\lambda}_i$ is the weighted mean of the actual number of trips for site i, and β_i is the estimated slope of the demand curve for site i. We present consumer surplus estimates for both day-trippers and overnighters at each of the seven sites. To convert the welfare estimates into quantities that can be more easily interpreted and more readily applied, we divide CS_i by the average number of persons in the group, the average number of trips, and the average number of days onsite per trip to produce a per-person, per-day measure of consumer surplus—the average value of a beach day to the average individual in the sample. All means used in calculating consumer surplus are estimated using the inverse of the actual number of trips as a weight to correct for endogenous stratification.

Results

Estimation results for the endogenous stratified Poisson models are shown in tables 3 and 4. The majority of the variables are statistically significant and consistent with prior expectations. The negative and significant coefficients for own travel

Table 3

Estimation Results for the Poisson Recreational Beach Demand Model: Day Trip

Site	Coeff. Estimate	Standard Error	p-value
TCOST	–0.004	0.001	0.006
TCOST*CARSON	0.001	0.003	0.686
TCOST*HATTERAS	–0.001	0.003	0.630
TCOST*MACON	–0.013	0.002	0.000
TCOST*PEA	–0.027	0.004	0.000
TCOST*TOPSAIL	–1.65e-04	0.002	0.918
TCOST*WRIGHTS	–0.013	0.003	0.000
SUBCOST1	0.003	0.001	0.007
SUBCOST1^2	–3.98e-06	1.16e-06	0.001
SUBCOST2	0.003	0.002	0.226
SUBCOST2^2	–2.12e-05	6.54e-06	0.001
INCOME	1.49e-05	1.84e-06	0.000
HIGHINC	0.030	0.150	0.843
MISSINC	–0.684	0.207	0.001
BACHELOR	–0.726	0.098	0.000
POSTBAC	–0.048	0.129	0.711
MALE	–0.165	0.097	0.091
NONWHITE	0.359	0.134	0.007
ENVMEM	0.040	0.148	0.788
AGE	–0.007	0.004	0.088
MULTI	0.279	0.124	0.024
CARSON	–0.258	0.218	0.236
HATTERAS	–0.371	0.664	0.576
MACON	2.370	0.229	0.000
PEA	1.925	0.375	0.000
TOPSAIL	0.176	0.181	0.330
WRIGHTS	0.993	0.212	0.000
Constant	1.596	0.195	0.000
Log-likelihood	–569.297		
Pseudo R^2	0.435		
Number of observations	130		

Notes: Number of observations is 130. Dependent variable is the number of beach site visits in the past year.

Table 4
Estimation Results for the Poisson Recreational Beach Demand Model: Overnight

Site	Coeff. Estimate	Standard Error	p-value
TCOST	–0.005	0.002	0.007
TCOST*CARSON	–0.001	0.003	0.719
TCOST*HATTERAS	–4.14e-04	0.002	0.802
TCOST*MACON	0.002	0.002	0.350
TCOST*PEA	0.003	0.002	0.073
TCOST*TOPSAIL	0.001	0.002	0.594
TCOST*WRIGHTS	0.002	0.002	0.359
SUBCOST1	0.004	0.001	0.000
SUBCOST1^2	–3.78e-06	1.02e-06	0.000
SUBCOST2	–0.006	0.001	0.000
SUBCOST2^2	4.67e-06	8.09e-07	0.000
INCOME	1.39e-06	2.20e-06	0.526
HIGHINC	–0.016	0.169	0.926
MISSINC	–0.144	0.190	0.449
BACHELOR	0.369	0.119	0.002
POSTBAC	0.777	0.148	0.000
MALE	–0.457	0.105	0.000
NONWHITE	–0.434	0.205	0.034
ENVMEM	0.225	0.125	0.073
AGE	0.009	0.004	0.032
MULTI	0.158	0.117	0.175
CARSON	–1.772	0.514	0.001
HATTERAS	0.088	0.287	0.760
MACON	–1.481	0.450	0.001
PEA	–2.069	0.392	0.000
TOPSAIL	–0.811	0.368	0.027
WRIGHTS	–0.553	0.272	0.042
Constant	2.181	0.306	0.000
Log-likelihood	–650.898		
Pseudo R^2	0.306		
Number of observations	274		

Notes: Number of observations is 274. Dependent variable is the number of beach site visits in the past year.

costs indicate that the number of trips is inversely related to own travel costs for each model, implying a downward-sloping demand curve. For the day trip model, three of the demand slope coefficients are different from the base case, Cape Lookout. Day trip demand is elastic for Cape Lookout, Pea Island, Hatteras, Fort Macon, and Wrightsville Beach, with estimated price elasticites of –1.07, –4.15, –1.44, –3.01, and –4.02, respectively. The remaining sites, Rachel Carson and Topsail Island, are price inelastic, with estimates of –0.28 and –0.74, respectively. For the overnight model, only one slope coefficient is different from the base case. Estimates suggest overnight trip demand at Cape Lookout, Hatteras, Rachel Carson, Fort Macon, Topsail Island, and Wrightsville Beach are price elastic, with estimates of –1.02, –2.14, –1.53, –1.58, –1.83, and –1.47, respectively. The remaining site for this model, Pea Island, is price inelastic, with an estimate of –0.50.

The coefficients for travel costs to the first substitute site are, as expected, positive and significant in each model, which suggests that those households with higher travel costs to substitute sites make more trips to the site of interest, *ceteris paribus*.

The coefficient for travel costs to the second substitute site is statistically insignificant for the day trip model and exhibits a counter-intuitive negative sign for the overnight model. The effect of income on the number of trips is positive in each model, but not significant in the overnight model. Thus, for day trips, we can claim that beach recreation at the study sites is a normal good, *ceteris paribus*. The binary variable for visitors with a high income (above $100,000) is statistically insignificant in each model. This variable was included to control for censoring of income for those households with income greater than the highest income category. The negative coefficient on the missing income variable in the day trip model suggests that people who did not report their income make fewer beach trips.

The effects of education on the number of trips differ markedly across the two models. Respondents with a college or post-graduate education make more overnight trips, while the college educated make fewer day trips. Stark differences are also found with regards to race and age across the two models. Nonwhites demand more day trips, but fewer trips that involve an overnight stay. Older respondents make fewer day trips, but more overnight trips. These apparent differences support our strategy of estimating separate models for day and overnight trips. Male survey respondents have a significantly lower demand for beach visits—a result consistent across both models.

The Poisson models are used to estimate consumer surplus for the two user groups at each of the seven North Carolina beaches via equation (3). Following equation (3), the weighted mean of the actual number of trips for each site and user group is divided by the site-specific slope coefficient (β_i). The weighted means reflect a correction for endogenous stratification (Shaw 1988). Table 5 presents consumer surplus estimates expressed as value (in 2003 USD) per person per day. The value of access is expressed as a per-person, per-day measure by dividing consumer surplus, from equation (3), by the weighted averages of: (*i*) the number of trips per year; (*ii*) the number of days onsite per trip (assumed constant across all trips); and (*iii*) size of the traveling group, where again the weights correct for endogenous stratification. Daily consumer surplus per capita is an approximation of the net benefits of a day at the beach.

Our estimates of consumer surplus range from $11 to $80 per person per day for beach users making single day trips and from $11 to $41 per person per day for beach users spending one or more nights onsite. It is interesting that the unit-value is generally higher for day users, since the quantity of days per trip is necessarily lower for this group—a result consistent with a downward-sloping marginal value function. However, since there are apparent differences among the two user groups, their preferences (*i.e.*, marginal values) are likely divergent (*i.e.*, not on the same scale). We use the Krinsky-Robb bootstrapping procedure to generate 95% confidence intervals around our welfare estimates (Krinsky and Robb 1986). We generate 5,000 sets of random parameter vectors from the distribution of the estimated parameters and compute 5,000 consumer surplus estimates. The consumer surplus estimates are sorted in ascending order, and the 95% confidence bounds are found by dropping the top and bottom 2.5% of the estimates. For the day trip model, our confidence intervals include zero for only one site—Rachel Carson. We have little confidence in the Rachel Carson estimate, but the rest of the welfare estimates are significantly different from zero for this model. The confidence intervals are noticeably tight for Fort Macon, Wrightsville Beach, and Pea Island. Our confidence bounds for the overnight model are not as good. Only four of the seven confidence bounds do not include zero, and these bounds are generally not as tight as that of the day trip estimates.

To examine the sensitivity of these welfare estimates to the valuation of travel time, we estimate two additional sets of models—one which values travel time at $\frac{1}{4}$

Table 5
Consumer Surplus and Congestion Estimates for Seven North Carolina Beaches

	Observations		Consumer Surplus		
Beach Site	Day Trip	Overnight	Day Trip	Overnight	Average Congestion
PEA ISLAND	14	39	\$11.29 (\$9.45-\$14.04)	\$41.45 (\$0-\$401.03)	12.96 (10.48)
FORT MACON	10	47	\$18.14 (\$15.10-\$22.55)	\$12.65 (\$0-\$111.58)	12.63 (14.45)
WRIGHTSVILLE	14	59	\$21.83 (\$17.61-\$28.66)	\$15.24 (\$0-\$130.06)	127.64 (119.62)
HATTERAS	12	71	\$60.37 (\$32.46-\$252.09)	\$11.14 (\$6.27-\$39.03)	94.16 (67.41)
CAPE LOOKOUT	30	13	\$69.18 (\$40.42-\$221.29)	\$19.89 (\$11.56-\$65.20)	20.77 (11.89)
RACHEL CARSON	17	15	\$78.74 (\$0-\$786.90)	\$24.49 (\$14.27-\$81.94)	7.04 (6.25)
TOPSAIL	34	31	\$79.60 (\$46.34-\$246.36)	\$14.03 (\$6.08-\$89.14)	74.40 (66.69)

Notes: The consumer surplus estimates are per person per day. Krinsky-Robb procedure is used to calculate the 95% confidence intervals for consumer surplus and reported in parentheses. Congestion is measured as the number of people on the beach within sight of our surveyor. Standard deviations of congestion are given in parentheses.

the wage rate and one which value travel time at the full wage rate. We consider first the value of time at $\frac{1}{4}$ the wage. For day trips, consumer surplus per person per day ranges from \$9.47 (Pea Island) to \$80.59 (Topsail Island). The percentage variation ranges from 38% lower to 16% greater welfare estimates from our baseline model (valuing time at $\frac{1}{3}$ the wage). For overnight trips, consumer surplus per person per day ranges from \$10.17 (Hatteras Island) to \$48.58 (Pea Island), with deviation ranging from –10% to +17%. We turn next to the value of time at the full wage. Assuming consumers value travel time at their full wage rate, consumer surplus per person per day ranges from \$22.87 (Pea Island) to \$386.60 (Rachel Carson) for day trips. The percentage variation ranged from 17% to 391% greater than the estimates from our baseline model. For overnight trips, consumer surplus per person per day ranged from \$21.32 (Topsail Island) to \$88.88 (Pea Island), with deviation ranging from +28% to +114%.[7]

Ideally, we would like to have accounted for quality differences in the beach sites in demand estimation, but information was limited, and the available information has little explanatory power. One important site characteristic is beach congestion (*i.e.*, number of persons per unit area), as this can impact the quality of the recreational experience. The literature on outdoor recreation suggests a consis-

[7] These results are available from the authors upon request.

tent but weak relationship between congestion measures and the quality of user experience. For example, Stewart and Cole (2001) found that Grand Canyon backpackers were negatively affected by encountering more groups, but the resultant effect was small. While many studies have concluded that increasing numbers of encounters leads to lower satisfaction with the overall recreational experience (Graefe, Vaske, and Kuss 1984; Manning *et al.* 2000), other studies suggest that, depending on the setting and individual expectations, higher numbers of people can actually increase visitor satisfaction (Ditton, Fedler, and Graefe 1983). In situations where people are expecting, if not desiring, crowds as a part of their experience, congestion can be a positive factor.

The only information available in this study regarding congestion was a count of the number of people in sight of our surveyor while administering the survey. Our surveyors counted the number of people in their near vicinity every hour. Average congestion levels at each site are included in table 5. While we would like to account for this quality attribute in modeling demand, observed congestion at one point in time clearly cannot be linked to the number of trips that a household makes in a year. Congestion at any point in time is a random observation that may not be representative of the site at other times, and the overall level of congestion that the household experiences during their times at the beach may vary substantially over the course of one trip and multiple trips within a year.

Without a good proxy for the household's experience with congestion while onsite, we are forced to use secondary measures to examine the relationship between recreational value and congestion. We use the Spearman Rank-Order Correlation Test (see Siegel and Castellan 1988). We rank each site by mean consumer surplus, with the site with highest estimated surplus receiving a rank of '1' and so forth. Next, we rank each site by availability of space. Thus, the site with least congestion receives a rank of '1' and so forth. The Spearman Rank-Order test looks for correlation among the ranks, the null hypothesis being that the two measures are independent. Our estimated rank correlation coefficients are –0.0357 for the day trip model and 0.4286 for the overnight model, each of which is less than the critical value associated with seven observations, a confidence level of 0.05, and a one-sided alternative—0.714. The correlation coefficient for day trips is, in fact, negative. Hence, we fail to reject the hypothesis that consumer surplus and personal space are independent in either of our models. Note, however, we are not controlling for other sources of site heterogeneity in this non-parametric test.

Although further analysis of the variance of consumer surplus across different beach sites is beyond the scope of this paper, one possible reason for this variation may be related to the types of experiences that beach visitors are seeking. One well-established model of social behavior within the recreation literature that may help explain this phenomenon is the Recreation Opportunity Spectrum (ROS). The ROS is a tool developed by the U.S. Forest Service and adapted by other resource management agencies to ensure that users have a variety of experience opportunities available to them through a diverse array of opportunities in a range of outdoor settings (Clark and Stankey 1979). This framework assumes that the combination of different settings and activities produce distinct experience opportunities and should satisfy the needs and motives of different types of users.

Each setting (beach site) can be seen as providing a unique set of experience opportunities. Thus, the strength of motivations and corresponding trip costs are likely to vary considerably across different types of settings. Since the beaches examined within this project were chosen to represent a diverse set of characteristics, it is likely that each is providing different experience opportunities and attracting different types of visitors with different motives. Although there appears to be no strong correlation between the site characteristics that were measured in our survey and the calculated consumer surplus, two of the top three beaches in terms of day trip consumer surplus (Rachel Carson and Cape Lookout) share the characteristic of being inaccessible by automobile. Both of these sites: (*i*) require visitors to arrive by ferry, water taxi, or private watercraft;[8] (*ii*) are not as well known as the other beaches in the sample; and (*iii*) may offer visitors the perception of exclusivity not found at other beaches. Although accessible by vehicle, Topsail Beach is also a lesser-known beach destination and may provide visitors with a similar perception. Keep in mind that these potential explanations are speculative, and that despite much research to date, recreation choice behavior is diverse, complicated, and not yet thoroughly understood. Future research examining differentials in willingness to pay and trip cost estimates between visitors seeking different experiences or having different travel motivations is recommended.

Although the travel cost method used in this study has the advantage of estimating net value based on observed behavior, it provides only a limited measure of the total benefits from beaches. Many natural resources, including beaches, can exhibit significant non-use values. People may value beaches for their role in providing wildlife habitat and protecting coastal properties from storm damage, and may be willing to pay to preserve beaches for the option of future use for themselves and perhaps others. However, these components of beach values are not reflected in our estimates, and our estimates represent only use values of current and potential users.

Conclusions

This study provides estimates of consumer surplus for two user groups and seven beaches in North Carolina. To this end, we use the travel cost model with data pooled over seven sites. The endogenous stratified Poisson regression model is used to account for avidity bias and truncation stemming from onsite sampling. Depending upon the site, we find the net benefits of a day at a North Carolina beach range from $11 and $80 for users that make single day trips and $11 to $41 for users that stay onsite overnight. Of the seven welfare estimates produced for daily visitors, six are different from zero at a significance level greater than 5%. Only four of the seven welfare estimates for overnight visitors are different from zero at better than 5%. In general, we have less confidence in the results of the latter model because we expect larger mis-measurement and greater variation in mis-measurement of the price of a visit due to the fact that we do not observe onsite costs in our dataset. In addition, the assumption of car travel could be erroneous for overnight users, producing additional errors in the measurement of travel cost.

Our estimates of the value of a beach day are of the same order of magnitude as previous results for visitors in Florida traveling from long distances and for beach sites in the Northeastern U.S. Our estimates are somewhat larger than the estimated loss from elimination of a beach site on the Chesapeake Bay, and are considerably larger than the previous findings derived from stated preference methods for New Jersey beach users and local users of Florida beaches. We hope these results provide information for practitioners and policy makers who must formulate beach preservation decisions.

Unfortunately, we were not able to fully examine the effect of site characteristics on net benefits. Results of a non-parametric ranking test (Spearman Rank-Order

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[8] Both Rachel Carson and Cape Lookout require short trips over the Pamlico Sound. We do not include the cost of transit across water in our travel cost estimates as separate arguments because these costs are not observed and are only a small part of total travel cost.

Correlation test) suggest that mean consumer surplus and average personal space are not positively correlated. However, our measure of congestion (presumably inversely related to personal space) is imperfect; it was based solely on an "eyeball" count of persons on the beach at the time of the interview, and it is not standardized as a measure per unit area. Thus, our conclusions regarding personal space are not based on a very powerful test. However, even with data well suited for the purpose, we might not be able to find a clear correlation between personal space and net benefits. The reason is that visitors may exhibit heterogeneous preferences for personal space. Some visitors may desire congested beaches for the social atmosphere that they offer, while others may desire more personal space. Since the level of congestion is something that can be affected through policies (both beach nourishment or changes in access), this is an area for future research.

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