Monetary Values and Restoration Equivalents for Lost Recreational Services on the Gulf Coast of Texas Due to Oil Spills and Other Environmental Disruptions

A Final Report Submitted to

The Coastal Response Research Center

Submitted by

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Project Period: 1/1/2006 – 12/31/2008

12/31/2008
(Revised 5/22/2009)

Coastal Response
Research Center

This project was funded by a grant from NOAA/UNH Coastal Response Research Center. NOAA Grant Number(s): NA04NOS4190063. Project Number: 06-090

UNIVERSITY of NEW HAMPSHIRE

Abstract

This purpose this research was threefold: (1) to monetize lost recreational use value due to a closure of the Padre Island National Seashore in Texas, (2) to identify non-monetary restoration equivalents for the same closure, and (3) to estimate values for closures when the loss is for a short-term (days or weeks) and people may response by simply delaying their trips to Padre. All three objectives were achieved by estimating a travel cost random utility model using data on recreation trips to the Texas Gulf Coast by 884 individuals drawn in from a probabilistic-based stratified sample. The monetary values suggested that the lost due closure of the National Seashore may be quite large – on the order of $50 million per year and this excludes overnight trips and nonuse value. The restoration equivalent analysis suggested numerous ways to compensate users for a closure. The most promising were beach cleaning, providing vehicle free access, and waiving beach fees. Compensatory actions in the Corpus Christi area near Padre Island did the best at aligning compensation with those individuals who actually suffer losses. The most effective actions were on Padre Island itself after it was reopened. The short-term closure analysis suggests that there is considerable substitution across time periods (people simply delaying trips). If this result holds up in further analysis it may suggest that the loss due to short-term closures are much lower than measured using conventional models. In our analysis when delayed trips are incorporated into the model, the losses are only one-third the size of the losses from the conventional model. The monetary results from our first objective are of immediate use in NRDAs where transfer of values from one beach area to another is common practice. The methods in the second and third objectives (as well as the first) are transferable to other areas but the actual results are area specific.

Keywords: Beaches, Economic, Value, Restoration, Compensation, Texas

Acknowledgments

I acknowledge Ami Kang and Stela Stefanova for first-rate research assistance. Both helped with data handling and model estimation. The ‘we’ used in the body of this report refers to Ami, Stela, and me. The compensatory restoration research (objective 2) is the subject of Ami’s PhD dissertation. The short-term closure research (objective 3) is the subject of a book chapter that Stela and I coauthored. I thank Chris Leggett of Industrial Economics Inc. and Kevin Boyle of Virginia Tech for collaboration on data collection and initial model estimation. I thank the National Park Service for initial funding. I thank Christy Poulos of the Research Triangle Institute for her work on the transfer analysis using our model. And finally, I thank CRRC for their interest and open mindedness in funding social science research. I especially thank Nancy Kinner, Amy Merten, Kim Newman, and Kathy Mandsager for their encouragement, positive attitude, patience, and efficiency through the entire process. I would also like to thank two anonymous outside reviewers for excellent comments on an earlier draft of this report.

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1.0 Introduction

Governmental agencies carrying out damage assessments due to oil spills require methods to evaluate the economic harm caused by such accidents. The guiding legislation sometimes calls for valuation of damages in monetary terms and other times in non-monetary (restoration equivalent) terms. In this research we estimate economic values in monetary and non-monetary terms for beach closures that may result from an oil spill. Our application is to beach use on the Texas Gulf Coast and focuses on the closure of the Padre Island National Seashore. The Padre Island National Seashore is one of several seashores managed by the National Park Service (NPS). It is located on the Gulf Coast of Texas southeast of Corpus Christi and is approximately 70 miles long (Figure 1).

We used data from a random survey of 884 Texas residents making trips over five months to 65 beaches. Using these data we estimated a travel cost random utility model and then simulated the model to mimic beach closures. Finally, using conventional applied welfare economic analysis, we valued the loss due to closure.

There are numerous applications of the travel cost random utility model to beach use (see Table 1). However, none have been applied the Texas Gulf Coast or to a National Seashore. None have been used for non-monetary compensation. And, none have considered short-term closure losses. This research is an effort to fill these gaps in economic research. Given the widespread use of the Texas Gulf Coast for beach use and the potential for an oil spill or other disruption in the area, it seems like a natural area for modeling.

2.0 Objectives

The overall objective of our project was to value the loss of beach closures due to oil spills. The project had three objectives: (1) to estimate in monetary terms the economic loss due to beach closures on Padre Island National Seashore that may result from an oil spill or other disruption, (2) to identify restoration equivalent projects (non-monetary values) for the same closures, and (3) to estimate short term substitution across time periods that may result in the event of a closure. As noted above, all three objectives have application in natural resource damage assessment due to an oil spill. Application in Texas to Padre and other beaches is an obvious use of our model and results. There are also transfer applications to other ocean beaches and application of the methodology to recreation use in other settings such as fishing, boating, hiking and so forth.

3.0 Methods

Since all three objectives used the same model with slight variation, we will present that model first. This will be followed by a discussion of our data set.

3.1 Model

We estimated separate site choice and trip frequency models. This approach was popularized by Bockstael, Hanemann, and Kling (1987) and used by Hausman, Leonard, and McFadden (1995). Herriges, Kling, and Phaneuf (1999) refer to this approach as a ‘linked’ model. An alternative is the repeated discrete choice model where the frequency stage is estimated as a binary choice (see Morey, Rowe, and Watson (1993)). As discussed by Bockstael and McConnell (2007) and shown by Parsons, Massey, and Tomasi (1999), the binary repeated discrete choice and Poisson (or Negative Binomial) at the frequency stage are nearly equivalent mathematically and there is no efficiency loss in estimating the model sequentially.

3.1.1 Site Choice

Consider the site choice portion of our model first. We assume a person has decided to make a beach trip and is considering which beach to visit. Each beach gives a site utility of u_{nit}, where $n = 1,...,N$ is a person in our sample, $i = 1,...,S_n$ is a beach on the gulf coast within 300 miles of person *n*’s residence, and $t = 1,...,T_n$ is a trip taken by person *n* during the season. A person is assumed to choose the beach with the largest site utility giving trip utility of $v_{nt} = \max(u_{n1t},.....,u_{nS_nt})$ on trip *t*.

Site utility in our model takes the form

(1) $$u_{nit} = \beta_{tc} tc_{ni} + \beta_x x_i + \varepsilon_{nit}$$

where tc_{ni} is the trip cost of reaching site i for person n. It includes out-of-pocket travel as well as time cost. The vector x_i is a set of site characteristics and ε_{nit} is a random error term. Trip costs vary across sites and people by virtue of travel and time costs from residences to beaches. Site characteristics vary across sites and are constant across trips and people.

Following conventional random utility theory, the observed trip data are treated as the outcome of a stochastic process, where individual *n*’s probability of choosing alternative *k* on a given trip is

(2) $$pr_{nt}(k) = pr(\tilde{u}_{nk} + \varepsilon_{nkt} > \tilde{u}_{ni} + \varepsilon_{nit} \text{ for all } i \neq k)$$

where $\tilde{u}_{ni} = \beta_{tc} tc_{ni} + \beta_x x_i$ represents the deterministic portion of site utility and ε_{nit} represents the stochastic portion. The likelihood of observing the pattern of choices made by our sample then is

$$\text{(3)} \quad \Lambda = \prod_{n=1}^{N} \prod_{k=1}^{S_n} \prod_{t=1}^{T_n} pr_{\text{nt}}(k) \cdot w_{\text{nt}}(k)$$

$w_{nt}(k) = 1$ if person n chooses alternative k on trip t

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

The standard multinomial logit specification for the probability of visiting a site has the well known closed form

$$\text{(4)} \quad pr_{nt}(k) = L_{nkt} = \frac{\exp(\beta_{tc} tc_{nk} + \beta_x x_k)}{\sum_{i=1}^{S^n} \exp(\beta_{tc} tc_{ni} + \beta_x x_i)} .$$

Equation (4) follows from the assumption that the error terms in equation (2) are independent and identically distributed type 1 extreme value random variables (see Train (2003, Chapter 3)). In our mixed logit model, the assumption of independence of irrelevant alternatives is relaxed allowing a more realistic pattern of substitution across sites. The mixed logit probability is an integral over a standard logit

$$\text{(5)} \quad pr_{nt}(k) = \int L_{nkt}(\beta_{tc}, \beta_x) f(\beta_x \mid \mu_x, \varphi_x) d\beta_x$$

where L_{nkt} is the multinomial logit probability shown in equation (4), $f(\beta_x \mid \mu_x, \varphi_x)$ is a mixing distribution (normal in our case), with mean μ_x and standard deviation φ_x. Now, we seek estimates of the parameters $\beta_{tc}, \mu_x, \varphi_x$. Since integration of equation (5) is not possible, the parameters are estimated using simulated maximum likelihood.

As noted, the mixed logit model relaxes the assumption of independence of irrelevant alternatives in the standard logit and allows for a more general pattern of substitution across sites (see Train 2003, Ch. 6). Sites with the same attributes, such as the presence of lifeguards or same region, will exhibit correlation via the mixing distribution. The greater the standard deviation φ_x for a given attribute, the greater the degree of correlation and hence substitution between sites with the presence of the same attributes.

Estimation proceeds as follows. Specify a distribution for $f(\beta_x \mid \mu_x, \varphi_x)$ using hypothetical starting values for μ_x, φ_x. Draw R values of β_x from this distribution giving β_x^r where $r = 1, ..., R$. Form a simulated probability

(6) $pr_{nt}(k) = \frac{1}{R}\sum_{r=1}^{R} L_{nk}(\beta_x^r)$

This is an average logit probability, averaged over the R draws on β_x^r from the mixing distribution. In our application we use a separate set of draws for each individual for each trip choice and assume independent normal distributions for each parameter. The probability in equation (6) is then entered into the likelihood function for each success or visit made by a person in our sample. This gives a simulated likelihood. The maximum simulated likelihood estimator then is the value of the vector $\beta_{tc}, \mu_x, \varphi_x$ that maximizes Λ. The procedure and numerical methods used to solve for the maximum are discussed in detail in Train (2003, Chapter 6).

Turning to the trip utility then, we see that $v_{nt} = \max(u_{n1t}, ..., u_{nS_nt})$ is stochastic from the researcher's perspective since the site utilities are random. Following Hanemann (1999), we use expected trip utility $E(v_{nt}) = E\left(\max(u_{n1t}, ..., u_{nS_nt})\right)$ in our linked model and welfare analysis. In the standard multinomial logit model expected trip utility has the well known log-sum form (see Hanemann (1999) or Ben-Akiva and Lerman (1985))

(7) $E(v_n) = \ln\sum_{i=1}^{S_n} \exp(\beta_{tc} tc_{ni} + \beta_x x_i)$.

Expected trip utility in the mixed logit model takes the same form as the log-sum expression in equation for the standard logit, but is formed by simulation to account for the variability of the parameter estimates for β_x. The expected trip utility then is the mean of the log-sum, averaged over the draws on β_x^r

(8) $E(v_n) = \frac{1}{R}\sum_{r=1}^{R}\left\{\ln\sum_{i=1}^{S_n} \exp(\beta_{tc} tc_{ni} + \beta_x^r x_i)\right\}$.

Per trip values are computed using equation (8). Expected utility is calculated with all beaches open and then with selected (Padre Island Beaches) closed. The difference, often times referred to as a log-sum difference, is the change in expected utility due the closure. Dividing by the coefficient on the trip cost, the marginal utility of income, monetizes the change.

3.1.2 Trip Frequency

To account for changes in the number of trips taken over a season due to site closures, we used a linked trip frequency model

(9) $T_n = f(E(v_n)/-\beta_{tc}, z_n)$

where T_n is the number of trips taken to all sites in the season by person *n*, z_n is a vector of individual characteristics believed to influence the number of trips taken in a season, and $E(v_n)/-\beta_{tc}$ is the expected value of a trip since $-\beta_{tc}$ is the marginal utility of income from the site choice model. We expect a positive relationship between T_n and $E(v_n)/-\beta_{tc}$ -- the greater the expected value of a trip, the more trips a person takes.

The trip frequency equation maps out something akin to an individual's trip supply schedule for a season. The rising function captures the increasing opportunity cost of taking trips as the number of trips increases. We estimated the trip frequency model using a Negative Binomial regression (Negbin 2 discussed by Greene (2008, p. 913)) to account for the integer nature of trip data and over dispersion that was evident in our simpler Poisson regression

$$\text{(10)} \qquad \Pr(T_n) = \frac{\Gamma(\theta + T_n)}{\Gamma(\theta)\Gamma(T_n + 1)} r_n^{T_n} (1 - r_n)^{\theta}$$

$$\text{where } r_n = \lambda_n / (\theta + \lambda_n) \text{ and } \lambda_n = \exp(\alpha(E(v_n)/-\beta_{tc}) + \delta z_n)$$

Again, $E(\hat{v}_n)/-\beta_{tc}$ is the expected value of a trip for person *n* estimated from the site choice model. The fitted form for equation (10) is used to predict the change in trips by each person in the sample due to a beach closure and, in turn, is used to estimate the seasonal change in trip utility.

How the model is applied (and modified) will be described in results section for each of the three objectives. The next section describes the data set used in estimation.

3.2 Data

The choice data used to estimate our model were collected in 2001 and are 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 (closest point on the coast) 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 and to oversample residents living near the Gulf Coast and Padre Island.

The initial telephone survey was conducted in May and administered to the adult member of the household (> 17 years old) with the most recent birthday. English and Spanish versions of the survey were offered. We had a 23% response rate – complete interviews divided by total households contacted. Users and nonusers of Texas Gulf coast beaches were identified in this initial survey. We define a user as anyone who had visited the coast in the past five years and reported that they were likely to 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 surveys on Texas Gulf coast beach use. Basic demographic information was gathered on each respondent in the initial phone survey.

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. The materials included in the mailing were intended to help respondents identify beaches and remember/record the actual dates of their trips. As an incentive, individuals who agreed to participate in the follow-up survey were given a phone card with 100 minutes 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 their beach trips for the previous month. Of the 1012 respondents who agreed to participate in the follow-up surveys, 884 (87%) completed the June survey, 803 (79%) completed the survey through July, 741 (73%) through August, 670 (66%) through September, and 601 (59%) through October. Keeping respondents participating in the survey effort for five months was challenging; this repeated survey approach was used to reduce errors in trip recall and for another modeling effort focusing on the dynamics of trips over a season we needed time specific trip data. We estimated our site choice model using observed trip data from all 884 respondents for the months they reported data. In our trip frequency model we included a variable from number of months sampled. Then, in predicting number of trips for the season for each person this variable was set to 5 months or a full season.

The characteristics of our sample respondents are shown in Table 3. These are weighted means to account for sample stratification and are the variables used in the vector z_n in equation (9) in estimation.

The second part of our data set covers the characteristics of the 65 beach sites -- the x_i vector in equation (1). 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 on-site visits to confirm the beach characteristics. This effort included interviews with beach managers at the city, county, and state levels; independent travel guides; visits to each of the beaches; and reviews of on-line maps of the area. The Padre Island National Seashore was divided into six separate beaches following the National Park Service definitions.

As shown in Table 4, 48 beaches (74%) are on the Gulf coast, 4 (6%) are in state parks, 22 (34%) are remote, and 26 (40%) are vehicle free. 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 access.

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. For this reason, many of beaches are actively cleaned manually and/or by machine. We include separate variables for machine and manual cleaning. We also include separate dummy variables to identify beaches with restrooms, lifeguards, and concessions.

To distinguish beaches by water quality we included two variables: closure/advisory and red tide. We had originally hoped to use an objective measure of water quality but such data are not gathered uniformly across the beaches. Some are monitored more heavily, some get intermittent readings, some none at all, and some are checked only when problems are expected. 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 their area. Red tide is a type of harm aglae bloom common in Texas that is toxic to fish and creates discolored patches of ocean water that have a reddish tint. It can cause skin irritation and to many beach goers diminishes the quality of their beach experience. This information was used to construct the closure/advisory and red tide dummy used in the model. We have 11 beaches (17%) with a closure/advisory history during the year and 12 beaches (18%) with red tide episodes.

Respondents reported a total of 2,692 trips over the five-month period -- 28% of all trips were less than 30 miles one-way, 44% were less than 50 miles, and 81% were less than 100 miles. Only 7% of all trips were taken to the beach closest to a person's home and only about 44% 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 past 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. This is AAA cost estimate for 2001 and includes fuel and depreciation. Time cost is valued at one-third of household income divided by 2000 as a proxy for foregone household wages. One-third of the wage is commonly used in travel cost studies (see for example Egan and Herriges (2009) or English (2008)). Distances and times to beaches were calculated using *PC Miler*. Average trip cost of reaching the chosen site was $56. The average cost to all sites was $182. Each person's choice set included all beaches within 300 miles of their residence. The average choice set size is 53 beaches. The minimum is 14 and the maximum is 65.

4.0 Results

4.1 Coefficient Estimates

Our estimation results are shown in Tables 5 and 6. For the most part the estimates are as expected. Consider the site choice model in Table 5. The coefficient on trip cost, our marginal utility of income, is negative and significant in both models. All else constant people prefer a beach closer to home. The log-length variable scales beaches to account for size and is positive and significant as well. Neither of these variables was estimated with a random coefficient.

The following variables (ignoring the regional dummies for now) have positive and statistically significant mean coefficient estimates in site utility: restroom, machine cleaning, manual cleaning, and vehicle free access. Among these only, manual cleaning has a large and significant estimated standard deviation. Beaches without vehicle access on the sand are required by law to have off-sand parking facilities to accommodate visitors, so the vehicle free variable may be picking up the effect of better parking facilities at these beaches over the beaches with vehicle access. Or, it may be picking up a preference by beachgoers for beaches without cars nearby for safety, view disamenity, and conflicting uses.

The variables with negative and statistically significant mean coefficient estimates include: remote, redtide, closure/advisory, and concession. Remote is as expected, as is redtide and closure/advisory reflecting both fewer days a site is available during the season and the ‘signal’ that a beach is prone to pollution problems. Concession is the only surprise. However, notice that it is estimated with a large relative standard deviation, suggesting sizable unobserved heterogeneity in the data over this attribute. The remote and closure/advisory variables also have large relative standard deviation estimates. The range for the closure/advisory standard deviation still places it in the negative range of site utility for nearly any draw from the distribution.

Variables without statistical significance for their mean coefficients include: gulf access, statepark, and lifeguard. All three have large estimated standard deviations suggesting that these attributes matter but in ways that vary over the sample.

The regional constants, Galveston through South Padre Island, are all positive and significant. The excluded region is Sabine Pass, the northernmost region with the fewest visits among the six regions. The coefficients on the standard deviations for Corpus Christi and Galveston are the largest relative to their means suggesting greater shared similarities within each of these regions and hence greater substitution among sites. The Padre constant is also quite large suggesting highly correlated unobserved site attributes and strong substitution among sites for Padre Island beaches.

The trip frequency portion of the model shown in Table 6 The model predicts an increase in the number of trips with statistical significance for people who have children under the age of 17; have a college education or higher; or own a boat, fishing equipment or property near the beach. The tie with boat ownership is not as obvious as fishing equipment or property. It may simply show an increased proclivity for outdoor recreation. The model predicts a decrease in the number of trips with statistical significance for people owning a pool suggesting that a pool may serve as a substitute for the beach. The coefficient on the expected value of a trip, the log sum divided by the trip cost coefficient, has the expected sign and is an important predictor in the model. Still, for the extent of the beach closures we consider in the next section, there is little adjustment in the number of trips taken to the coast as a result of the closure. Greater than 97% of the substitution is to other sites when the closures occur. Given the similar and proximity of sites and the number of sites that remain open, this is no surprise. Finally, the number of months in survey works as expected – positive and significant. The longer a person is in the sample, the larger the predicted number of trips. In prediction, we set number of months to 5 for each respondent.

4.2 Monetary Values (Objective 1)

Our monetary valuation estimates are shown in Table 7 and reported in 2001$. We report mean per trip, per season, and a loss to trips ratio for each scenario for each model. Our Padre Island scenarios include the closure of all six beaches, the three northernmost beaches, and the three southernmost beaches. Our estimated mean per trip losses are $10.03 for all six beaches, $4.65 for the three northern beaches, and $0.23 for the three southern beaches. These relative values reflect the concentration of day trips on the northern beaches at the seashore. Closing all six beaches is significantly larger than the sum of the closure of the two sets of three. This result is due to the large coefficient estimate for the standard deviation on the Padre Island constant which captures the high degree of substitution among Padre sites. Losing a subset of beaches on Padre Island allows for a Padre substitute with closure, but losing all six beaches leaves no substitute forcing individuals to visit a non-Padre beach. The standard deviation coefficient estimate here is working much like an inclusive value coefficient in a nested logit model where the smaller the inclusive value coefficient is the greater the loss for losing the full nest and the smaller the loss for losing individual sites within the nest. See Hauber and Parsons (2000) and Herriges and Kling (1997) for more discussion.

Among the most popular beaches in each region, East Beach in Galveston has the largest loss at $2.58 per trip. East Beach is the most frequently visited beach in Texas and, as noted above, is located near major population centers in the state. The least valued beach among each region's most popular beach is Sea Rim State Park in the northern most region of the Gulf Coast with per trip values of $0.13.

Table 7 also shows our estimates in terms of per season loss for the same set of scenarios. As described above these estimates account for adjustments in the total number of trips taken when there is a site closure and thereby allow for no-trip substitution. The mean decrease in trips taken is less than 0.1 trips for the closure of all Padre sites. Since there is only a slight adjustment in total number of trips in our model and the number of trips on average (weighted to account for stratification) is near two, this makes sense. Otherwise, the pattern for the seasonal estimates is the same as the per trip estimates. Mean values per season range from $19.89 for the closure of all Padre Island sites to $0.39 for the closure of Sea Rim State Park. Our aggregate seasonal (five months from May to September) values based on a user population of approximately 2.5 million beach goers ranged from $49.7 million for the closure of all Padre Island sites for a season to $600 thousand for the closure of Sea Rim State Park.

Finally, Table 7 also shows our estimates as a loss to trip ratio, which is defined as the estimated aggregate loss over the sample divided by the number of respondents displaced due to the closure. It tells the analyst what the approximate welfare loss is per trip to the closed site. Although this measure is rarely reported in the published literature, we report it because it is often used in benefit transfer applications. When the number of displaced trips to a specific site or sites is easy to predict, as is often the case in transfers, one may seek a corresponding loss per trip to the specific site or sites. Our estimates give a loss to trip ratio in the range of $87 to $19. The loss to trip ratio is higher for the loss of groups of sites versus single sites capturing the notion that the set of available substitutes and spectrum of utilities is shrinking as the number of sites lost increases.

4.3 Non-Monetary Values (Objective 2)

Natural Resource Damage Assessment (NRDA) cases often call for compensation in non-monetary or restoration equivalent terms (see Flores and Thacher (2002) and Jones and Pease (1997)). For this objective we present an approach that uses only the site choice portion of the model to determine compensatory restoration equivalents in non-monetary terms for hypothetical beach closures on the Padre Island National Seashore.

We seek compensatory restoration projects that pass a Kaldor-Hicks Test. Does the monetary value of the restoration project equal or exceed the monetary value of the loss due the beach closure? If so, the restoration project is potentially Parteo-improving. We identify the characteristics of beaches that are most valued to users and then systematically alter these characteristics at beaches seeking improvements larger in absolute value than the losses due to closure. Our most valued beach characteristics are beach cleaning programs, vehicle free zones, and lifeguards. After identifying a plausible set of Kaldor-Hicks restoration projects, we then analyze how well each project does in compensating those actually harmed by the closures. We considered two measures of how well a project aligns compensation with losses: (1) the mean per person absolute difference of seasonal compensation and loss and (2) the R^2 from a linear regression (without a constant term) of compensation on loss. The smaller the mean absolute difference and the closer the R^2 is to 1.0, the better the alignment. Since we are using a regression without a constant term, the R^2 may be less than zero. For our purposes, where we seek a measure of a fit to a 45 degree line the measure still satisfies our need. An R^2 below 0 will be indicative of extremely poor alignment, and an $R^2 = 1$ will be perfect alignment.

Five attributes were considered for compensatory restoration: machine cleaning, manual cleaning, vehicle free access, restrooms, and lifeguards. We also used waiving beach fees on Padre Island as compensation in one of our scenarios. Keep in mind when interpreting vehicle free access as a compensatory project, it will in most instances include the provision better parking facilities so that ‘access’ is maintained. We assumed any compensatory restoration action that takes place commences two years after the closure of the Padre Island National Seashore and that Padre Island will have reopened.

Given the pace of such deliberations, this seems like a reasonable, perhaps even generous, time frame.

Our strategy for identifying compensatory restoration projects that pass the Kaldor-Hicks criterion is as follows. We first calculated the welfare improvement for adding each attribute to the beaches currently without the attribute. For example, if a beach does not presently (2001) have machine cleaning, we calculate the welfare gained associated with introducing cleaning on that beach only. Then, we calculate the number of years that attribute must be kept active on the beach to ensure that the Kaldor-Hicks criterion is passed. The most effective (highest valued) attributes will require the fewest years. Future years are discounted at a real rate of 3%. We assume stable preferences extend indefinitely. Next, we consider the alignment of compensation with loss for each project to identify those projects that best target compensation toward individuals actually suffering welfare loss due to a closure. Based on the individual projects' Kaldor-Hicks ranking and alignment rankings, we select a set of practical bundles that were likely to be desirable for compensatory restoration.

Table 8 lists the actions at individual beaches by the 25 projects with the fewest number of years required to fully compensate a season closure on Padre. The number of years to full compensation is shown in column 5. Machine cleaning appears to be the most effective policy, followed by establishing vehicle-free areas, manual cleaning, and adding restrooms. The restoration project with the largest impact and hence fewest years required before reaching full compensation is machine cleaning on the Fort Crockett Seawall Beach located in Galveston. To compensate for the closure entirely it would have to remain in place for 6.4 years beginning two years after the Padre closure. Machine cleaning on Malaquite Beach on the Padre Island National Seashore is the project with the second largest impact requiring 7.6 years before reaching full compensation. The areas where compensation is most effective are near large population centers where beach use is highest – Galveston and Corpus Christi.

Although each project listed in Table 8 passes our Kaldor-Hicks test, how well they align compensation with damages on an individual-by-individual basis may vary significantly. Columns 6 and 7 in Table 8 show our alignment measures for each of the top 25 Kaldor-Hicks projects. The mean absolute difference between compensation and loss per person for each project is shown in column 6. The lower the value, the better the alignment. Perfect alignment is $0. Column 7 shows the R^2 for the regression of compensation on loss for each project.

As shown and as one might expect, the projects outside the Corpus Christi region have much higher absolute differences and much lower R^2s (deviations from the 45 degree line where compensation and loss align perfectly) than the projects in Corpus. This stands to reason. The beaches most frequently visited by individuals visiting Padre are other beaches in the Corpus Christi area. Similarly, Galveston area beach goers are seldom observed visiting Padre Island for day trips. The project with the quickest payback, machine cleaning on Fort Crockett, has an absolute difference between compensation and loss of $41.63 and a R^2 of .04. This stands in stark contrast with Malaquite Beach which has an absolute difference of only $3.63 and a R^2 of .98.

Based on the individual Kaldor-Hicks projects we construct project combinations with short payback periods and favorable alignment. The latter limited us to project combinations using Corpus Christi area beaches. For Padre Island we only consider projects on the three northernmost beaches where use is heaviest. We considered three machine cleaning scenarios, three vehicle-free scenarios, and three Padre-focused scenarios.

Table 9 shows the years required for each project bundle to pass Kaldor-Hicks along with our measures of alignment. Five of the project groups (the top five on the list) require less than 4 years before compensation is compete. All of these have a mean absolute difference of about $6 (where the annual loss due to closing Padre is estimated at $30), with the exception of Clean C where the mean difference is under $4. All have a strong correlation between compensation and loss. Clean C stands out as the project with the best alignment and has a short period of required for compensation.

The cost of the projects will vary widely, not just across project types (vehicle free versus cleaning) but all across the same project at different beaches. Some beaches will require more frequently cleaning than others for natural reasons. Just due to size alone, the cost of cleaning one beach can be quite different than another. The equipment, labor, maintenance, and (in some cases) dumping costs can rise into the hundreds of thousands of dollars. There is also some controversy about how the cleaning is done. Seaweed and other natural debris are believed by many to help maintain beach width. The form of compensatory restoration might even call for investment in new cleaning technologies that inhibit erosion. Vehicle access is costly largely because state law requires a beach community to provide ample parking for beach access if vehicles are prohibited on a beach – one parking space for every 15 feet of beach and entry to the beach every half-mile. The cost of land adjacent to beach areas is, of course, costly. Lifeguard costs are apt to be less beach-dependent. At $15/hour, ten lifeguards for a beach would cost about $1200/day ignoring equipment, shelter, training, and perhaps other associated cost. Finally, the fee for entry to all but North Beach on Padre Isalnd is $10 for a weekly pass. The cost here could be quite large – the National Park Service estimates that about 80,000 people visited Padre Island in July 2001 and about 40,000 in September.

In all our cases listed in Table 9, and in any cases generated from a RUM model, we would expect some ground truthing of the results. Are these feasible? Are there other legal, political, physical, or other constraints missed in the simple choice model that rules out some of the suggested set of projects. No doubt these constraints as well as the costs would be part of the deliberations between the responsible party and the state. Also, it interesting to note that in considering the candidate projects passing the Kaldor-Hicks Test, some of the projects that may be available for use as compensatory restoration (perhaps at a low cost) may be projects that should be undertaken anyway. For example, suppose a beach near an urban area is not routinely cleaned, but doing so would provide large net benefits. Wise management would presumably have been already cleaning the beach. If not, a 'cheap and easy' restoration project is available to provide compensation – made possible through poor beach management. If beaches are managed optimally, the cost of restoration will be higher since projects with large payoffs will already be exploited. Oddly then, entities responsible for oil spills are better off if they spill in an area where beaches are managed poorly than an area where they are managed well. If Pigouvian-like incentive structures are a goal (or one goal) for compensatory restoration projects, this is important consideration. If responsible parties find that they compensate for losses at less than the full cost of the damages to society, a signal is sent for suboptimal precaution.

4.4 Short Term Closures (Objective 3)

Random Utility Models are generally not well suited to handle short-term site closures and substitution across time periods within a given season. For example, a closure of a beach for a weekend or two weeks may result in people delaying trips to the closed site until later in the season. In effect, these people are substituting across time instead of sites. This is a common occurrence in damage assessment cases where the short-term closure of a site may have little impact on the total visitation to the site over a season implying that people have delayed trips in response to the closure.

For our third objective we designed and estimated a RUM model that accounts for substitution over time and used it to value short-term closures. The model combines revealed and stated preference data and uses a version of the model shown in Table 5 that incorporates the SP data.

As part of the survey discussed in the previous section, all respondents visiting the Padre Island National Seashore (14% of the sample) were asked if they would have visited another site if Padre had been closed. If they responded yes, they were asked to report which site. If they responded no, they were asked if they would take a trip later in the season to 'make up' for their lost trip to Padre. These stated preference (SP) data along with the reported trip revealed preference (RP) data are used to estimate a RUM model where a trip to Padre later in the season is treated as an alternative in the choice set. This allows us to estimate the utility for delaying a trip versus making a trip to another site and, in turn, to estimate the loss of a beach closure at Padre Island that accounts for substitution of delayed trips. We find that accounting for delayed trips to Padre reduces the estimated welfare loss significantly -- about 67% to 71%.

Our analysis proceeds as follows. An individual's choice set if Padre is open is $C \in \{C_1, C_2\}$. C_1 is the set of all non-Padre sites, and C_2 is the set of Padre sites. If Padre is closed the choice set is the conventional RP only set $C^* \in \{C_1\}$. Using the new RP-SP data the choice set is instead $C^c \in \{C_1, C_2^c\}$ where C_2^c is a delayed trip to a Padre site. In the RP only setting, the respondent is forced to visit another site or stay home. In the RP-SP setting, the respondent can visit another site, stay at home, or visit Padre later in the season.

To analyze the welfare implication of accounting for delayed trip substitution, let site utility for a Padre site j be $U_j^o = \alpha^o + \beta x_j + \beta_{tc}(y - tc_j) + \varepsilon_j$ where α^o is a constant shared by each of the Padre sites in our model in the current period when Padre is open. Similarly, let site utility for a delayed trip to a Padre site be $U_j^c = \alpha^c + \beta x_j + \beta_{tc}(y - tc_j) + \varepsilon_j$ where α^c is a constant shared by Padre sites visited later in the season. The parameters β are the same in the two periods and the site characteristics are the same since a person gets essentially the same trip, it is simply delayed. However, we assume there is some decline in utility for having to delay the trip so $\alpha^c < \alpha^o$ and thus $U_j^o > U_j^c$.

In the formulation accounting for delayed trips then the expected trip utility has the form

(11)

$$E(v_{RP\&SP}^c) = \ln\left(\sum_{i\in\{C_1\}} \exp\{\beta x_i + \beta_{tc}(y - tc_i)\} + \sum_{j\in\{C_2\}} \exp\{\alpha^c + \beta x_j + \beta_{tc}(y - tc_j)\}\right).$$

The compensating (or equivalent) variation in the RP only versus RP-SP for a Padre closure then is $w_{RP} = \left\{E(v_{RP}^c) - E(v^o)\right\}/\beta_{tc}$ versus $w_{RP\&SP} = \left\{E(v_{RP\&SP}^c) - E(v^o)\right\}/\beta_{tc}$ where the latter accounts for delayed trips and former does not. We expect $w_{RP\&SP} < w_{RP}$. But, the real question is by how much? That is, by accounting for delayed trip substitution, how much is the estimated welfare loss attenuated versus conventional approaches?

To compare the two measures of welfare empirically, we estimate two models: Padre Open and Padre Closed. Padre Open uses RP data only and is composed of choices while Padre is open. Padre Closed uses RP and SP data and substitutes trip choices reported by Padre visitors in SP responses in the event of closure for their initial RP responses. For those who do not visit Padre when it is open, we assume their preferred site is unchanged in event of the Padre closure, so their choices are retained in the Padre Closed Model. Both models include a site-choice component and a trip frequency component. In estimation we constrain all the parameters in the Padre Closed Model to be the same as the Padre Open Model, except for the alternative specific constants (and all standard deviations in the mixed logit form) on the Padre sites. This keeps the choice structure constant but allows us to estimate the discount assigned to delaying a trip to Padre – α^o versus α^c. The Padre Open Model is then used to calculate the welfare loss in the conventional way not allowing for delayed trips (w_{RP} and W_{RP}). Padre Closed Model is used to calculate the welfare loss allowing for delayed trip substitution ($w_{RP\&SP}$ and $W_{RP\&SP}$). The results are driven by the extent of delayed visitation to Padre in our SP question. The greater the portion of users that opt for delayed trips over other sites or staying home, the closer α^c will be to α^o and the lower the losses will be. The form of these models is the same as the model presented earlier. We estimated the combined model allowing for scale differences. The Padre dummies are lower for all sites. These results appear in our full paper.

The loss in a standard logit model (not reported in the section 4.1) accounting for delayed trips is about 29% of the conventional analysis. Loss to trip ratio values are near $77 in the conventional analysis, and $22 in the analysis accounting for delayed trips. The drop is smaller in the mixed logit model. The loss is about 33% of the conventional model with the loss to trip ration loss near $25 when delayed trips are accounted for versus $76 when they are not. Given the large number of respondents that opt for taking a trip to Padre to make up for a lost trip, 76%, this result is not surprising.

One drawback to our method is that it implicitly assumes a one-day, one-time closure of Padre Island since the stated preference question only makes reference to the current trip. If the actual closure is for a longer period, say weeks or months, it is not clear that our response data captures individuals' responses entirely. For example, if Padre is closed for one month and a person has three trips displaced, will all three be 'replaced' by later trips or will this induce trips to other sites? Or, will there be fewer 'replacement' trips simply because there are less open dates later in the season? To the extent a trip later in the season is not longer the next better alternative, our adjustment overstates the size of the correction. That is, the losses would be a larger fraction than the 33% suggested above.

5.0 Discussion of Importance of Oil Spill Response/Restoration

Natural Resource Damage Assessments (NRDAs) call for defensible measures of economic value based on accepted principles of microeconomics. In our analysis we have estimated the value of beaches closures on the Padre Island National Seashore. A five-month closure was valued at approximately $10 per trip with an aggregate value of approximately $50 million. This excluded overnight trips, nonuse values, and all uses other than recreation. These estimates add to a rather limited set of valuation estimates available for damage assessment cases and do so using more advanced econometric techniques than most of the existing studies. The model and data are available for simulation and for use in NRDA applications.

NRDA's also often call for damage assessments in non-monetary or restoration equivalent terms. Economic models have rarely been used to provide such measures. We have provided a method for computing non-monetary measures and include an application of the method to beach closure on the Texas coast. We found that beach cleaning and providing vehicle-free access to beaches on beaches near Padre Island or on Padre Island after its reopening were the most effective at providing full compensation and aligning compensation with loss by individuals. The method is transferable to other beach applications as well as other recreational uses.

Finally, in NRDA applications where beach closures occur and are for only a short period, such as days or weeks, existing models are of limited use because they fail to account for substitution across time periods. We have provided a method whereby such estimates can be made using combined stated-preference and revealed-preference data. The results suggest that models that fail to account for temporal substitution may lead to large overstatements of losses. In our case the losses were only one-third the full losses once temporal substitution was accounted for. Again, our method should be transferable to other applications.

6.0 Technology Transfer

The results of our research have been 'transferred' to other professional economist engaged in valuation largely via the conference presentations mentioned in the next section and personal communication with practitioners currently involved in such cases. The Texas data are being prepared for a web site that will allow easy transmission to interested users.

7.0 Achievement and Dissemination

Manuscripts, Submissions, and Publications

(1) "Valuing Beach Closures on the Padre Island National Seashore" revise and resubmit to *Marine Resource Economics.* Based on objective 1.

(2) "Valuing Short Term Site Closure in a RUM Model of Recreation Demand" accepted for publication in book edited by John Whitehead and Tim Haab on combining revealed and stated preference methods. Based on objective 3.

(3) "Compensatory Restoration in a Random Utility Model of Recreation Demand" submitted for publication to *Contemporary Economic Policy*.

(4) "State Dependence and Long Term Site Capital in a Random Utility Model of Recreation Demand" under review at *Environmental and Resource Economics.* Related to objective 3.

The project has stimulated several other research initiatives that do not fit neatly into the three objectives listed above. These include (i) exploring the properties of substitution and welfare analysis in mixed logit models, (ii) analyzing the impact of vehicle restrictions on recreation values in the Mid-Atlantic, and (iii) evaluating the impact of climate-related variables on beach use in Texas.

Graduate Students that Worked on Project

Ami Kang, PhD Marine Studies, 2009. (Ami is now employed at NOAA.)

Stela Stefanova, PhD Candidate, Economics

Presentations

Southern Economics Association Meetings 2007, New Orleans, LA
Southern Economics Association Meetings 2008, Washington DC
Northeastern Economics Association Meetings 2006, Rehoboth Beach, DE
Clean Gulf Workshop 2007, Tampa, FL
Estuarine Research Federation 2007, Providence, RI
NCSU Camp Resources (Graduate Student Symposium) 2008, Wilmington, NC

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Table 1: Travel Cost Random Utility Models Applied to Beach Recreation

Data Set	Published Studies	Resource Changes Valued
1974 Boston Area In-person/At-home survey Boston area residents 30 Beaches	Binkley and Hanemann (1975) Hanemann (1978) Feenberg and Mills (1980) Bockstael, Hanemann, and Strand (1984) Bockstael, Hanemann, and Kling (1987)	Changes in water quality measured 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) Haab and Hicks (1997) Hicks and Strand (2000)	Changes in water quality measured by nitrogen, phosphorous, and fecal coliform.
1987 New Bedford Harbor 5 beaches	McConnell (1986) Haab and Hicks (1997)	na
1994 Florida Phone Survey Central Florida residents 297 Beaches	Environmental Economics Research Group (1998)	Closure of beaches due to Tampa Bay oil spill.
1997 Mid-Atlantic Mail survey Delaware residents 62 Beaches	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) 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) 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 and Larson (2005a) Lew and Larson (2005b)	Closure of beaches.
2004 North Carolina Phone survey North Carolina residents 17 Beaches	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 (8 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: Characteristics of 65 Beaches in Model

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%
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 5: Mixed Logit Site Choice Model

Variable	***Mixed Logit Parameter Estimates*** (t-statistics in parenthesis)	
	Estimated Mean of Coefficient	*Estimated Standard Dev. of Coefficient*
Trip Cost	-.0579 (11.9)	-
Log Length	.532 (10.0)	-
Gulf Access	.505 (1.5)	1.42 (2.8)
State Park	-.019 (0.02)	1.95 (1.7)
Remote	-.488 (2.1)	1.30 (2.9)
Vehicle Free	1.69 (11.3)	.088 (.24)
Manual Clean	1.93 (4.8)	5.17 (7.1)
Machine Clean	2.24 (7.8)	.620 (1.0)
Rest Room	.433 (3.4)	.015 (.07)
Lifeguard	-.022 (0.2)	5.00 (6.0)
Concessions	-2.59 (5.3)	6.79 (5.2)
Red Tide	-2.61 (5.5)	.11 (.10)
Closure/Advisory	-17.4 (3.2)	16.43 (3.8)
Padre	.02 (.01)	9.77 (5.9)
Sabine Pass	-	.386 (.38)
Galveston	3.01 (4.1)	2.38 (3.8)
Freeport	3.32 (4.1)	.698 (0.9)
Port Lavaca	-1.00 (.77)	3.37 (3.0)
Corpus Christi	1.39 (1.6)	4.51 (6.5)
South Padre Island	2.13 (1.9)	.683 (0.5)
Log Likelihood	-3903	
Trip Occasions	2692	

Table 6: Negative Binomial Trip Frequency Model

Variable	***Parameter Estimates***
Constant	-3.69*
Log Sum/$-\beta_{tc}$	.016*
Log (Age)	.028
Work Full Time	.119
Child Under 17	.155*
High School	-.204*
College	.235*
Grad School	.281*
Retire	-.051
Spanish	.042
Female	-.105
Own Boat	.257*
Own Pool	-.214*
Own Fish Equip.	.132*
Own Coastal Prop.	.133
Number of Waves Completed	.276*
Dispersion	.250
Log Likelihood	
No. People Taking at Least One Trip	561
No. People Taking No Trips	323

** Statistical Significance with 99% Confidence.*

Table 7: Welfare Losses for Selected Scenarios (2001$)

Beach(es) Closed	***Region***	***Per Trip Loss***	***Per Season Loss***	***Loss to Trips Ratio***
Padre Island Scenarios:				
All 6 PI Beaches	Corpus	$10.03	$19.89	$86.63
3 Northern PI Beaches	Corpus	4.65	8.12	50.58
3 Southern PI Beach	Corpus	0.23	0.44	19.17
Non-Padre Island Scenarios (Most Popular Beach in Each Region):				
Sea Rim State Park	Sabine Pass	0.13	0.22	37.97
East Beach	Galveston	2.58	5.71	22.97
Surfside Beach	Freeport	0.57	1.41	31.98
Magnolia Beach	Port Lavaca	0.17	0.23	23.03
Rockport Beach	Corpus	0.64	1.06	34.37
City of South Padre Island Beach	South Padre Island	0.21	0.39	21.24

Table 8: Summary of Top 25 Individual Projects by Time Required to Pass Kaldor-Hicks

Project ID	Region	Beach Name	Project	Years Required to Meet Kaldor-Hicks	Mean Absolute Difference Between Compensation and Loss (2001$)	R^2 on Regression (w/o constant) of Compensation on Loss[1]
1	Galveston	Fort Crockett	Machine cleaning	6.41	$42	.04
2	Corpus Christi	PAIS Malaquite Beach	Machine cleaning	7.65	4.8	.98
3	Galveston	Bolivar Flats	No vehicle	7.68	42	.04
4	Galveston	Galveston Island SP	Machine cleaning	8.82	42	.05
5	Galveston	Crystal Beach	No vehicle	9.01	42	.04
6	Galveston	Galveston's Western Beach	Manual cleaning	10.19	42	.06
7	Corpus Christi	Port Aransas Park	No vehicle	10.23	12	.90
8	Corpus Christi	J.P. Luby Park	No vehicle	10.53	15	.85
9	Galveston	Fort Crockett	Manual cleaning	10.82	43	.04
10	Galveston	High Island Beach	No vehicle	11.49	43	.01
11	Galveston	Fort Travis Beach	No vehicle	12.85	42	.04
12	Corpus Christi	PAIS North Beach	No vehicle	13.36	3.6	.97
13	Corpus Christi	PAIS North Beach	Machine cleaning	13.57	3.6	.97
14	Galveston	Texas City Dike	No vehicle	13.81	42	.03
15	Galveston	Bolivar Flats	Manual cleaning	14.03	43	.03
16	Galveston	Caplen Beach	No vehicle	14.68	43	.03
17	Galveston	Galveston Beach Pocket Park #3	Manual cleaning	14.83	42	.05
18	Galveston	Gilchrist Beach	No vehicle	15.10	43	.01
19	Galveston	Crystal Beach	Manual cleaning	15.15	43	.03
20	Corpus Christi	PAIS North Beach	Lifeguard	15.72	6.5	.94
21	Galveston	Pointe San Luis	No vehicle	16.58	40	.08
22	Corpus Christi	PAIS Malaquite Beach	Lifeguard	18.14	8.9	.94
23	Galveston	High Island Beach	Manual cleaning	18.86	44	.01
24	Corpus Christi	North Beach (Corpus Christi Beach)	Machine cleaning	18.92	19	.84
25	Corpus Christi	PAIS South Beach	Lifeguard	20.65	6.4	.95

PINS = Padre Island National Seashore

1. Since we are using a regression without a constant term to predict proximity to a 45 degree line, the R^2 may be less than zero.

Table 9: Candidate Bundled Projects for Compensation Restoration

Project	Years Required to Meet Kaldor-Hicks	Mean Absolute Difference Between Compensation and Loss ($)	R^2 on Regression (w/o constant) of Compensation on Loss[1]
Padre C	2.55	$6.12	.93
Padre B	3.23	5.98	.94
Clean C	3.72	3.41	.98
Padre A	3.76	6.02	.94
Vehicle C	3.86	6.34	.89
Clean B	4.88	4.16	.96
Vehicle A	5.69	12.27	.88
Vehicle B	8.94	3.67	.96
Clean_A	10.79	18.24	.87

* Padre A: Machine cleaning on PINS: North Beach, Malaquite Beach and South Beach & Lifeguard on PINS: North Beach and Malaquite Beach
* Padre B: Padre A & No Entrance Fee into PINS: Malaquite Beach and South Beach
* Padre C: Padre B & No Vehicle on PINS: North Beach and South Beach
* Clean A: Machine Cleaning on 2 Corpus Christi Region Beaches off Padre: North Beach (Corpus Christi Beach) and McGee Beach
* Clean B: Machine Cleaning on Padre Island: North Beach, Malaquite Beach and South Beach
* Clean C: Clean A & Clean B
* Vehicle A: Vehicle Free on 2 Corpus Christi Beaches off Padre: Port Aransas Park Beach and J.P. Luby Park Beach
* Vehicle B: Vehicle Free on PINS: North Beach and Malaquite Beach
* Vehicle C: Vehicle A & Vehicle B

PINS = Padre Island National Seashore

1. Since we are using a regression without a constant term to predict proximity to a 45 degree line, the R^2 may be less than zero.

Figure 1: The Texas Gulf Coast and Beaches Included in the Choice Set by Region