Valuing Beach Access and Width with Revealed and Stated Preference Data[1]

John C. Whitehead[2], Christopher F. Dumas[3], Jim Herstine[4], Jeffery Hill[5], Bob Buerger[5]

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[2] Department of Economics, Appalachian State University, Boone, NC 28608; email: whiteheadjc@appstate.edu.

[3] Department of Economics and Finance, University of North Carolina Wilmington, Wilmington, NC 28403.

[4] Department of Health and Applied Human Sciences, University of North Carolina Wilmington, Wilmington, NC 28403.

[5] Department of Environmental Studies, University of North Carolina Wilmington, Wilmington, NC 28403.

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Abstract: In this paper we present results from a study of recreation demand for southern North Carolina beaches. We combine revealed preference and stated preference data in order to estimate the changes in recreation demand that might occur with beach nourishment and parking improvements necessary to satisfy the requirements for US Army Corps of Engineers cost-share. We illustrate the numerous ways that hypothetical bias in contingent behavior data can lead to increases in the estimates of the economic benefits of recreation and recreation quality improvement. Hypothetical bias affects estimates of the number of trips and slope coefficients. Hypothetical bias does not affect elasticity or consumer surplus per trip estimates. When the product of trips and consumer surplus per trip is taken as an estimate of consumer surplus per season, hypothetical bias leads to upwardly biased seasonal consumer surplus estimates. These results suggest that stated preference recreation demand data, in isolation from revealed preference data, may be suitable for estimation of consumer surplus per trip but not consumer surplus per season.

Introduction

Coastal communities are experiencing extraordinary growth in population and land development, increasing the recreational activities and property value at risk to beach erosion. Recent severe storm cycles and chronic beach erosion have heightened interest in beach protection. In many areas, environnmental concerns have constrained beach protection options. For example, in 1986, the State of North Carolina's Coastal Resources Commission set guidelines to ban hard oceanfront structures such as jetties, groins and seawalls. In 2003, the North Carolina State Legislature passed legislation making hard oceanfront structures illegal. As a result, North Carolina relies on other forms of beach protection, such as beach sand nourishment, to maintain oceanfront beaches. Beach sand nourishment is the placement of sand on beaches to increase beach width for the purposes of protecting property and maintaining recreation opportunities (Jones and Mangun 2001).

Many coastal communities have been successful in securing federal cost-share funding (65 percent Federal, 35 percent local) for beach renourishment projects designed and constructed by the U.S. Army Corps of Engineers (USACE) (USACE 2004). USACE projects must be justified on the basis of benefit cost analysis. These projects are designed primarily to reduce coastal property damage caused by hurricanes and other storms. In addition to storm damage reduction benefits, project benefits may include incidental recreation benefits up to fifty percent of project costs. USACE project guidelines further stipulate that in order to qualify for federal cost sharing, the local beach community must, at a minimum, provide public access to the beach every one half mile and parking with a one quarter mile radius of those access points. In many locations, satisfying this stipulation requires the creation of additional or expanded beach access and parking facilities.

In this paper we present results from a study of recreation demand of southern North Carolina beaches. We combine revealed preference and stated preference data in a single-site travel cost method context in order to estimate the changes in recreation demand that might occur with beach nourishment and parking improvements necessary to satisfy the requirements for USACE cost-share. The next section provides a review of the beach valuation literature. Then we describe the revealed and stated preference methods. We then present the survey data and empirical methods. Empirical results and conclusions follow.

Literature Review

The economics literature has considered various aspects of beach nourishment: costs (e.g., Parsons and Powell 2001), storm damage benefits to property owners (e.g., Pompe and Rinehart 1994), recreation benefits to property owners (e.g., Edwards and Gable 1991) and recreation benefits to non-property owners (Silberman and Klock, 1988). In this section we focus on the recreation benefits of beach nourishment that are enjoyed by non-property owners. These have been estimated using the travel cost method and the contingent valuation method. None of these studies have considered the related issue of beach access.

The travel cost method is a revealed preference method that is most often used to estimate recreation benefits. The travel cost method begins with the realization that the major cost of outdoor recreation is the travel and time costs incurred to get to the recreation site. Since individuals reside at varying distances from the beach, the variation in distance and the number of trips taken are used to trace out a demand curve for beach recreation. The empirical relationship between distance and recreation site choice and/or intensity is used to derive the benefits of beach trips and beach characteristics (e.g., beach width).

Parsons, Massey and Tomasi (1999) estimate the value of beach width at Delaware, Maryland and New Jersey beaches using the random utility model variant of the travel cost method. They find that beach width between 75 and 200 feet is preferred in the site selection model. The lost economic value of a reduction in beach width to 75 feet is economically significant. The major strength of the travel cost method is that it is based on actual choices. With such revealed preference data, individuals consider the costs and benefits of their actions and experience the consequences of their actions. The major weakness of the travel cost method is its reliance on historical data. Proposed changes in beach width, access, or parking may be beyond the range of historical experience for many beachgoers.

Stated preference methods can be used to estimate the benefits of changes in beach characteristics beyond the range of experience. Stated preference approaches include the contingent valuation method (CVM), choice experiments (CE) and contingent behavior (CB). The CVM uses willingness to pay responses to hypothetical situations to estimate recreation benefits (Boyle 2003). McConnell (1977) and Bell (1986) use the CVM and find that the economic value of beach recreation per person increases with increasing beach width. These authors attribute this result to the reduction in crowding associated with wider beaches. Silberman and Klock (1988) use the CVM to estimate the recreation use values of beach nourishment in New Jersey. They find that visitation would increase substantially in the nourished beaches but decrease in the other beaches. Lindsay et al. (1992) use the CVM to estimate willingness to pay for beach erosion protection measures, including seawalls and beach nourishment, in Maine and New Hampshire. Their focus is on the factors that affect willingness to pay.

More recently, Shivlani, Letson and Theis (2003) use the CVM to estimate the benefits of beach nourishment in south Florida. Willingness to pay is higher when wildlife habitat is included as a characteristic of beach nourishment. Landry, Keeler and Kriesel (2003) use the CVM to estimate the value of various erosion management alternatives in Georgia. Day trippers are willing to pay higher parking fees for beach nourishment.

Choice experiments are a stated preference approach that involves respondent choices among hypothetical scenarios with various characteristics, including cost (Holmes and Adamowicz 2003). Huang, Poor and Zhao (2007) consider the tradeoffs associated with beach nourishment in New Hampshire and Maine. They find that erosion control is less preferred when it has negative wildlife, water quality and off-site erosion impacts.

The contingent behavior method is a stated preference approach that directly elicits trip information from survey respondents. The method involves the development of a hypothetical situation where respondents are informed about the current problem and a proposed policy designed to mitigate the problem for a specified cost. A hypothetical question is presented that confronts respondents with a choice between the staus quo and improved environmental quality at increased cost. For example, Landry (2005) asks respondents about hypothetical recreation trips with and without a beach erosion control control program with a specified cost to the recreationist. He finds that respondents are willing to take more trips with increased beach width, even at higher cost, relative to their status quo number of trips.

One strength of the contingent behavior approach is its flexibility. Hypothetical choices may be the only way to gain policy relevant information. The major weakness of the contingent behavior approach is its hypothetical nature. Respondents are placed in unfamiliar situations in which complete information is not available. The strengths of the revealed preference approaches are the weaknesses of the stated preference approaches.

The combination and joint estimation of revealed and stated preference data exploits the contrasting strengths of the alternative approaches while minimizing their weaknesses (Whitehead et al. forthcoming). Revealed preference data can be enhanced by stated preference data. Stated preference allows analysis of behavior beyond the range of historical experience. Hypothetical bias can be a major problem with stated preference data. In many cases, hypothetical choices may not reflect budget, and other, constraints on behavior. For example, in a contingent behavior survey beachgoers may respond to a hypothetical trip question with their good intentions of making weekly beach trips. Yet, when the actual choice must be made, unexpected constraints arise and fewer trips are taken. Combining revealed preference and stated preference data allows mitigation of hypothetical bias present in stated preference data.

In contrast to previous efforts at valuing beach nourishment and improved access, in this paper we jointly estimate a travel cost recreation demand model using revealed and stated preference data. Three hypothetical scenarios are considered: status quo, improved parking and access and increased beach width. As in Whitehead, Haab, and Huang (2000) we consider the impact of hypothetical scenarios on demand elasticities and consumer surplus estimates. We are able to correct for hypothetical bias because we elicit the status quo stated preference response and include it in the empirical model.

Survey Data

The study area includes seventeen beaches in five southeastern North Carolina counties. Bogue Banks, a barrier island, is located in Carteret County, and encompasses a twenty-four mile stretch of beach communities. Topsail Island, a barrier island, is located in both Pender and Onslow Counties and encompasses a twenty-two mile stretch of beach communities. New Hanover County encompasses a thirteen mile stretch of beach communities and lies between Pender and Brunswick County. The Brunswick County beaches are located between the Cape Fear River and the South Carolina border and encompass a twenty-four mile stretch of beach communities.

The target population was chosen based upon the results of an on-site survey conducted during the summer of 2003 at the study area beaches (Herstine et al., 2005). The majority of day users (approximately 73%), the primary users of public beach parking, traveled 120 miles or less to get to the beach. Survey Sampling, Inc. provided telephone numbers within the 120 mile beach travel distance study area. The telephone survey was administered by the Survey Research Laboratory (SRL) at the University of North Carolina Wilmington during May 2004. The response rate was 52 percent.

Of the survey respondents 1509 stated that they had considered going to an oceanfront beach in North Carolina during the past year (2003). Of this number, 1186 (79 percent) actually took an oceanfront beach trip to the North Carolina coast in 2003. Of these, 937 (79 percent) took an oceanfront beach trip to the southeastern North Carolina beaches in 2003. Of all respondents who took at least one trip to the southeastern North Carolina coast, 96 percent planned to take at least one oceanfront beach trip to this area in 2004. After deleting cases with missing revealed or stated preference information, travel distance information, income, or other demographics, the remaining sample size is 636. Comparing the demographics of the useable sample of respondents to those beachgoers excluded from the analysis, the useable sample has greater annual household income and lower travel costs (described below). We can expect the usable sample to be more avid beachgoers than the excluded beachgoers. Aggregation of our results to the population should proceed with this caveat.

The number of revealed preference beach trips made by each survey respondent to any of the beaches in the study region in 2003 was elicited by asking how many of the respondent's oceanfront beach trips were made to beaches along the southern North Carolina coast from the Beaufort/Morehead City area in Carteret County to the South Carolina border (see Q5 in the Appendix). The responses include both day and night trips, although most were day trips, as all telephone survey respondents lived within 120 miles of the beach study area. The average annual number of trips is 11 (Table 1). Respondents who planned to take at least one oceanfront beach trip to the southeastern North Carolina coast during 2004 were asked how many trips they intended to take (Q22). The average number of planned trips in 2004 with current access and width conditions is 13.

Respondents were asked about their perceptions of current beach access and parking quality (Q24). Thirty-nine percent of respondents think that the current beach parking situation is either good or excellent. The following hypothetical scenario was then presented to respondents: "Suppose that parking facilities and beach access at southeastern North Carolina oceanfront beaches were improved so that you would not have to spend time searching for a parking space or access area, the parking space and access area would be located within reasonable walking distance of the oceanfront beach, and parking was free or reasonably priced. Also suppose that the number of beach users at the oceanfront beaches does not change." Under these conditions, 65 percent of respondents think that the improved parking situation would be either good or excellent (Q25) and the average number of beach trips under these improved conditions would be 17 (Q27-Q28).

Respondents were then told that "the width of the dry sand beach area from the dune to the ocean at high tide at southeastern North Carolina oceanfront beaches is between 10 and 100 feet with an average of 75 feet." Sixty-nine percent of respondents think that the current beach width conditions are either good or excellent (Q32). The following beach nourishment policy was then presented to respondents: "Suppose a beach nourishment policy is implemented for all southeastern North Carolina oceanfront beaches. Beach nourishment would be performed in each county periodically, at least once every 3 to 5 years, for the 50-year life of the project. Periodic nourishment is done to maintain an increased beach width to provide shore protection and recreation benefit. The goal would be to make the average beach width increase by 100 feet."

The respondents are split on whether beach nourishment is the right beach management option. Forty-four percent of respondents think that adding 100 feet of width to the beaches would be the right amount, 21 percent think that the current beach width is fine, and 18 percent think that people should not alter the width of the beach (Q33). Fifty-eight percent of respondents either strongly support or support the beach nourishment policy (Q34). Eighty-five percent of respondents think that the beach nourishment policy would be an effective means of maintaining beach width (Q35). The average number of beach trips with the nourishment policy is 14 (Q36-Q37).

Travel distances and time between each survey respondent's home zip code and the zip code of the population center of each beach county are calculated using the ZIPFIP correction for "great circle" distances (Hellerstein et al. 1993). The minimum travel distance to the study area is used for computing travel cost to the aggregate site. Travel time is calculated by dividing round trip distance by 50 miles per hour. The cost per mile used is $0.37, the national average automobile driving cost for 2003 including only variable costs and no fixed costs as reported by the American Automobile Association (AAA Personal communication, 2005). Thirty-three percent of the wage rate is used to value leisure time for each respondent. The round-trip travel cost is

$p = (2 \times c \times d) + (\theta w \times [2 \times d / mph])$ where c is cost per mile, d is one-way distance, θ is the fraction of the wage rate, w, and mph is miles per hour. The average travel cost to the southern NC beaches is $90. We propose that the Outer Banks beaches in northern NC are substitute sites for much of the sample. We measure travel costs to the central location for access to the Outer Banks beaches, the town of Manteo, and measure travel costs in the same way. The average travel cost to the substitute site is $203. Average annual household income is $59 thousand in 2003 dollars.

Empirical Methods

The telephone survey collects revealed preference (RP) and stated preference (SP) data for analysis using the single-site travel cost method (TCM). The RP data is based on beach trips that were actually taken in 2003. The SP data is based on future trips that would be taken in 2004 under various hypothetical conditions. The SP data is used to simulate a change in demand resulting from changes in beach quality. SP trip questions are asked about future trips (1) under status quo conditions, (2) with an improvement in parking conditions (i.e., no time spent searching for a parking spot, reasonable fees, and no change in congestion) and (3) with an increase in beach width (i.e., adding an average increase of 100 feet to beach width with periodic beach nourishment every 3 to 5 years).

The Poisson regression model is typically used to study count data such as numbers of beach trips. Assume that x_{it} is the number of beach trips taken by individual i in scenario t, which is drawn from a Poisson distribution with mean λ_{it}

(1) $$\Pr(x_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{x_{it}}}{x_{it}!}, x_{it} = 0,1,2,...$$

The natural log of the mean number of trips is assumed to be a linear function of prices, income and scenario dummy variables. To allow for variation across beachgoers that cannot be explained by the independent variables, we assume that the mean number of trips also depends on a random error, u_{it}. The pooled single-site RP-SP Poisson demand model is

(2) $$\ln \lambda_{it} = \beta_0 + \beta_1 op_i + \beta_2 cp_i + \beta_3 y_i + \beta_4 A + \beta_5 W + \beta_6 SP + u_{it}$$

where *op* is the own-price (i.e., round trip travel costs to the beach site), *cp* is the cross-price (i.e., round trip travel costs to a substitute site), *y* is income, $\beta_0 - \beta_6$ are coefficients, individuals are indexed *i* = 1, …, 636, and t = 1, …, 4 denotes seasonal trip demand under RP status quo, SP status quo, SP improved parking and SP increased width scenarios, respectively, in the pseudo-panel data. Dummy variables *A* (*A* = 1 when t =3) and *W* (*W* = 1 then t = 4), are demand shift quality variables for the access and width scenarios. The *SP* dummy variable is included to test for hypothetical bias. *SP* = 1 for hypothetical trip data (t = 2, 3 or 4) and 0 for revealed trip data (t = 1). We also include variables interacted with the *SP* dummy variable, described below.

Pooling the data suggests that panel data methods be used to account for differences in variance across sample individuals, *i*, and scenarios, *t*. The distribution of trips conditioned on u_{it} is Poisson with conditional mean and variance, λ_{it}. If $\exp(\lambda_{it})$ is assumed to follow a gamma distribution then the unconditional trips, x_{it}, follow a negative binomial distribution (Hausman, Hall and Griliches 1984). We include interaction terms between the stated preference dummy variable and the own-price, cross-price and income variables in equation (2) which allows comparisons between simulated RP and SP demands.

(3)

$$\ln \lambda_{it} = \beta_0 + \beta_1 op_i + \beta_2 cp_i + \beta_3 y_i + \beta_4 A + \beta_5 W + \beta_6 SP + \beta_7 (op_i \times SP) + \beta_8 (cp_i \times SP) + \beta_9 (y_i \times SP) + u_{it}$$

We also estimate models that interact the demand quality shift variables, *A* and *W*, with own-price, cross-price and income. In these models only the interaction between improved access, *A*, and own-price was statistically significant. For this model we add $\beta_{10}(op_i \times A)$ to equation (3). For each model we estimate trips, elasticities and consumer surplus with the *SP* dummy variable set equal to zero to simulate *RP* demand, denoted RP_{Sim}. We set the stated preference dummy variable equal to zero to account for those stated preference trips under status quo conditions that exceed the revealed preference trips under status quo conditions. We assume that the difference in trips represents overstatement of future trip taking behavior (i.e., hypothetical bias). In comparison, for each model we also predict trips with the *SP* dummy variable set equal to one to simulate stated preference demand.

With the semi-log functional form in equations (2) and (3) the own-price, cross-price and income elasticities estimated for the RP_{Sim} scenario (that is, with $SP = 0$) are

$$
(4) \qquad \begin{aligned} e_{op} \mid RP_{Sim} &= \beta_1 \overline{op} \\ e_{cp} \mid RP_{Sim} &= \beta_2 \overline{cp} \\ e_y \mid RP_{Sim} &= \beta_3 \overline{y} \end{aligned}
$$

Including additive interaction terms between the stated preference dummy variable and the own-price, cross-price and income variables in equation (3) allows us to calculate elasticities for the SP scenario

$$
(5) \qquad \begin{aligned} e_{op} \mid SP &= (\beta_1 + \beta_6)\overline{op} \\ e_{cp} \mid SP &= (\beta_2 + \beta_7)\overline{cp} \\ e_y \mid SP &= (\beta_3 + \beta_8)\overline{y} \end{aligned}
$$

and test for differences in elasticities between the RP_{Sim} and *SP* scenarios.

With the semi-log functional form the economic benefit per beach trip in the RP_{Sim} scenario for the representative beachgoer as measured by average consumer surplus CS per trip is

$$
(6) \qquad \frac{CS \mid RP_{Sim}}{\hat{x}_{SP=o}} = \frac{1}{-\beta_1}
$$

where $\hat{x}_{SP=0}$ is the predicted trips for the representative beachgoer with $SP = 0$ and all independent variables are set at sample means (Bockstael and Strand 1987).

The economic benefit of an improvement in beach access per trip is

$$
(7) \qquad \frac{\Delta CS \mid RP_{Sim}}{\hat{x}_{SP=0}} = \frac{(\hat{x} \mid A=1) - (\hat{x} \mid A=0)}{-\beta_1}
$$

The economic benefit of an increase in beach width per trip is

$$(8)\qquad \frac{\Delta CS \mid RP_{Sim}}{\hat{x}_{SP=0}} = \frac{(\hat{x} \mid W=1) - (\hat{x} \mid W=0)}{-\beta_1}$$

The corresponding SP scenario estimates of economic benefit per beach trip are

$$(9)\qquad \frac{CS \mid SP}{\hat{x}_{SP=1}} = \frac{1}{-(\beta_1 + \beta_7)}$$

$$(10)\qquad \frac{\Delta CS \mid SP}{\hat{x}_{SP=1}} = \frac{(\hat{x} \mid A=1) - (\hat{x} \mid A=0)}{-(\beta_1 + \beta_7)}$$

$$(11)\qquad \frac{\Delta CS \mid SP}{\hat{x}_{SP=1}} = \frac{(\hat{x} \mid W=1) - (\hat{x} \mid W=0)}{-(\beta_1 + \beta_7)}$$

In the empirical results that follow we consider differences between the simulated revealed preference and stated preference values for elasticity, consumer surplus per trip, and change in consumer surplus. The null hypotheses are that estimates of elasticities and consumer surplus do not vary across scenarios. The alternative hypotheses are that the unadjusted stated preference estimates of the regression coefficients and number of trips are prone to hypothetical bias, resulting in estimates of elasticities and consumer surplus that do vary across scenarios.

Results

Three recreation demand models are estimated using a random effects Poisson specification (Haab and McConnell, 2002). The pseudo-panel data set has 636 cases (survey respondents) and 4 scenarios: *RP* status quo, *SP* status quo, *SP* improved parking and *SP* increased width. The first model uses demand shift variables *SP, A*, and *W* to specify hypothetical scenarios.[6] The second model interacts the *SP* variable with the own-price, cross-price and income variables to determine whether RP status quo scenario elasticities differ from SP status quo scenario elasticities. The third model interacts *A* and *W* with prices and income to determine whether elasticities differ across the three SP scenarios.

In each model the coefficient on the own-price variable is negative and statistically significant, the coefficient on the cross-price variable is positive and

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[6] Some of the respondents take both day and overnight trips. The results are robust to exclusion of those day trippers who also take overnight trips. We also estimated preliminary models with demographic variables for marital status, sex, race, age and education. In these models married respondents and those with more education took more beach trips. Inclusion of these variables has no effect on the key coefficients in the demand model: price, cross-price and the stated preference demand shifters. However, inclusion of these variables affects the income coefficient by decreasing its value. This is due to the positive correlation between marital status, education and household income. The decreased income coefficient decreases the income elasticity. Since there are theoretical reasons for including income in the demand model and not demographic variables, we choose to omit the demographic variables to limit the effects of multicollinearity.

statistically significant and the coefficient on the income variable is positive and statistically significant (Table 2). In each model the *SP* dummy variable is statistically significant indicating that respondents state that they will take more trips under status quo conditions than the revealed preference data indicate. We interpret this result as evidence of hypothetical bias.[7] Hypothetical bias exists because stated preference trips exceed revealed preference trips under similar benefit and cost conditions. In Model 2 the *SP* interaction terms are each statistically significant in addition to the *SP* shift variables indicating that *SP* slope coefficients differ from *RP* slope coefficients. Using a likelihood ratio test, Model 2 is statistically superior to Model 1 (χ^2 = 69.90[3 df]).[8] In Model 3, we

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[7] Without evidence to the contrary, stated preference trips that exceed revealed preference trips under similar quality and cost conditions should be considered an overstatement of trips. The appropriate contrary evidence would be actual trips that correspond to the stated preference trips. In a predictive validity natural experiment, Whitehead (2005) provides some evidence that stated preference hurricane evacuations correspond to revealed preference hurricane evacuations after correcting for hypothetical bias using the interpretation of hypothetical bias employed in this paper.

[8] In a preliminary model each of the individual *SP* scenario interaction variables are statistically significant suggesting that elasticities differ across scenarios. However, Model 2 is statistically superior to this preliminary model (χ^2 = 14.61[9 df]). In several other preliminary models we (1) alternately constrain the nine *SP* scenario interaction coefficients to be equal to determine if they differ across scenario and (2) include those that differed with the *SP* interaction variables to determine if the scenario interaction coefficients differed from the baseline *SP* interaction coefficients.

find that only the *SP* access variable *A* interacted with the coefficient on the own-price variable differed from its corresponding *SP* status quo interaction coefficient. Using a likelihood ratio test, Model 3 is statistically superior to Model 2 (χ^2 = 12.71[1 df]).

In Table 3 we present predicted trip estimates. For each model in Table 2 we predict trips with the *SP* dummy variable set equal to zero to simulate revealed preference demand, RP_{Sim}. Using RP_{Sim} demand, 9 trips are predicted under status quo beach conditions, 12 trips are predicted with improved access and 10 trips are predicted with increased width in Models 1-3. Using the standard errors of the trip estimates we construct 95% confidence intervals for the RP_{Sim} trip estimates. The 95% confidence intervals overlap for the status quo, improved access and increased width scenarios with Model 1. With statistically superior Model 2, the trip estimates are significantly different. With Model 3, baseline trips and trips with increased width are significantly different.

For comparison, we also predict trips with the SP dummy variable set equal to one to simulate stated preference demand unadjusted for hypothetical bias. The estimated number of trips is about 20 percent larger under SP demand for each beach condition scenario. We interpret the statistically significant 20 percent differences in trips between RP_{Sim} and *SP* demands as evidence of hypothetical bias.

In Model 1, where demand is allowed to shift depending on RP_{Sim} or *SP* specification but elasticities are constrained to be equal across specifications, the own-price elasticity is -0.96, the cross-price elasticity is 0.85 and the income elasticity is 0.30 (Table 4). In Model 2, both demands and elasticities are allowed to shift across specifications. In Model 2, the *SP* demand has lower own-price elasticity (in absolute value) than the RP_{Sim} demand. The *SP* demand also has lower cross-price and income elasticities. The income elasticity shows the largest difference with a 77 percent increase from the *SP* demand to the RP_{Sim} demand. These results are consistent with the general notion that respondents are less responsive to economic factors in a hypothetical situation. In Model 3, demands and elasticities are allowed to shift across SP / $\mathrm{RP}_{\mathrm{Sim}}$ specification and across beach condition scenario. Similar results are found for Model 3 except that the *SP* own-price elasticity for the improved beach access scenario is larger than the *SP* own-price elasticity under status quo beach conditions. However, none of the differences in elasticities are statistically significant according to the 95% confidence intervals constructed from the standard errors.

The baseline consumer surplus per trip estimates are about $90 (Table 5). The increase in the consumer surplus per trip with the improvement in beach access is about $25. The increase in the consumer surplus per trip with the increase in beach width is about $7. For each of these beach condition scenarios there are no statistically significant differences between RP_{Sim} and *SP* specifications.

Combining the consumer surplus per trip estimates from Table 5 with the trip estimates in Table 3, the annual consumer surplus is $869 from Model 1 when using the RP_{Sim} specification. The annual consumer surplus estimates from Models 2 and 3 are lower than those from Model 1 when using the RP_{Sim} specification. Annual consumer surplus estimates are larger when the *SP* specification is used. In Models 2 and 3, the 35 percent and 39 percent differences between RP_{Sim} and *SP* annual consumer surplus estimates are likely economically significant; however, the differences are rarely statistically significant in this empirical application based on 95% confidence intervals. When using these values for policy analysis, care should be taken to consider the statistical uncertainty of the estimates.

The increase in annual consumer surplus with the improvement in beach access is \$298 in Model 1 when using the RP_{Sim} specification. In Models 2 and 3 the increase in consumer surplus is 35% and 22% larger when using the *SP* specification; however, these differences are not statistically significant. The increase in the annual consumer surplus with the increase in beach width is \$68 in Model 1 when using the RP_{Sim} specification. In Models 2 and 3 the increase in consumer surplus is 35% and 39% greater when using the *SP* specification; although likely economically significant, again these differencs are not statistically significant in this empirical application. When using these values for policy analysis, care should be taken to consider the statistical uncertainty of the estimates.

Conclusions

In this paper we estimate the demand for beach recreation in southern North Carolina using both revealed and stated preference data in order to estimate the benefits of improvements in beach access and beach width. We illustrate the numerous ways that hypothetical bias in contingent behavior data can lead to overestimation of the economic benefits of recreation and recreation quality improvement. We find that hypothetical bias affects estimates of regression coefficients and the number of trips. However, since elasticities and consumer surplus per trip estimates are nonlinear functions of regression slope coefficients, hypothetical bias may not necessarily lead to statistically significant differences in elasticity or consumer surplus per trip estimates, and we find that it does not in this empirical application. However, when the product of trips and consumer surplus per trip is taken to estimate consumer surplus per season, hypothetical bias may lead to economically significant differences in seasonal consumer surplus estimates. Altogether, these results suggest that when revealed preference data are unavailable, stated preference recreation demand data may be suitable for estimation of consumer surplus per trip but not consumer surplus per season.

Hypothetical bias can be mitigated by setting stated preference dummy variables equal to zero in order to simulate revealed preference demands. Note that this is only possible when a stated preference scenario describing status quo conditions is included in the survey design. Otherwise, shifts in stated preference demand related to quality change may be confounded with hypothetical bias. Future research should always include a stated preference demand scenario describing status quo conditions.

The consumer surplus per trip estimates in this study are high relative to those in the single-site TCM beach valuation literature. This may be due to the aggregation of a large number of beaches into a single recreation site. For example, in Model 1 the consumer surplus per trip is $94. Bin et. al (2005) estimate that the value of a day trip to individual North Carolina beaches ranges from $11 to $80. Ongoing research with a subset of these data compares the single-site travel cost method results to results from multiple site models that better consider substitution possibilities (Whitehead et al, 2007). Whitehead et al. (2007) find some evidence of convergent validity; i.e., the change in consumer surplus values from the single-site demand models lie between estimates from the multiple site models.

Using the Model 3 estimates with the hypothetical bias correction we aggregate the benefit estimates to provide an illustration of their usefulness for policy analysis. Note that this is only an illustration. Our sample of respondents is likely more avid than the population. With about 1.58 million households in the study region and about 64 percent of these beach recreation participants, the annual aggregates benefit of southern North Carolina beach trips is about $791 million. The annual recreation benefit of improved access is about $325 million and the annual recreation benefit of increased width is about $62 million. After adjusting for avidity, these benefit estimates could be compared to cost estimates to determine the economic efficiency of coastal management policies.

Figure 1. North Carolina Counties in the Telephone Survey Sample

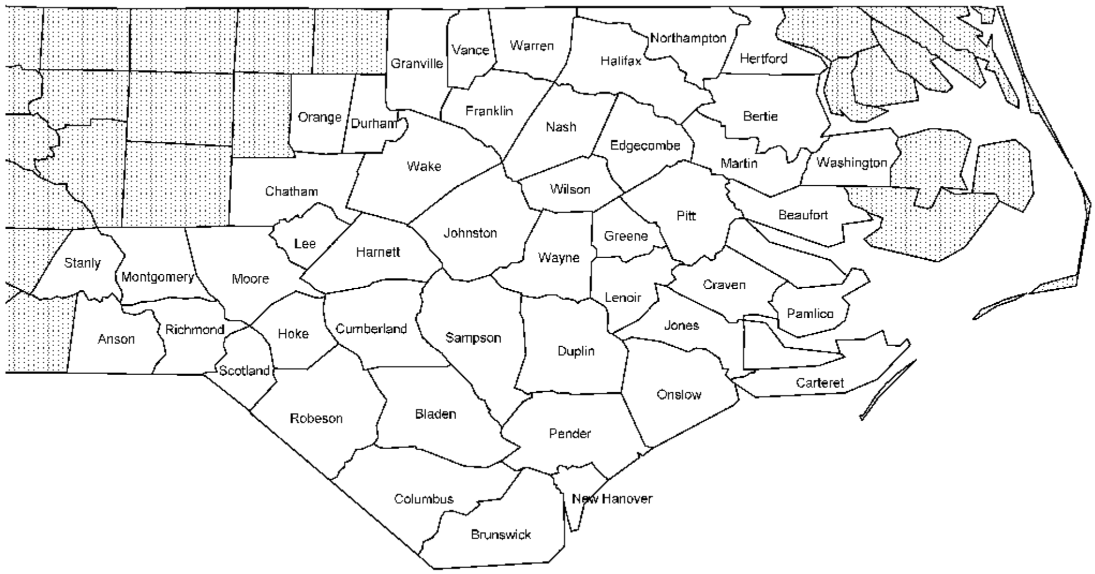

Table 1. Data Summary

Variable	Description	Mean	StdDev
Trips (t=1)	Revealed preference	11.01	23.10
Trips (t=2)	Stated preference with current conditions	13.01	24.99
Trips (t=3)	Stated preference trips with improved access	16.93	30.05
Trips (t=4)	Stated preference trips with increased width	13.99	25.78
Own-price	Travel cost to southern NC beaches	90.44	61.30
Cross-price	Travel costs to substitute (outer banks) NC beaches	203.17	56.89
Income	Household income	59.10	26.91

Table 2. Stated and Revealed Preference Random Effects Poisson Beach Recreation Demand

	Model 1		Model 2		Model 3	
Variable	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Constant	2.0247	21.32	1.8167	18.61	1.8168	18.62
Own-Price	-0.0106	-15.79	-0.0114	-16.19	-0.0114	-15.65
Cross-Price	0.0042	7.15	0.0046	7.82	0.0046	7.67
Income	0.0051	4.05	0.0079	6.01	0.0079	5.45
SP status quo[a]	0.1664	15.26	0.4244	17.58	0.4092	16.74
A: SP improved access[b]	0.2634	23.65	0.2634	23.34	0.3033	23.44
W: SP increased width[c]	0.0727	3.68	0.0727	3.62	0.0727	3.54
Own-Price × SP			0.0010	10.51	0.0013	10.81
Cross-Price × SP			-0.0005	-4.43	-0.0006	-4.37
Income × SP			-0.0034	-14.37	-0.0034	-13.83
Own-Price × A: SP improved access					-0.0007	-5.03
alpha	1.12	14.60	1.12	14.38	1.12	14.27
LL	-8210.81		-8175.86		-8169.50	
Cases	636		636		636	
Periods	4		4		4	

[a]Dummy variable for all SP scenarios.

[b]SP dummy variable for scenario 2.

[c]SP dummy variable for scenario 3.

Table 3. Predicted Trip Estimates

	Model 1		Model 2		Model 3	
Scenario	RP_{Sim}[a]	SP[b]	RP_{Sim}	SP	RP_{Sim}	SP
Baseline	9.23 (0.40)[c]	10.90 (0.48)	8.95 (0.39)	10.98 (0.48)	8.95 (0.39)	11.07 (0.49)
Improved Access	12.01 (0.55)	14.19 (0.62)	11.64 (0.54)	14.28 (0.63)	12.12 (0.57)	14.07 (0.62)
Increased Width	9.93 (0.49)	11.73 (0.53)	9.62 (0.48)	11.80 (0.53)	9.62 (0.48)	11.91 (0.55)

[a] Trips predicted with the SP dummy variable set equal to zero.

[b] Trips predicted with the SP dummy variable set equal to one.

[c] Standard errors in parentheses.

Table 4. Elasticity Estimates

	Model 1	Model 2		Model 3	
Elasticity	RP_{Sim} [a]	RP_{Sim}	SP[b]	RP_{Sim}	SP
Own-price	-0.96 (0.06)[c]	-1.03 (0.06)	-0.94 (0.06)	-1.03 (0.07)	-0.92 (0.07)
Cross-price	0.85 (0.12)	0.94 (0.12)	0.83 (0.12)	0.94 (0.12)	0.83 (0.12)
Income	0.30 (0.07)	0.46 (0.08)	0.26 (0.08)	0.46 (0.09)	0.26 (0.09)

[a] Trips predicted with the SP dummy variable set equal to zero.

[b] Trips predicted with the SP dummy variable set equal to one.

[c] Standard errors in parentheses.

Table 5. Consumer Surplus Estimates

	Model 1	Model 2		Model 3	
Scenario	RP_{Sim}[a]	RP_{Sim}	SP[b]	RP_{Sim}	SP
Per Trip	94.08 (5.96)[c]	87.43 (5.40)	95.90 (6.54)	87.43 (5.59)	98.44 (7.01)
Per Trip Change with Improved Access	24.78 (1.66)	23.03 (1.57)	25.26 (1.85)	26.52 (1.75)	27.92 (1.92)
Per Trip Change with Increased Width	6.84 (1.82)	6.36 (1.75)	6.97 (1.92)	6.36 (1.78)	7.16 (2.02)
Annual	868.55 (67.87)	782.34 (60.33)	1052.70 (87.79)	782.33 (61.41)	1090.12 (93.35)
Annual Change with Improved Access	297.71 (26.16)	268.16 (24.08)	360.83 (31.93)	321.40 (28.20)	392.97 (33.02)
Annual Change with Increased Width	67.92 (19.83)	61.18 (18.44)	82.32 (24.02)	61.18 (18.76)	85.25 (25.47)

[a] Trips predicted with the SP dummy variable set equal to zero.

[b] Trips predicted with the SP dummy variable set equal to one.

[c] Standard errors in parentheses.

Appendix. Survey questions used in this study

Revealed Trips

Q2. Did you actually take any oceanfront beach trips to the North Carolina coast in 2003?

Yes – go to Q3

No – go to Q21

Q3. How many oceanfront beach trips to the North Carolina coast did you take in 2003?

_____ Trips

Q4. How many of these oceanfront beach trips were day trips, where you returned to your home on the same day that you left?

_____ Trips

Q5. How many of your oceanfront beach trips were to the southeastern North Carolina coast from the Beaufort/Morehead City area in Carteret County to the South Carolina border?

_____ Trips

Stated Trips 1

Q20. Do you plan to take at least one oceanfront beach trip to the North Carolina coast from the Beaufort/Morehead City area to the South Carolina border during 2004?

Yes

No → go to Q23

Q21. As best as you can predict, how many oceanfront beach trips to the North Carolina coast do you plan to take during 2004?

______Trips → go to Q22

If 0, go to Q23

Q22. How many of these oceanfront beach trips do you plan to take to the North Carolina coast from the Beaufort/Morehead City area to the South Carolina border?

_____ Trips

Stated Trips 2

Q24. In general, would you say that current parking facilities at southeastern North Carolina oceanfront beaches are excellent, good, fair, or poor?

a. Excellent

b. Good

c. Fair

d. Poor

Q25. In general, would you say that current beach access at southeastern North Carolina oceanfront beaches are excellent, good, fair, or poor?

a. Excellent

b. Good

c. Fair

d. Poor

Q26. Suppose that parking facilities and beach access at southeastern North Carolina oceanfront beaches were improved so that you would not have to spend time searching for a parking space or access area, the parking space and access area would be located within reasonable walking distance of the oceanfront beach, and parking was free or reasonably priced. Also suppose that the number of beach users at the oceanfront beaches does not change. Would you say that improved parking conditions at southeastern North Carolina oceanfront beaches would be excellent, good, fair, or poor?

a. Excellent

b. Good

c. Fair

d. Poor

Q27. Compared to the number of oceanfront beach trips that you plan to take to the North Carolina coast from the Beaufort/Morehead City area to the South Carolina border during 2004, would you take more trips, fewer trips, or the same number or trips with improved parking facilities and access areas?

a. More → go to Q28

b. Fewer → go to Q29

c. The same → go to Q30

Q28. About how many more oceanfront beach trips would you take to the North Carolina coast from the Beaufort/Morehead City area to the South Carolina border with improved parking facilities and beach access?

_____ Trips

Q29. About how many fewer oceanfront beach trips would you take to the North Carolina coast from the Beaufort/Morehead City area to the South Carolina border with improved parking facilities and beach access?

______Trips

Stated Trips 3

Q32. The width of the dry sand beach area from the dune to the ocean at high tide at southeastern North Carolina oceanfront beaches is between 10 and 100 feet with an average of 75 feet. Would you say the current width is excellent, good, fair or poor?

a. Excellent

b. Good

c. Fair

d. Poor

Q33. Do you think adding 100 feet of width to the beach would:

a. Improve the beach and be about the right amount

b. Improve the beach, but not be enough width

c. Improve the beach, but would be too much extra width

d. Not improve the beach; beach width is fine as is

e. Not improve the beach; people should not alter the width of a beach

f. Other

Q34. Beach nourishment is where sand is pumped to artificially widen the beach. Do you strongly support, support, neither support or oppose, oppose, or strongly oppose beach nourishment for southeastern North Carolina oceanfront beaches?

a. Strongly support

b. Support

c. Neither support or oppose

d. Oppose

e. Strongly Oppose

Q35. Suppose a beach nourishment policy is implemented for all southeastern North Carolina oceanfront beaches. Beach nourishment would be performed in each county periodically, at least once every 3 to 5 years, for the 50-year life of the project. Periodic nourishment is done to maintain an increased beach width to provide shore protection and recreation benefit. The goal would be to make the average beach width increase by 100 feet. Do you think this policy would be very effective, somewhat effective or not effective in increasing beach width?

a. Very effective
b. Somewhat effective
c. Not effective

Q36. Think about the number of oceanfront beach trips that you plan to take to the North Carolina coast from the Beaufort/Morehead City area to the South Carolina border during 2004. Would you take more trips, fewer trips, or the same number of trips if the average beach were 100 feet wider?

a. More → go to Q37
b. Fewer → go to Q38
c. The same → go to Q37

Q37. About how many more oceanfront beach trips would you take to the North Carolina coast from the Beaufort/Morehead City area to the South Carolina border if the average beach were 100 feet wider?

_____ Trips

Q38. About how many fewer oceanfront beach trips would you take to the North Carolina coast from the Beaufort/Morehead City area to the South Carolina border if the average beach were 100 feet wider?

______Trips

References

AAA. 2005. Personal communication. American Automobile Association, Heathrow, FL.

Bell, F.W. 1986. Economic Policy Issues Associated with Beach Renourishment. *Policy Studies Review*. 6:374-381.

Bin, Okmyung, Craig E. Landry, Christopher L. Ellis and Hans Vogelsong. 2005. Some Consumer Surplus Estimates for North Carolina Beaches. *Marine Resource Economics* 20(2):145-162.

Bockstael, Nancy E. and Ivar E. Strand, Jr. 1987. The Effect of Common Sources of Regression Error on Benefit Estimates. *Land Economics* 63(1):11-20.

Boyle, Kevin J. 2003. Contingent Valuation in Practice. in *A Primer on Nonmarket Valuation*, ed. By Patricia A. Champ, Kevin J. Boyle, and Thomas C. Brown, London: Kluwer.

Edwards, Steven F. and Frank J. Gable. 1991. Estimating the Value of Beach Recreation from Property Values: An Exploration with Comparisons to Nourishment Costs. *Ocean and Shoreline Management* 15:37-55.

Haab, Timothy C., and Kenneth E. McConnell. 2002. *Valuing Environmental and Natural Resources: The Econometrics of Non-market Valuation*, Northampton, MA: Edward Elgar.

Hausman, J., B.H. Hall, and Zvi Griliches. 1984. Econometric Models for Count Data with an Application to Patents—R&D Relationship, *Econometra* 52:909-938.

Hellerstein, D., D. Woo, D. McCollum, and D. Donnelly. 1993. ZIPFIP: A Zip and FIPS Database. Washington D.C.: U.S. Department of Agriculture, ERS-RTD.

Herstine, Jim, Jeffery Hill, Bob Buerger, John Whitehead and Carla Isom. 2005. Determination of Recreation Demand for Federal Shore Protection Study Area: Overview and Methodology. Final Report Prepared for The U.S. Army Corps of Engineers, Wilmington District.

Holmes, Thomas P. and Wiktor L. Adamowicz. 2003. Attribute-Based Methods. in *A Primer on Nonmarket Valuation*, ed. By Patricia A. Champ, Kevin J. Boyle, and Thomas C. Brown, London: Kluwer.

Huang, Ju-Chin, P. Joan Poor and Min Qiang Zhao. 2007. Economic Valuation of Beach Erosion Control. *Marine Resource Economics* 22(3):221-239..

Landry, Craig E. 2005. Recreational Benefits of Beach Erosion Control: A Comparison of Revealed and Stated Preference Results. Department of Economics Working Paper #0522, East Carolina University.

Landry, C., A. Keeler, and W. Kriesel. 2003. An Economic Evaluation of Beach Erosion Management Alternatives. *Marine Resource Economics* 18(2): 105-27.

Jones, Sheridan R., and William R. Mangun. 2001 Beach Nourishment and Public Policy After Hurricane Floyd: Where Do We Go From Here? *Ocean and Coastal Management* 44:207-220.

Lindsay, Bruce E., John M. Halstead, Helen C. Tupper and Jerry J. Vaske. 1992. Factors Influencing the Willingness to Pay for Coastal Beach Recreation. *Coastal Management* 20:291-302.

McConnell, K.E. 1977. Congestion and Willingness to Pay: A Study of Beach Use. *Land Economics*. 53(2):185-195.

Parsons, George R., D. Matthew Massey and Ted Tomasi. 1999. Familiar and Favorite Sites in a Random Utility Model of Beach Recreation. *Marine Resource Economics* 14:299-316.

Parsons, George R. and Michael Powell. 2001. Measuring the Cost of Beach Retreat. *Coastal Management* 29:91-103.

Pompe, Jeffrey J. and James R. Rinehart. 1994. Estimating the Effect of Wider Beaches on Coastal Housing Prices. *Ocean and Coastal Management* 22:141-152.

Shivlani, M. P., Letson, D., and M. Theis. 2003. Visitor preferences for public beach amenities and beach restoration in South Florida. *Coastal Management* 31 (4): 367-386.

Silberman, Jonathan and Mark Klock. 1988. The Recreation Benefits of Beach Nourishment. *Ocean and Shoreline Management* 11:73-90.

United States Army Corps of Engineers. 2004. Economic and Environmental Planning and Guidance. United States Army Corps of Engineers. Publication number ER 1105-2-100. Available http://www.usace.army.mil/inet/usace-docs/eng-regs/er1105-2-100/.

Whitehead, John C. 2005. Environmental Risk and Averting Behavior: Predictive Validity of Revealed and Stated Preference Data. *Environmental and Resource Economics*, 32, 301-316.

Whitehead, John C., Timothy C. Haab and Ju-Chin Huang. 2000. Measuring Recreation Benefits of Quality Improvements with Revealed and Stated Behavior Data. *Resource and Energy Economics* 22, 339-354.

Whitehead, John C., Daniel Phaneuf, Christopher F. Dumas, Jim Herstine, Jeffrey Hill and Bob Buerger. 2007. "Convergent Validity of Revealed and Stated Recreation Behavior with Quality Change: A Comparison of Multiple and Single Site Demands," 07-17, Working Papers from Department of Economics, Appalachian State University.

Whitehead, John C., Subhrendu K. Pattanayak, George L. Van Houtven and Brett R. Gelso. Forthcoming. Combining Revealed and Stated Preference Data to Estimate the Nonmarket Value of Ecological Services: An Assessment of the State of the Science, *Journal of Economic Surveys*.