WORKING PAPER SERIES*

DEPARTMENT OF ECONOMICS

ALFRED LERNER COLLEGE OF BUSINESS & ECONOMICS

UNIVERSITY OF DELAWARE

WORKING PAPER NO. 2008-10

VALUING BEACH CLOSURES ON THE PADRE ISLAND NATIONAL SEASHORE

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*http://lerner.udel.edu/economics/workingpaper.htm

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March 2008

*Funded by the National Oceanic and Atmospheric Administration's Coastal Response Research Center at the University of New Hampshire and the National Park Service. We thank Ben Sigman for outstanding work on site definition and data assembly. We also thank Roger vonHaefen for comments, and Nancy Bockstael and John Duffield for help in the early stages of designing our survey.

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Abstract

In this paper we estimate the economic loss of hypothetical beach closures on the Padre Island National Seashore on the Gulf Coast of Texas. We use a travel cost random utility maximization (RUM) model with data from a random phone survey of Texas residents completed in 2001. We simulate realistic closures that may occur in event of an oil spill or other disruption. For comparison we valued the loss of beach closures in the heavily populated Galveston area. The aggregate losses on Padre Island were highest on weekend days in July estimated at $171,000 per day of closure (2001$). They were lowest on weekdays in September at $25,000. Per trip losses were about $28. A similar closure of beaches near Galveston resulted in losses of $263,000 (week day) and $852,000 (weekend day) with a per trip loss of $30.

Key words**: random utility model, beach use, non-market valuation**

Valuing Beach Closures on the Padre Island National Seashore

1. Introduction

The Padre Island National Seashore is one of several seashores managed by the National Park Service (NPS).[1] NPS advertises Padre Island as the longest remaining stretch of undeveloped barrier island in the world. It is located on the Gulf Coast of Texas southeast of Corpus Christi. Figure 1 is a map we used in our survey as an insert to help people identify beach areas. Padre is shown about midway down the Texas coast and highlighted in red. It runs for approximately 70 miles from north to south. It is accessible only by road at its northern entrance and by water at several southern locations. The most popular beaches are located on the 5 northern most miles of the island. These are accessible by paved road or packed sand and have ample parking and facilities for beach goers, anglers, and others. From the five-mile marker south the beaches become more natural and remote with all access by four-wheel drive only. Visitors use the park for typical beach activities like sunbathing, swimming, walking, surf-fishing, windsurfing, wildlife viewing and so on. Camping is also popular.

Our purpose is to estimate the potential economic loss due to beach closures on Padre Island that may result from an oil spill or other disruption. Our intention is to provide a model and a set of estimates that may be useful in damage assessment and benefit-cost analyses of measures designed to prevent beach closures such as regulations on land-based pollution, oil transport, and so forth. To this end we estimate a travel cost random utility maximization (RUM) model using a data set on reported beach trips to the Texas Gulf coast by 884 randomly selected Texas residents in 2001. Our focus is on day trips and our choice model includes 65 beaches on the Gulf coast of Texas of which six are part of the Padre Island National Seashore (PINS). This covers all of the

[1] Other national seashores include Assateague Island (VA), Canaveral (FL), Cape Hatteras (NC), and Fire Island (NY). For a complete listing of all parks in the National Park Service system go to http://www.nps.gov/archive/parks.html. The Padre Island web site is at http://www.nps.gov/pais/.

beaches in Texas with beach use, even those with modest visitation. Also, about 80% or more of all beach trips in Texas are for a single day. We estimated a nested-logit model and consider non-participants as well as participants. We simulated the model to value closures of all PI beaches, the welfare effects of having a history of recent closures on PI, and the welfare effects of have a history of recent red-tide episodes on PI. All are hypothetical but potentially realistic scenarios. We also estimated the loss associated with a closure of beaches in the Galveston area. Finally, the data are such that we can estimate losses separately for weekday and weekend trips and for each of the five months in our data set running from May to September.

Our application is one in a long line of studies applying the travel cost random utility model to beach use. Indeed the first ever application of a random utility model to recreation was a beach study by Hanemann (1978). To get a sense of the breadth and time frame of these analyses, Table 1 shows a list of applications. Each row corresponds to a different data set and shows the best source for documentation on the survey, papers published using the data, and how it has been used in valuation. The table is organized chronologically.

Applications began in the mid-1970s. There are fewer than 10 major data sets and about 25 publications. The list may not be exhaustive. Areas covered include Boston, New Bedford Harbor (MA), the Chesapeake Bay, the Mid-Atlantic, Florida, Lake Erie, San Diego, Southern California, and North Carolina. The number of beaches included in these models varied from as few as 5 in the New Bedford Harbor data to 297 in the Florida data. In all cases beaches were defined using commonly understood area delineations or nearby towns.

The site characteristics included in the models varied widely reflecting the differences in the beach areas and differences in the purposes of the models. For example, several studies focused on valuing water quality improvements, so effort was placed on obtaining good measures of water quality. Some studies have as few as 3 covariates and others have over a dozen. For example, Hicks and Strand (2000) use only three site characteristics – travel cost, a water quality index, and a facilities index. Parsons and Massey (2003) use over a dozen – travel cost, amusements, boardwalk, width, surf quality, park, park within, development density, facilities, parking, private, length. Hanemann et. al. (2004) use even more.

All models use logit estimation but the form varies widely. Bockstael, Haneman, and Kling (1987), Bockstael, Hanemann, and Strand (1986), Haab and McConnell (2002), Whitehead et. al. (2007), and Parsons (2003) estimated nested logit models. Hick and Strand (2000) and Haab and Hicks (1997) estimated simple multinomial logit models. Parsons and Massey (2003) and von Haefen, Phaneuf, and Parsons (2004) estimate mixed logit models. Von Haefen, Phaneuf, and Parsons (2004) and Whitehead et. al. (2007) also estimated a Kuhn Tucker form.

Some of the applications model the participation decision (whether to visit a beach or not) and others do not. Interestingly the earlier studies using the Boston, Chesapeake Bay, and Mid-Atlantic data included a participation component, which complicates estimation and interpretation, but provides a more complete picture of behavior and welfare change. Later studies began to exclude this part of the model to help focus on specific methodological issues. The San Diego and Lake Erie studies, for example, ignore participation altogether. Now lets turn to our model and the application to Texas beaches.

2. Model

We estimated our model of beach use using observed data on day trips by 884 Texas residents over five summer months in 2001. We used a repeated discrete choice model originally considered by Morey, Rowe, and Watson (1993) and discussed in Parsons (2003). Each individual is assumed to decide on a beach trip each day of the summer over 150 days. Taking no-trip is assumed to give an individual a 'no-trip utility' of u_{otn} and taking a trip gives 'site utility' of u_{itn}, where $i = 1,...,65$ is a beach on the gulf coast (with $i = o$ for no trip), $t = 1,...,150$ is a trip choice occasion or day, and $n = 1,...,884$ is a person in our sample. On each choice occasion a person is assumed to choose the alternative with the largest utility giving a 'choice occasion utility' of $v_{tn} = \max(u_{otn}, u_{1tn}, ...,u_{65tn})$.

No-trip utility in our model takes the form

(1) $u_{otn} = \alpha_y y_n + \alpha_m month_t + \alpha_d day_t + \varepsilon_{otn}$

where y_n is a vector of individual characteristics believed to influence whether or not a person takes a trip on a given choice occasion, $month_t$ is vector of five monthly dummy variables, day_t is a dummy variable for a weekend day, and ε_{otn} is an error term capturing aspects of utility unobserved by the researcher. The variables in y_n include age, education, ownership of surf-fishing gear, number of children in the household, and so forth. These variables are constant over the season. The vector $month_t$ and scalar day_t allow the no-trip utility to vary over the season and by weekend versus weekday.

Site utility takes the form

(2) $u_{itn} = \beta_{tc} tc_{in} + \beta_x x_i + \beta_{pm}(p_i \cdot month_t) + \varepsilon_{itn}$

where tc_{in} is the trip cost of reaching site i for person n and includes out of pocket travel as well as time cost. The vector x_i includes variables for lifeguards, managed cleaning of beaches, vehicle access, beach size, and so forth. The variable p_i is a dummy equal to 1 if the beach is located on the Padre Island National Seashore. The interactive term, $p_i \cdot month_t$, captures Padre-specific seasonality. We included this term to improve trip prediction to the sites of interest in our policy analysis. Site utility also includes an error term for unobserved aspects.

Equations (1) and (2) then form our *Baseline Model*. We also present two variations on this model. One considers interactive variables in site utility to identify observed heterogeneity in the data. The other drops all of the site characteristics and instead includes travel cost, Padre seasonality, and a separate alternative specific constant for each site.

Since site and no-trip utilities are random from the researcher's perspective, the observed trip data are treated as the outcome of a stochastic process. Let $j = 0,1,...,66$ denote one of 66 alternatives available to an individual on each choice occasion -- no-trip plus 65 beaches. Individual n's probability of choosing alternative k on choice occasion t then is

(3) $pr_{tn}(k) = pr(\tilde{u}_{ktn} + \varepsilon_{ktn} > \tilde{u}_{jtn} + \varepsilon_{jtn} \text{ for all } j)$

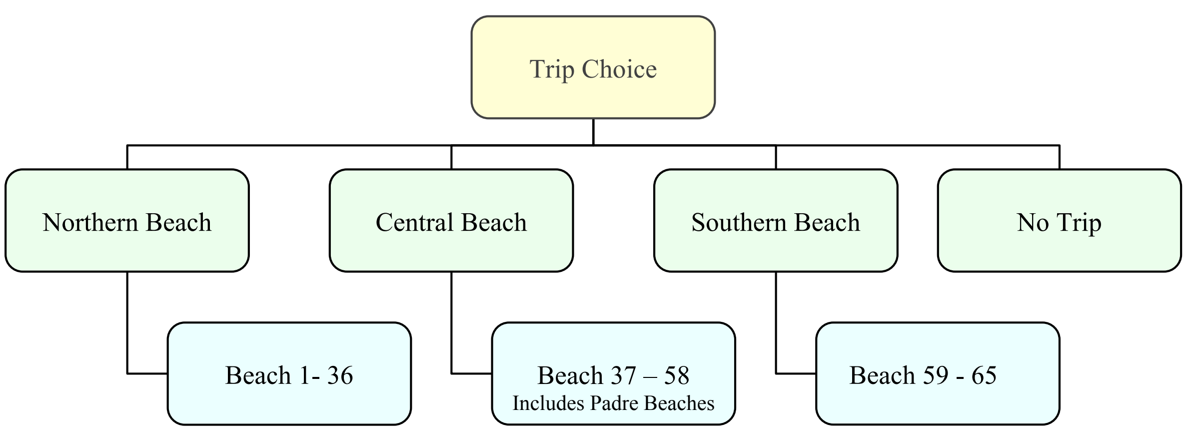
where $\tilde{u}$ represents the deterministic component of utility. Over the course of a season, person n makes T_n such choices. In principle $T_n = 150$ for each respondent, however, due to attrition in the sample some people provided trip data for only a portion of the full season. If, for example, person 1 provided only two months of data, $T_1 = 60$. The likelihood of observing the pattern of choices made by our sample of 884 persons then is

$$(4) \quad L = \prod_{t=1}^{T_n} \prod_{n=1}^{884} \prod_{k=1}^{66} pr_{tn}(k) \cdot w_{tn}(k)$$

$w_{tn}(k) = 1$ if person n chooses alternative k on choice occasion t

$w_{tn}(k) = 0$ if not.

Maximum likelihood estimates of the parameters in equations (1) and (2) are the values of α and β that maximize L. The form of $pr_{tn}(k)$ is determined by the distribution assumed for ε_{itn} and ε_{otn} in equations (1) and (2). In our model we assume a generalized extreme value nested logit error term structure where different regions on the coast are assumed to form different nests. Sites within a given nest share unobserved characteristics that appear in the error term and induce correlation across alternatives. This also induces the desired effect that sites within a given nest are better substitutes for one another than sites outside the nest. Shared unobserved factors inlcude management, physical, and/or access similarities within regions that go unaccounted for in our set of explanatory variables. Nested logit models have been popular in the recreation demand literature. For some examples of other applications to recreation demand see Bockstael, Haneman, and Kling (1987), Parsons and Kealy (1992), Morey et. al. (2002), Schwabe et. al. (2001), Whitehead et.al. (2007), and Hanneman et. al. (2005). Our nesting structure is shown below.



The form of the probabilities for nested logit models is well known. (See Morey (1999) or Train (2003, Chapter 4) for more on their theory and structure.) In our case, the probability that person *n* visits site *k* in period *t* assuming the site is in nest N is

$$(5)\quad pr_{tn}(k \mid N) = \frac{\exp(\tilde{u}_{ktn} / \lambda_N)}{\exp(I_{Ntn})} \cdot \frac{\exp(\lambda_N I_{Ntn})}{\exp(\lambda_N I_{Ntn}) + \exp(\lambda_C I_{Ctn}) + \exp(\lambda_S I_{Stn}) + \exp(\tilde{u}_{otn})}$$

where N, C, and S denote north, central, and south nests, and

$I_{Ntn} = \ln \sum_{j \in N} \exp(\tilde{u}_{jtn} / \lambda_N),$
$I_{Ctn} = \ln \sum_{j \in C} \exp(\tilde{u}_{jtn} / \lambda_C),$ and
$I_{Stn} = \ln \sum_{j \in S} \exp(\tilde{u}_{jtn} / \lambda_S).$

The probability that person *n* takes no trip in period *t* is

$$(6)\quad pr_{tn}(o) = \frac{\exp(\tilde{u}_{0tn})}{\exp(\lambda_N I_{Ntn}) + \exp(\lambda_C I_{Ctn}) + \exp(\lambda_S I_{Stn}) + \exp(\tilde{u}_{otn})}$$

Entering equations (5) and (6) into (4) gives our likelihood function for estimation. Three new parameters are included -- λ_N, λ_C, and λ_S. These are the 'inclusive value' or 'dissimilarity' coefficients for each nest. They capture the degree of substitution among the utilities within a given nest. The closer λ is to 0 the greater the correlation and hence the great the degree of substitutability among the sites. As λ approaches 1 the correlation and degree of substitution diminishes. To be utility-theoretic for all levels of explanatory variables $0 \leq \lambda_N$, λ_C, and $\lambda_S \leq 1$. See Herriges and Kling (1997) or Hauber and Parsons (2000) for more on welfare estimation and dissimilarity coefficients in nested logit models.

We considered other nesting structures as well -- a three level nested model with the three regions grouped together, nesting by gulf coast versus bay, nesting by vehicle-free versus vehicle-allowed, and nesting into more disaggregated regions. All of these models gave inclusive value coefficient estimates greater that one (in some cases substantially so) implying misspecified nests. We also considered mixed logit versions of the model that allowed for correlation among sites along the same lines as our geographic nests and implicitly along the lines of some of our explanatory variables. These models invariably failed to converge or gave parameter estimates that suggested a seriously ill-fit model. When we dropped the no-trip choice from our specification (substantially reducing the size of the data set since an observation would not be needed for each day of the season for each person), the mixed logit model converged, was robust, and preformed much as we had expected. In our judgment, losing the no-trip choice (a common substitute in the event of a beach closure) was too high a price to pay for the added model sophistication, so we chose the nested model. Finally, we also considered separate models for different types of beach use: fishing, swimming, and sunbathing. The results improved the fit of the models only slightly and gave coefficient estimates that tended to run counter to our intuition.

The welfare analysis for discrete choice random utility models for site closure is derived in Hanemann (1999) and shown in Parsons (2003). We follow that analysis directly. The welfare loss for person *n* on day *t* for the closure of the Padre Island National Seashore is

$$(7)\ w_{tn} = E(v_{tn}^{Padre\ Closure}) - E(v_{tn}^{Base}) / \beta_{tc}.$$

where $E(v_{tn}^{Base}) = \ln\{\exp(\tilde{u}_{otn}) + \exp(\lambda_N I_{Ntn}) + \exp(\lambda_C I_{Ctn}) + \exp(\lambda_S I_{Stn})\}$ is the expected choice occasion utility without closure and $E(v_{tn}^{Padre\ Closure}) = \ln\{\exp(\tilde{u}_{otn}) + \exp(\lambda_N I_{Ntn}) + \exp(\lambda_C I^*_{Ctn}) + \exp(\lambda_S I_{Stn})\}$ is the expected choice occasion utility with the closure of six Padre sites, where I^*_{Ctn} is the inclusive value for the central nest without the Padre sites and β_{tc} is the coefficient on trip cost in the site utility function. In this case $I^*_{Ctn} = \ln \sum_{j \in C^*} \exp(\tilde{u}_{jtn} / \lambda_C)$ where C^* is the set of all sites in the central region excluding the six Padre sites. Equation (7) gives a conventional compensating surplus measure of loss per person per day. It will used in our derivation of aggregate loss and per trip loss in the results section.

3. Data

The choice data used to estimate our model was collected in 2001 and is in two parts -- survey data of trips and site characteristic data for the 65 beaches. The survey data were gathered in a phone-mail-phone survey from May through September -- the peak season for beach visits. Texas residents living within 200 miles of the Gulf of Mexico were sampled by random digit dialing and recruited to participate in a follow-up survey of beach use. The sample was stratified as shown in Table 2 to avoid a sample dominated by residents of Houston, to assure adequate observation on trips to Padre Island, and to assure adequate participation rates in beach use. The initial survey was conducted in May and given to the adult member of the household (> 17 years old) with the most recent birthday. English and Spanish versions of the survey were offered. Users and nonusers were identified in the initial survey. We define a user as anyone who had visited the coast in the past five years and reported that they were likely make a visit during our survey period. Seventy seven percent of the people contacted in our initial phone survey were users – 1154 people. Of these, 1012 agreed to participate in five monthly follow-up surveys. Basic demographic information was gathered on each respondent in the initial phone survey. The follow-up surveys were confined to reporting beach trips.

Those who agreed to participate in the follow-up survey received a mail packet that included a map of the coast, a list of beaches, a calendar to help record trips from May through September, and a decorative magnet of the state of Texas for posting the calendar. As an incentive, individuals who agreed to participate in the follow-up survey were given a phone card with 100 hours of free calls. They were also told that they would receive a second card upon completion of entire follow-up survey. At the time phone cards were a popular way to make long distance calls from any location at reasonable rates.

Individuals were then contacted monthly by phone to report trips in the previous month. The materials included in the mailing were intended to help respondents identify beaches and report the actual dates of their trips. We believe the materials also gave respondents a sense of responsibility and helped keep them engaged in the survey. The monthly calls were intended to reduce the difficulty of recall. Of the 1012 respondents who agreed to participate in the follow-up surveys, 884 (87%) completed the survey through June, 803 (79%) through July, 741 (73%) through August, 670 (66%) through September, and 601 (59%) through October. Keeping respondents on-board for five months was difficult, but we were concerned about recall and for another modeling effort focusing on the dynamics of trips over a season we needed time specific trip data. Respondents reported a total of 2707 trips over the five-month period.

The variables used in the vector y_n in our 'no-trip utility' in equation (1) are shown in Table 3 and are adjusted to account for stratification. The age of our respondents ranges from 18 to 92 years and averages 41. About 62 % of the sample works full time, 49% have children under 17 years old, 34% have a college education, 9% are retired, 9% are Spanish speaking, and 60% are female. About 24% of respondents owned a boat, 24% a pool, and 49% surf cast fishing equipment.

The second part of our data set covers the characteristics of the sites -- the x_i vector in equation (2). We collected data on all of the public beaches on the Texas Gulf coast including information on facilities, amenities, services, and physical characteristics. The beaches included bay side and gulf beaches and were defined using the *2002 Texas Beach & Bay Access Guide* and a two-week field trip to the coast. The delineation of beaches was intended to be as the public generally perceived the boundaries. The beaches are listed in Table 4 running from north to south and grouped by the North, Central, and South nests used in our model. The Padre Island National Seashore is divided into six separate beaches following the National Park Service definitions -- the beaches are denoted by an asterisk in the table.

The beach characteristic data came from several sources: interviews with beach managers at the city, county, and state levels; the *2002 Texas Beach & Bay Access Guide*; other independent travel guides; field trips to each of the beaches; and on-line maps of the area. The variables used in our model, again the x_i vector in equation (2), are presented in Table 5 along with descriptive statistics. As shown, 48 beaches (74%) are on the Gulf (not bay) coast, 4 (6%) are in state parks, and 22 (34%) are remote. We defined remote as requiring a visitor to leave major roads to access the beach. These beaches tend to be more natural but are more difficult reach. Forty percent of the beaches are designated as vehicle free.

Many of the beaches in Texas accumulate debris from the waters of the Gulf of Mexico. Some is natural (seaweed, etc.) and some is from human sources. This is due to the currents in the Gulf and an enormous amount of human activity such as shipping, pleasure boating, fishing, oil platforms, and so forth. Management plans for many beaches involve routinely manually cleaning or machine cleaning beach areas. As shown in Table 5, 33 beaches (51%) had manual cleaning and 36 (55%) had machine cleaning in 2001 -- (33%) had both types of cleaning, (23%) had manual cleaning only, (19%) had machine cleaning only, and (27%) had neither.

Many of the beaches are managed for use and include restrooms, lifeguards, and concessions. We include each of these as dummy variables in our model – 37 beaches (57%) had restrooms, 17 (26%) had lifeguards, and 15 (23%) had concessions. In the *2002 Texas Beach & Bay Access Guide* several of the beaches are listed as not suitable for fishing or not suitable for swimming. We included these in our model assuming participation would be lower at these beaches for these activities – only 3 beaches had 'no fishing' and 6 'no swimming'.

To distinguish beaches by water quality we included two variables: advisories and red tide. We had originally hoped to use a continuous objective measure of quality but such data are not gathered uniformly across the beaches. Some are monitored more heavily, some get intermittent readings, some none at all, some are checked only when problems are expected and so on. An objective measure was problematic to say the least. We opted for a subjective measure based on interviews with beach managers for the different areas. Among the questions we asked the managers was whether or not there had been any beach advisories, closures, or red tide events at any of the beaches in your area. This information was used to construct the advisory/closure and red tide dummy used in the model. We have 11 beaches (17%) with an advisory/closure history during the year and 12 beaches (18%) with red tide episodes. The other arguments included in our site utility function are trip cost and Padre monthly dummies.

Table 6 is a frequency distribution of trips taken by distance traveled (again adjusted for stratification). About 30% of all trips were less than 30 miles one-way. About 50% were less than 50 miles, and 80% were less than 100 miles. It also interesting to note (not shown in the table) that only 4% of all trips were taken to the beach closest to a person's home and only about 36% were taken to one of the five closest beaches. This implies a large number of trips taken to enjoy specific characteristics of a beach. For example, an individual may travel pass a nearby beach because it does not have lifeguards or because it allows vehicles on the beach. Travel cost was calculated at 36.5 cents per mile plus any fee paid to use a beach. Time cost is valued at one-third of household income divided by 2000 as proxy for a person's wage. Distances and times to beaches were calculated using Rand MacNally's *Mile-Maker PC*. Average trip cost (travel plus time cost assuming 4 hours on site) of reaching the chosen site was $ 118. The average cost to all sites was $ 260.

Tables 7, 8, and 9 describe the trip taking behavior of our sample further. Table 7 shows the number of trips taken by the sample that completed all five waves of the survey. As shown, 41% took only one trip during the five-month sampling period, 65% took two or fewer, and 75% took three or fewer. This is a common profile for trip counts in recreation demand data sets. Also, most people visited only a few sites over the season. Seventy percent visited only one, 85% visited two or less, and 95% visited 5 or less. Table 8 shows the ten most popular beaches. These beaches account for 60% of all trips to the coast. Seven are in the North Region and three are in Central Region following our nesting structure. East Beach in Galveston was the most visited with 13% of all trips. East Beach is a large beach located in a major coastal population center. The second and third most visited beaches are also located in Galveston – Western Beach and Stewart Beach Park. The only Padre Island beach to make the top ten list is North Beach with 6% of all trips. Table 9 shows how the distribution of trips breaks down over the Padre sites. About 9% of all trips were to Padre. The sites are shown running north to south in the table. As expected the northern beaches have higher visitation.

The monthly visitation rates to the Padre Island beaches reported in our sample tract the trips reported by the National Park Service reasonably closely as shown in Figure 2. Since the National Park Service counts people as they enter the park, we expect their numbers to be reasonably accurate. This being the case, our survey seems to overstate the number of trips somewhat. Our phone sample is likely to suffer from avidity bias, attrition, and some recall issues. In combination these appear to lead to some overstatement. In our welfare analysis we calibrate the model to account for this apparent over reporting.

3. Results

Coefficient Estimates

Our estimation results are shown in Tables 10 and 11 for all three models. Table 10 shows the coefficient estimates for site utility and Table 11 shows the estimates for no-trip utility. Recall that we have estimated three versions of the model: *Baseline, Interactive,* and *Alternative Specific Constant Only*. Note that we do not report the 65 alternative constant estimates for the *Alternative Specific Constant Only Model.*

Consider the site choice portion of the model first. For the most part the estimates are as expected. The coefficient on trip cost, our marginal utility of income, is negative, significant, and robust across the three specifications. The log-length variable scales beaches to account for size and is positive and significant as. Over the geographic variables, all else constant, people appear to prefer beaches on the gulf instead of a bay, to be somewhat indifferent as to whether or not they are in a state park, and to prefer beaches that are not remote. The negative sign on the remote dummy may be picking up some of the higher implicit cost of reaching the remote beaches – implicit cost beyond what travel cost only captures.

Over the managed aspects of the beaches, again all else constant, people appear to prefer the beaches that limit vehicle access. We had originally thought the population would be divided on this attribute so we included two interactive variables to pick-up some of this anticipated effect in the *Interactive Model* – ownership of a 4-wheel drive vehicle and ownership of surf-cast fishing equipment. We thought these two groups would have a preference for beaches that allowed vehicles. The signs are as expected by neither give coefficient estimates large enough to suggest that people owning such equipment *prefer* beaches that allow vehicles. Instead, the estimates suggest that they have less intense preferences, but still prefer, vehicle free beaches. Beaches without vehicle access on the sand are required by law to have off-sand parking facilities to accommodate visitors, so the vehicle free variables may be picking up the effect of better parking facilities at these beaches over the beaches with vehicle access.

As expected, beaches with managed cleaning are preferred to beaches without, and beaches with machine cleaning are preferred to those with manual cleaning. Having restrooms or lifeguards increases the probability that a person will visit a beach, but the presence of concessions reduces the probability.   Here we introduced another interactive term in the *Interactive Model* – lifeguard interacted with having children under 17. We reasoned that people with children would seek out beaches with lifeguards, but the results suggested otherwise giving a negative and significant coefficient on the interactive term. Sites designated as unsuitable for fishing or swimming are less desirable than those suitable for these uses. And finally, beaches with a history of red tide episodes or closures during the year have a lower visit probability. This picks up both fewer days a site is available during the season and the 'signal' that a beach is prone to pollution problems.

The coefficients on the Padre-month interactions increase from May through July, fall in August, and increase again in September in all three specifications. (In the *Alternative Specific Constant Only Model* May is the excluded month, which is required in this model only since there is a constant on each site in the choice set.) These coefficients imply that, all else constant, there is a preference for Padre beaches versus all other beaches, but the preference is not stable over the season. Finally, validating our nesting structure, all inclusive value coefficients are greater than 0 and less than 1. This implies a model that is consistent with utility theory and implies that there is better substitution within than across nests. The model seems to do a reasonable job of predicting attributes that would matter to people. While some are insignificant statistically and the concessions variable seems to have the wrong sign, the relative signs and sizes of most the coefficients give a behavioral result we expected.

Now lets turn to the participation portion of the model or the no-trip utility shown in Table 11. Negative coefficients here imply lower no-trip utility and hence a higher probability of taking a trip. For example, all else constant, the model predicts that beach visitation declines with age (without statistical significance) and is higher on weekend days versus weekdays.

The model also predicts a higher probability of taking a trip, and with statistical significance, for people who work full time, have children under the age of 17, have a college education or higher, own a boat, fishing equipment, or property near the beach. The tie with boat ownership is not as obvious as fishing equipment or property, but it may simply be signaling a proclivity for outdoor water-based recreation activities.   The probability of taking a trip increases, but not with statistical significance, for men versus woman, retired folks, and English versus Spanish speaking beach goers. The model predicts with significance a higher probability of not taking a trip for those who own a pool. A pool may serve as a substitute for a beach trip.

The monthly dummy variables, where May is excluded, show an increased probability of staying home in the succeeding months.   Recall that people who reported trips for only a portion of the season have their reported months only included in the model. So, these dummies are not predicting fewer trips due to fewer people reporting. They are predicting fewer trips because the people who remain in the sample report less trip taking later in the season. We have not been able to confirm or refute this seasonality from outside data sources and so accept it as is but note that the number of trips in any given month can be calibrated to fit outside projections if available. We have done a version of this using the National Park Service estimates and discuss our approach in the next section.

Calibration Using National Park Service Padre Island Trip Data

The National Park Service gathers data daily on trips taken to Padre Island. They count visitors as they enter the park and sort out day versus overnight visitors using camping permits. Figure 2 compares our sample estimate of day trips to Padre Island to the National Park Service's estimate. The patterns are similar, but we tend to exceed their estimates. This may be due to avidity bias in our survey – people who visit beaches more often may be more interested in participating in a survey about beach use. We over predict by about 13% in May, 15% in June, 54% in July, and 75% in September, and under predict in August by 44%. Given our special interest in Padre Island, we decided to calibrate the visitation in our model to mimic rates observed in NPS data. We do this by adjusting the alternative specific constants until predicted visitation matches desired visitation (see Train (2003, p. 37 for a discussion).

Originally we thought that we would calibrate visitation to the Padre beaches only – resetting the Padre interactions until the aggregate number of trips each month to Padre Island equaled the NPS estimate. Unfortunately, this ignores predicted visitation to all other beaches in the state. Presumably, if our survey tends to over predict at Padre, it over predicts at all sites. Hence, we calibrated the model using the monthly alternative specific constants – the vector α_m in our no-trip utility is adjusted (increased for months where we over predict and decreased for months where we under predict. For example, the constant was adjusted for June until the predicted visitation rate dropped by 15% at all beaches. It is important to note here that this procedure keeps all other coefficients fixed so the relative ranking in the utilities among the beaches is unchanged.

Welfare Simulations

We considered four welfare scenarios: (1) the closure of all 6 beaches on the Padre Island National Seashore, (2) the impact of an 'adviosry/closure history' on Padre Island National Seashore, (3) the impact of a 'red tide history' on Padre Island National Seashore, and (4) the closure of 7 beaches on Galveston Island. The second and third scenarios need some explanation. Our model includes dummy variables for beaches that have a history of beach advisories/closures or red tide episodes before and during the 2001 season. These are beaches that have perennial pollution problems. In the last two scenarios we simulate the economic loss associated with Padre hypothetically having either an advisory/closure or red tide history by turning these dummies on for all Padre beaches.

The welfare estimates from the *Baseline, Interactive,* and *Alternative Specific Constant Only Models* gave estimates within to 2 to 3% of each other. The welfare loss is shown in Table 12 using the *Baseline Model* results. It is significant to note that the *Alternative Specific Constant Only Model*, which requires no information on site characteristics other than trip cost, gives nearly the same estimate as the other models for the site closure scenarios. In a sense this is not surprising since the model's predicted visitation rates must perfectly predict observed rates of visitation. The implication, however, is that if closure is the only concern for welfare estimation, then one may need not gathered detailed site characteristic data. If, however, quality changes are of interest, then the characteristic data will be necessary. Such is the case in our scenarios (2) and (3).

All the results in Table 12 are adjusted for stratification and calibrated to fit the National Park Service Visitation estimates. *Aggregate Loss* and *Per-Trip Loss* are shown by month and by week versus weekend day.

Aggregate Loss is for a single day and is

(8) $Aggregate\ Loss_t = \overline{w}_t \cdot Population$.

Population is the population of all Texas residents over the age of 17 living in a county within 200 miles of the coast in 2001, and $\overline{w}_t = \left\{ \sum_{n=1}^{884} w_{tn} \right\} / 884$ where w_{tn} is shown in equation (7) and is weighted to adjusted for stratification. Per-trip loss is

(9) $Per\text{-}Trip\ Loss_t = \dfrac{Aggregate\ Loss_t}{Displaced\ Trips}$

where *Displaced Trips* = number of displaced trips from Padre Island National Seashore due to the closure predicted by the model. *Per-Trip Loss* estimates are commonly used in benefits transfer in damage assessment cases. For example, it is often easy to estimate the number of displaced trips due to an oil spill. If one accepts that the ratio in equation (9) is roughly the same for the site study site (location where a model is estimated with primary data) and the policy site (location where the oil spill has occurred), a reasonable estimate of *Aggregate Loss* at the policy site by transfer is

$$(10)\ \ \textit{Aggregate Loss}^{\textit{policy site}} = \textit{Per-Trip Loss}^{\textit{study site}} \cdot \textit{Displaced Trips}^{\textit{policy site}}.$$

Again, so long as the ratio in equation (9) holds in moving form the study to the policy site, the transfer is valid. Our Table reports all three components of equation (9).

The aggregate loss for a closure of the Padre Island National Seashore is lowest in September and highest in July for both week day and weekend days. These are the lowest and highest months for visitation. In September the daily visitation rates are 884 per weekday and 2,895 per weekend day. In July, visitation is about twice as large at 1,869 and 6,030. For a one day closure in September during a weekday the loss is about $25,000. For a weekend day it is $82,000. All values are in 2001$. In July the aggregate loss is $53,000 for a weekday and $172,000 for a weekend day.

The *Per-Trip Loss* is stable across the months as one might expect since *Aggregate Loss* rises more or less proportionally with the number of trips taken. *Per-Trip Loss* is about $28 (2001$). These values are for day trips only and exclude non-use values and values related to other uses of the beach. For comparison, consider the two most recent estimates of *Per-Trip Loss* at other locations. Lew and Larson (2005b, p. 79) estimated a per trip loss of $28.27 (2005$) for day trips to beaches in San Diego, and Hanemann et. al. (2005, p.3) reported $11.21 (2005$) on average for day trips to beaches in Southern California. Both calculate *Per-Trip Loss* using the method applied here.

Table 13 shows the potential welfare impact of having a 'closure history' or a 'red tide history' on Padre Island. Table 13 shows the loss for July only. The impact of a 'closure history' is about half of the effect of a closure scenario considered above. This makes sense, since visitation would not cease but would be attenuated. The loss is $89,000 on a weekend day in July. The welfare impact of a 'red tide history' is higher but still below a closure at $119,000, about 70% of the closure loss. These losses should not be construed as what would occur for a one day red tide episode, rather they should be interpreted as the daily losses that might be realized if the Padre Island had been frequented by red-tide in the past and had have some recent episodes -- subtle but nonetheless different interpretation that give us some idea of the potential impact of such events. Finally, the welfare impact of closing eight beaches near Galveston is nearly five times larger than the Padre losses at $263,000 and $853,0000 for a week and weekend day in July. Again, given the proximity of these beaches to major population centers (Galveston and Houston), these results are expected.

4. Conclusions

We have demonstrated that the welfare loss associated with the closure of beaches on the Padre Island National Seashore in the event of an oil spill or other disruption are likely to substantial, reaching as high as $171,000 (2001$) for a closure of a weekend day in July. This value applies only to day-trips for beach recreation. It ignores over night beach use, non-use, and uses other than recreation, so the actual losses would be larger.

We also show that a similar closure of Galveston beaches would result in a loss that is five times larger than the Padre losses and that reoccurring closures or red tide episodes can have large welfare effects. Our findings are the first we are aware of for the Gulf coast and first that report estimates that vary by week versus weekend and by month.

We also found that there was little evidence of observed heterogeneity in our data, that many ‘reasonable’ nesting structures gave dissimilarity coefficients outside the unit interval, that more complex mixed logit models would converge only if the no-trip utility and all non-participants were excluded, and that an alternative specific constant only model predicted site closure losses as well as a model with a full set of site characteristics.

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Table 1: Selected Beach Data Sets Used in Travel Cost Random Utility Model Estimation

Data Set	Sources for Survey and Documentation	Applications	Valuation
1974 Boston Area In-person/At-home survey Boston area residents 30 Beaches	Hanemann (1978) Binkley and Hanemann (1975)	Hanemann (1978) Feenberg and Mills (1980) Bockstael, Hanemann, and Strand (1984) Bockstael, Hanemann, and Kling (1987)	Changes in water quality measure by oil, turbidity, COD, and fecal coliform.
1984 Chesapeake Bay On-site and Phone survey of area residents 12 Beaches	Bockstael, Hanemann, and Strand (1988)	Bockstael, Hanemann, and Strand (1988) Haab and Hicks (1997) Hicks and Strand (2000)	Changes in water quality as measured by nitrogen, phosphorous, and fecal coliform.
1987 New Bedford Harbor 5 beaches	McConnell (1986)	Haab and Hicks (1997)	None.
1994 Florida Phone Survey Residents of Central Florida 297 Beaches	Environmental Economics Research Group (1998)	Environmental Economics Research Group (1998)	Closure of beaches due to Tampa Bay oil spill.
1997 Mid-Atlantic Mail survey Delaware residents 62 Beaches	Massey (2002) www.fs.fed.us/nonmarketprimerdata/travel_cost_models.html	Parsons, Tomasi, and Massey (1999) Massey (2002) Parsons (2003) Parsons and Massey (2003) Haab and McConnell (2002) von Haefen, Phaneuf, and Parsons (2004) von Haefen, Massey, and Adamowicz (2005)	Closure of beaches and change in width of beaches.
1998 Lake Erie Beach Data Set On-site survey 15 Beaches in Ohio	Murray (1999) www.fs.fed.us/nonmarketprimerdata/travel_cost_models.html	Murray, Sohngen, and Pendelton (2001) Yeh, Haab, and Sohngen (2006)	Change in swimming advisories where advisories are measured as number of advisories in past two years.
1999-2000 Southern California Phone Survey Southern California Residents 53 beaches	Hanemann et. al. (2004) www.marineeconomics.noaa.gov/SCBeach/Welcome.html	Hanemann et. al. (2004) Hanemann et. al. (2005)	Closure of beaches and changes in water quality as measured by a composite index of several pollutants.
2000-01 San Diego Phone/Mail/Phone Survey San Diego County Residents 31 Beaches	Lew (2002)	Lew (2002) Lew and Larson (2005a) Lew and Larson (2005b)	Closure of beaches.
2004 North Carolina Phone survey North Carolina Residents 17 Beaches	Whitehead et. al. (2007)	Whitehead et. al. (2007)	Change in width of beaches.

Table 2: Areas of Stratification

Strata	Percent of All Respondents
Stratum 1: Padre Island Area Coastal Counties (9 counties closest to the Padre Island National Seashore)	40%
Stratum 2: Other Coastal Counties (10 counties adjacent to the coast and not included in Stratum 1)	25%
Stratum 3: Harris County (Houston)	10%
Stratum 4: Inland Counties (80 counties located within 200 miles of the coast and not included in Stratum 1, 2, or 3)	25%

Table 3: Individual Characteristics

Variable	***Mean or % of Sample*** *(Adjusted for Stratification)*
Age	41 years
Yes/No Dichotomous Variables:	
Work Fulltime	62%
Children Under 17	49%
High School	32%
College	24%
Graduate School	10%
Retire	9%
Spanish	9%
Female	60%
Own Boat	24%
Own Pool	24%
Own Fishing Equip	49%
Own Coastal Property	7%

Table 4: Sixty-Five Beaches in the Choice Set by Nest

North Nest		***Central Nest***	***South Nest***
Texas Point NWR	Surfside Beach	Austwell Beach	Drum Point
Sea Rim SP	Quintana Beach CP	San Jose Island	Fred Stone CP
McFadden NWR	Quintana Beach	Rockport Beach Park	City of South Padre Island Beach
High Island Beach	Bryan Beach	Port Aransas Park	Isla Blanca Park
Gilchrist Beach	Sargent Beach	Port Aransas City Beach	Andy Bowie Park
Caplen Beach	Matagorda Peninsula	North Beach (Corpus Christi Beach)	Edwin K. Atwood
Crystal Beach	Port Alto Beach (Buchanan's Wits End)	McGee Beach	Mansfield Cut (SPI)
Bolivar Flats	Lighthouse Beach Park	Cole Park	Boca Chica Beach
Fort Travis Beach	Magnolia Beach	Mustang Island SP	
East Beach (RA Apffell)	Indianola Beach	J.P. Luby Park	
Stewart Beach Park	Port O'Connor Bayfront Park	Packery Channel Park	
Palm Beach at Moody Gardens	Matagorda Island SP	Whitecap Beach	
Fort Crockett	Matagorda Island WMA	Padre Balli Park	
Galveston Beach Pocket Park #3		Kleberg County Beach	
Galveston's Western Beach		North Beach*	
Galveston Island SP		Malaquite Beach*	
Jamaica Beach		South Beach*	
Pointe San Luis		Little Shell Beach*	
Texas City Dike		Big Shell Beach*	
Treasure Island		Mansfield Cut*	
San Luis Pass CP		Kaufer Hubert Memorial Park	
Christmas Bay SP			

**Beaches on the Padre Island National Seashore*

Table 5: Beach Characteristics

Beach Characteristics		***Number of Beaches***	***Mean or % of Beaches***
Beach length (miles)			5.35
<u>*Dichotomous Yes/No Variables*</u>:			
Gulf access	Beach is located on the Gulf	48	74%
State park	Beach is part of a state park	4	6%
Remote	Beach has a remote location	22	34%
Vehicle free	Vehicles not allowed on beach	26	40%
Manual cleaning	Beach is routinely manually cleaned	33	51%
Machine cleaning	Beach is routinely machined cleaned	36	55%
Rest room	Restrooms located at beach	37	57%
Lifeguards	Lifeguards at beach	17	26%
Concession	Concession located at beach	15	23%
No fishing	Not listed as a fishing area in 2002 *Texas Beach & Bay Access Guide*	3	5%
No swimming	Not listed as a swimming area in 2002 *Texas Beach & Bay Access Guide*	6	9%
Red tide history	Beach has a recent history of red tide	12	18%
Advisory/Closure history	Beach has a recent history of closures and/or advisories	11	17%

Table 6: Trips by Distance Traveled

Travel Mileage	**Percent of All Trips** *(Adjusted for Stratification)*	**Cumulative Percent** *(Adjusted for Stratification)*
Less Than 5 Miles	8%	8%
5 – 20	11%	19%
21 - 30	11%	30%
31 - 50	17%	47%
51 - 100	34%	81%
100 - 150	5%	86%
150 - 300	13%	99%
Greater Than 300 Miles	1%	100%

Table 7: Trips by Number of Trips Taken*

Number of Trips	***Percent*** *(Adjusted for Stratification)*
1	41%
2	24%
3	9%
4	7%
5	6%
6	3%
7	3%
8	1%
9	1%
10	1%
11 - 20	2%
21 - 30	< 1%
31 - 40	< 1%
41 - 50	< 1%
> 50	< 1%

*Computed only over the sample (n = 601) included in all five waves.

Table 8: Ten Most Visited Beaches

Beach Name	***Nest***	***Percent of All Trips*** *(Adjusted for Stratification)*
East Beach	North	13%
Galveston's Western Beach	North	9%
Stewart Beach Park	North	9%
Crystal Beach	North	7%
PAIS North Beach	Central	6%
Galveston Beach Pocket Park #3	North	4%
Fort Crockett	North	4%
Rockport Beach Park	Central	3%
Port Aransas City Beach	Central	3%
Galveston Island SP	North	3%
		60%

Table 9: Trips to Padre Island Sites

Beach Name	***Percent of All Trips to Padre*** *(Adjusted for Stratification)*
North Beach	64%
Malaquite Beach	14%
South Beach	19%
Little Shell Beach	1%
Big Shell Beach	1%
Mansfield Cut	2%

Table 10: Nested Logit Coefficient Estimates for Site Utility
(t-statistics in parenthesis)

Variable	***Baseline Model***	***Interactive Model***	***Alternative Specific Constant Model***
Trip Cost	-.026 (17.6)	-.026 (17.4)	-.025 (13.8)
Length	.205 (8.0)	.206 (8.1)	----
Gulf Access	.608 (4.8)	.599 (4.7)	----
State Park	-.019 (0.1)	-.017 (0.1)	----
Remote	-.146 (1.5)	-.145 (1.5)	----
Vehicle Free	.824 (8.3)	1.10 (9.1)	----
*VF*4 wheel*	----	-.138 (1.4)	----
VF Fish Equip*	----	-.415 (3.5)	----
Manual Clean	.375 (3.9)	.380 (3.9)	----
Machine Clean	.888 (7.5)	.887 (7.5)	----
Rest Room	.449 (5.4)	.445 (5.3)	----
Lifeguard	.278 (3.0)	.444 (4.0)	----
*LG*Child*	-----	-.329 (2.7)	----
Concessions	-.331 (3.5)	-.452 (4.1)	----
No Fishing	-.130 (1.1)	-.125 (1.1)	----
No Swimming	-.696 (3.1)	-.698 (3.2)	----
Red Tide	-.985 (6.1)	-.991 (6.1)	----
Closure	-.449 (2.8)	-.446 (2.7)	----
*Padre*May*	.791 (2.8)	.800 (2.8)	----
*Padre*June*	1.15 (4.2)	1.16 (4.3)	.357 (1.1)
*Padre*July*	1.88 (7.7)	1.90 (7.7)	1.10 (3.5)
*Padre*August*	.498 (1.4)	.522 (1.5)	-.256 (0.6)
*Padre*September*	1.97 (5.8)	1.98 (5.8)	1.20 (3.0)
North Const.	-10.4 (14.4)	-10.4 (14.5)	----
Central Const.	-9.77 (13.3)	-9.85 (13.3)	----
South Const.	-8.33 (11.9)	-8.62 (12.0)	----
North IV	.570	.578	.486
Central IV	.599	.602	.602
South IV	.750	.730	.716
Log Likelihood	-10677	-10665	-10382
Choice Occasions	150	150	150
Alternatives	66	66	66
People	884	884	884

Table 11: Nested Logit Parameter Estimates for No-Trip Utility
(t-statistics in parenthesis)

Variable	***Baseline Model***	***Interactive Model***	***Alternative Specific Constant Model***
Log (Age)	.149 (1.5)	.149 (1.6)	----
Work Full Time	-.311 (4.4)	-.305 (4.4)	----
Child Under 17	-.250 (4.1)	-.282 (4.0)	----
High School	.303 (4.0)	.305 (4.0)	----
College	-.244 (3.4)	-.243 (3.3)	----
Grad School	-.730 (7.2)	-.732 (7.2)	----
Retire	-.193 (1.5)	-.192 (1.5)	----
Spanish	.120 (1.2)	.110 (1.1)	----
Female	.079 (1.3)	.080 (1.3)	----
Own Boat	-.453 (7.0)	-.458 (7.0)	----
Own Pool	.272 (3.7)	.275 (3.7)	----
Own Fish Equip.	-1.01 (1.7)	-.249 (3.4)	----
Own Coastal Prop.	-.442 (4.3)	-.442 (4.3)	----
Weekend	-1.20 (21.3)	-1.20 (21.2)	-1.20 (21.2)
June	.138 (1.7)	.138 (1.7)	.134 (1.7)
July	.241 (2.9)	.243 (3.0)	.240 (2.9)
August	.158 (1.8)	.157 (1.8)	.168 (2.0)
Sept.	.897 (8.2)	.897 (8.2)	.903 (8.2)
Log Likelihood	-10677	-10665	-10382
Choice Occasions	150	150	150
Alternatives	66	66	66
People	884	884	884

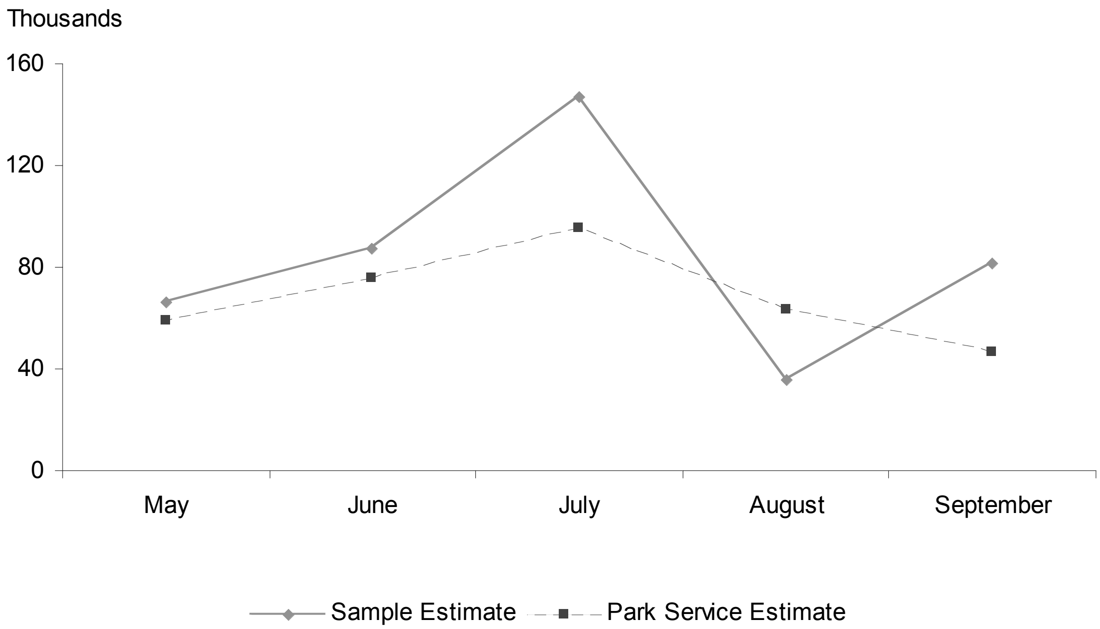
Table 12: Welfare Estimates for Closure of Six Padre Beaches

Month and Day of Week	*Aggregate Loss*	*Per Trip Loss*	*Number of Trips Displaced*
Weekday			
May	$32,194	$27	1,207
June	41,389	27	1,524
July	52,896	28	1,869
August	34,521	26	1,311
September	25,130	38	884
Weekend			
May	$103,445	$27	3,868
June	133,096	27	4,886
July	171,346	28	6,030
August	109,753	26	4,157
September	82,438	28	2,895

Table 13: Welfare Estimates for Closure of Padre, Red Tide History, Advisory/Closure History, and Closure of Galveston Beaches for July Weekend and Weekday

Month and Day of Week	*Aggregate Loss*	*Per Trip Loss*	*Number of Trips Displaced*
Weekday – July			
6 Padre Sites Closed	$52,896	$28	1,869
Red-Tide History Padre	37,188	27	1,365
Advisory-Closure History Padre	27,191	27	1,048
8 Galveston Sites Closed	263,065	30	8,782
Weekend – July			
6 Padre Sites Closed	$171,346	$28	6,030
Red-Tide History Padre	119,483	27	4,359
Advisory-Closure History Padre	88,523	26	3,349
8 Galveston Sites Closed	852,875	30	27,259

Figure 2: Day Trips to Padre Island National Seashore, 2001



Not sure if this one should also be added.

Figure ?: Close up of Padre Island National Seashore