2010

Compensatory Restoration in a Random Utility Model of Recreation Demand

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COMPENSATORY RESTORATION IN A RANDOM UTILITY MODEL OF RECREATION DEMAND

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Natural Resource Damage Assessment cases often call for compensation in non-monetary or restoration equivalent terms. In this article, we present an approach that uses a conventional economic model, a travel cost random utility model of site choice, to determine compensatory restoration equivalents for hypothetical beach closures on the Gulf Coast of Texas. Our focus is on closures of beaches on the Padre Island National Seashore and compensation for day-trip users. We identify restoration projects that compensate for beach closures and that have good alignment in terms of compensating those who actually suffer from the closures. (*JEL* Q26)

I. INTRODUCTION

Natural Resource Damage Assessment (NRDA) cases often call for compensation in non-monetary or restoration equivalent terms. For example, users of a damaged recreational fishery may seek a new fishing pier, expanded parking space, new launch sites, added natural areas, or increased stocking of fish in compensation for their losses. Although it is natural for economists to think in terms of monetary compensation for damages, a shift in legislation favoring restoration over monetary payment has moved the discussion into the non-monetary realm. Jones and Pease (1997), for example, discuss two approaches for non-monetary valuation using conventional welfare theoretic analysis: service-to-service scaling and value-to-value scaling.

Service-to-service scaling seeks restoration projects that deliver in-kind resource flows of equivalent value to those damaged. In cases where the restored resource is nearly the equivalent in function and location, the scaling is not difficult, although some discounting may have to be applied and the baseline level of the resource must be considered. In more common cases, the restored resources vary in function and location to the damaged resource, and the analysis becomes more complex. The restoration, for example, may involve improved access to a site or expanded protection of an open space in an entirely different area and with different uses. In these cases, some type of equivalency metric is needed. Habitat equivalency is a good example (Unsworth and Bishop 1994; Strange et al. 2002; Penn and Tomasi 2002). In any case, an explicit rendering of an individual's preferences is conspicuously missing from the service-to-service approach.

Value-to-value scaling, on the other hand, seeks restoration projects that are equivalent in absolute terms to the discounted present value of the damages in question. This approach, while non-monetary in the actual compensation, requires the knowledge of an individual's preferences to implement (Flores and Thacher 2002). The analyst must value the losses from the injury and the gains from the restoration project to conduct an evaluation. In principle, the calculation on both sides of this equation would use the usual welfare theoretic measures of compensating or equivalent variation.

In this article, we present a value-to-value scaling analysis using a travel cost random

*This study is funded by the National Oceanic and Atmospheric Administration's Coastal Response Research Center at the University of New Hampshire.

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ABBREVIATIONS
NRDA: Natural Resource Damage Assessment
RUM: Random Utility Maximization

Contemporary Economic Policy (ISSN 1465-7287)
Vol. 28, No. 4, October 2010, 453–463
Online Early publication July 12, 2010
doi:10.1111/j.1465-7287.2010.00219.x

utility model of site choice to determine compensatory restoration equivalents for hypothetical beach closures on the Gulf Coast of Texas. Our focus is on closures of beaches on the Padre Island National Seashore and compensation for day-trip users. Our approach follows principles laid out by Flores and Thacher (2002) and Jones and Pease (1997). The only other analysis we are aware of that is close in approach to ours is an NRDA by Triangle Economic Research in 1998. Interestingly, their application is also on the Gulf Coast of Texas. They consider compensatory restoration for a fishing site closure on Lavaca Bay. The restoration involved new facilities (better boat launches, parking, and restrooms, and bait shop) for the population of users. They developed restoration indexes based on a random utility model for comparing restoration alternatives to the loss.

In our analysis, 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 to the beach closure? If so, the restoration project is potentially Parteo improving (ignoring the cost of restoration itself). After estimating a random utility model of beach use in Texas, 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 of Padre Island. Our most valued beach characteristics are beach cleaning programs, vehicle-free zones, and rest rooms. After identifying a plausible set of Kaldor-Hicks restoration projects, we analyze how well each project does in compensating those actually harmed by the closures. Passing the Kaldor-Hicks criterion requires that the beneficiaries have larger monetary gains than the losers' monetary losses, but it provides no guarantee that the beneficiaries are those most harmed by the closures. To the extent that this matters in the analysis or settlement, it is important to evaluate the Kaldor-Hicks projects based on how well they align compensatory payments with losses. To this end, we also offer two simple measures of alignment for each of our Kaldor-Hicks projects.

We begin by laying out our model in the next section and then follow with sections on measures of compensation and alignment, data, estimation results, and conclusions.

II. TRAVEL COST RANDOM UTILITY MODEL OF SITE CHOICE

We model site (beach) choice using a mixed logit random utility maximization (RUM) model.[1] We consider day trips only. We assume each person n has utility $U_{nit} = \alpha tc_{ni} + \beta x_i + e_{nit}$ for a visit to site i on trip t—tc_{ni} is the trip cost of reaching site i, x_i is vector of site characteristics at site i, and e_{nit} is a random error. The probability individual n visits site k on trip t is

$$pr_{nt}(k) = \int L_{nkt}(\alpha, \beta) f(\beta|\ \ , \varphi) \mathrm{d}\beta$$

$$(1)\quad L_{nkt}(\alpha, \beta) = \exp(\alpha tc_{nk} + \beta x_k) \Big/ \sum_{i=1}^{S_n} \exp(\alpha tc_{ni} + \beta x_i),$$

where there are S_n sites in individual n's choice set, L_{nk} is a standard multinomial logit probability, and $f(\beta|\ \ , \varphi)$ is a mixing distribution (normal in our case) with mean   and standard deviation φ. The model and its properties are presented in detail in Train (2009, chapter 6).

The advantage of the mixed over standard logit model is that it induces correlation across sites over the attributes included in the mixing distribution. The correlation is realized through the stochastic portion of consumers' utility. This relaxes the assumption of independence of irrelevant alternatives and allows for a more general pattern of substitution across sites. For example, sites sharing attributes, such as the presence of lifeguards or same region, exhibit correlation via the mixing distribution. The greater the standard deviation φ for a given attribute, the greater the degree of correlation and hence substitution between sites sharing the attribute.[2] The parameters α, , φ are estimated by simulated maximum likelihood. The procedure and numerical methods are discussed in Train (2009, chapter 6).[3]

Expected utility on any given trip occasion in the mixed logit model is the log-sum expression

1. See Parsons and Massey (2003), Lew and Larson (2005, 2008), and Murray, Sohngen, and Pendelton (2001) for examples of RUM applications to beach use.

2. We tried models that allowed for a correlation among parameters but were only able to estimate models with three or fewer correlates. We decided to stay with models that used many, albeit independent, parameters.

3. We allow for correlation among each respondent's trips using Halton draws that are person specific instead of trip specific.

used in standard logit models but averaged over $\boldsymbol{\beta}^r$ as follows

(2)
$$E(v_n) = 1/R \sum_{r=1}^{R} \left\{ \ln \sum_{i=1}^{S_n} \exp(\alpha tc_{ni} + \boldsymbol{\beta}^r \boldsymbol{x}_i) \right\}.$$

$\boldsymbol{\beta}^r$ is one of R draws from the estimated distribution for $f(\beta| \ , \varphi)$. Each draw includes all elements in the vector $\boldsymbol{\beta}^r$. $E(v_n)$ is used throughout our welfare and compensatory restoration analysis in the next section as our baseline (without closure) expected trip utility.[4]

III. MEASURES OF COMPENSATION AND ALIGNMENT WITH LOSSES

Suppose sites 1 through 5 are closed due to an oil spill. If so, an individual's expected maximum utility on a given trip declines from $E(v_n)$ shown in Equation (2) to $1/R \sum_{r=1}^{R} \left\{ \ln \sum_{i=6}^{S_n} \exp(\alpha tc_{ni} + \boldsymbol{\beta}^r \boldsymbol{x}_i) \right\}$ where five sites are dropped from the log-sum. Alternatively, one can think of increasing trip costs to the closed beaches to infinity driving the utility for those beaches to zero. The welfare loss for closure of the sites is the difference in expected utility divided by the coefficient on trip cost (our marginal utility of income)

(3)
$$w_n = 1/R \sum_{r=1}^{R} \left\{ \ln \sum_{i=6}^{S_n} \exp(\alpha tc_{ni} + \boldsymbol{\beta}^r \boldsymbol{x}_i) \right\} - 1/R \sum_{r=1}^{R} \left\{ \ln \sum_{i=1}^{S_n} \exp(\alpha tc_{ni} + \boldsymbol{\beta}^r \boldsymbol{x}_i) \right\} \Big/ -\alpha.$$

Welfare declines for everyone in the sample except for those for whom sites 1–5 are not in the choice set, so $w_n \leq 0$ for all n. Summing overall individuals in the sample and multiplying by their number of trips taken gives a sample aggregate welfare loss $W = \sum_{n=1}^{N} \text{trips}_n \cdot w_n$, where there are N people in the sample and n denotes a person in the sample. If the sample is representative of the population, pW will be an unbiased measure of the total loss to the population of users where p is the ratio of the population size to the sample size.

4. Technically, Equation (2) includes an unknown constant. As it irrelevant in preference ordering and in valuation, we have excluded it here (see Train 2009, p. 55).

Now, consider a proposed compensatory restoration project that improves some attributes in the vector $\boldsymbol{x}_i$ at selected sites. A measure of welfare gain for such a project for person n is

(4)
$$\tilde{w}_n = 1/R \sum_{r=1}^{R} \left\{ \ln \sum_{i=1}^{S_n} \exp(\alpha tc_{ni} + \boldsymbol{\beta}^r \tilde{\boldsymbol{x}}_i) \right\} - 1/R \sum_{r=1}^{R} \left\{ \ln \sum_{i=1}^{S_n} \exp(\alpha tc_{ni} + \boldsymbol{\beta}^r \boldsymbol{x}_i) \right\} \Big/ -\alpha,$$

where $\tilde{\boldsymbol{x}}_i$ is the new attribute vector showing improvements at selected sites and assuming that the closed sites have reopened. Welfare either improves or stays the same for everyone in the sample, so $\tilde{w}_n \geq 0$ for all n. The sample aggregate gain then is $\tilde{W} = \sum_{n=1}^{N} \text{trips}_n \cdot \tilde{w}_n$ and the population aggregate gain is $p\tilde{W}$. The project passes our Kaldor-Hicks test for compensatory restoration if $p\tilde{W} \geq pW$. This measure misses compensation for overnight trips, nonuse value, any congestion effects that might ensue at sites where restoration is taking place, and other external effects that might be induced by restoration. It also assumes that the number of trips taken (trips_n) is approximately the same under the three scenarios considered: baseline, degraded, and compensated. This assumption could be relaxed by including a participation stage (or no-trip utility) in the model.

Of course, a large number of projects involving different combinations of changes to the vector $\boldsymbol{x}_i$ may pass our Kaldor-Hicks test and each will have its own distributional consequences. Some will align compensation with actual losses reasonably well and others will not. As one of the main impetuses for using compensatory restoration is to target compensation at those suffering losses, this is an important dimension of project outcomes. To this end, we consider two measures of the alignment of compensation with losses: (1) the absolute difference of seasonal compensation and loss per person and (2) the coefficient from a linear regression of compensation on loss (without a constant term).

The first measure is

(5)
$$D = 1/N \sum_{i=1}^{n} \text{trips}_n \cdot \mid \tilde{w}_n + w_n \mid$$

where $|\tilde{w}_n + w_n|$ is the absolute difference between compensation and loss per trip for person n for the season and trips_n is the number of trips taken by person n. Recall that $\tilde{w}_n \geq 0$ and $w_n \leq 0$ for all n. When $\tilde{w}_n + w_n > 0$, a person is overcompensated. When $\tilde{w}_n + w_n < 0$, a person is undercompensated. D increases as the deviations between compensatory payments and actual loss increase, indicating poorer alignment.

We also estimate a simple linear regression of compensation on loss as follows

$$\tilde{w}_n = \beta|w_n| + \epsilon. \tag{6}$$

An estimate of β near 1.0 would be good alignment—near a 45-degree line in a plot of compensation versus loss. The coefficient alone is not necessarily a good indicator of alignment (the dispersion around a fitted line where $\beta = 1.0$ can be large or small), but this measure, coupled with the mean absolute difference, does a good job of identifying projects where compensation and loss are comparable.

IV. 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 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 (≥18 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 5 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—1,154 people. Of these, 1,012 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. Of the 1,012 respondents who agreed to participate in the follow-up surveys, 561 took at least one trip and reported a total of 2,692 trips over the 5-month period.

The second part of our data set covers the characteristics of the sites—the $\boldsymbol{x}_i$ vector in Equation (1). We collected data on all the public beaches on the Texas Gulf Coast including information on facilities, amenities, services, and physical characteristics. This covers 65 beaches. The beaches included bay side and gulf beaches and were defined using the *2002 Texas Beach & Bay Access Guide* and a 2-week field trip to the coast. The delineation of beaches was intended to be, as the public generally perceived, the boundaries. The Padre Island National Seashore is divided into six separate beaches following the National Park Service definitions.

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 online maps of the area. The variables used in our model, again the $\boldsymbol{x}_i$ vector in Equation (1), are presented in Table 1 along with descriptive statistics. As shown, 48 beaches (74%) are on the *GULF COAST* (not bay) 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 to reach.

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, and oil platforms. Management plans for many beaches involve routinely manually cleaning or machine cleaning beach areas. As shown in Table 1, 33 beaches (51%) had *MANUAL CLEANING* and 36 (55%) had *MACHINE CLEANING* in 2001. In addition, 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*.

To distinguish beaches by water quality, we included two variables: *CLOSURE* and *REDTIDE*. We had originally hoped to use an objective measure of quality but such data are not gathered uniformly across the beaches. Some

TABLE 1
Beach Characteristics

Beach Characteristics		**Number of Beaches**	**Mean or % of Beaches**
Beach length (miles)			5.35
Dichotomous yes/no variables			
GULF COAST	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 machine cleaned	36	55%
RESTROOMS	Restrooms located at beach	37	57%
LIFEGUARDS	Lifeguards at beach	17	26%
CONCESSIONS	Concession located at beach	15	23%
REDTIDE	Beach has a recent history of red tide	12	18%
CLOSURE	Beach has a recent history of closures and/or advisories	11	17%

are monitored heavily, some get intermittent readings, some are not monitored, and some are checked only when problems are expected. An objective measure was problematic. We opted for a subjective measure based on interviews with beach managers for the different areas. Among the questions, we asked the managers whether 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 closure and red tide dummies used in the model. We have 11 beaches (17%) with a *CLOSURE* history during the year and 12 beaches (18%) with *REDTIDE* episodes.

After adjusting for stratification, 28% of all reported trips were less than 30 miles one way, 44% were less than 50 miles, and 81% were less than 100 miles. 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 2,000 as proxy for a person's wage. Distances and times to beaches were calculated using *PC Miler*. The average round trip cost of reaching the chosen site was $75. The average cost to all sites was $194. Each person's choice set included all beaches within 300 miles of their residence. The average choice set size is 54 beaches. The minimum is 14, and the maximum is 65.

GALVESTON and *CORPUS CHRISTI* were the most popular regions with 56% and 25% of all trips. The regions are shown in Figure 1. We also include regional constants in our model to account for unobserved differences across the regions as well as a dummy variable for all sites located on Padre Island.

V. RESULTS

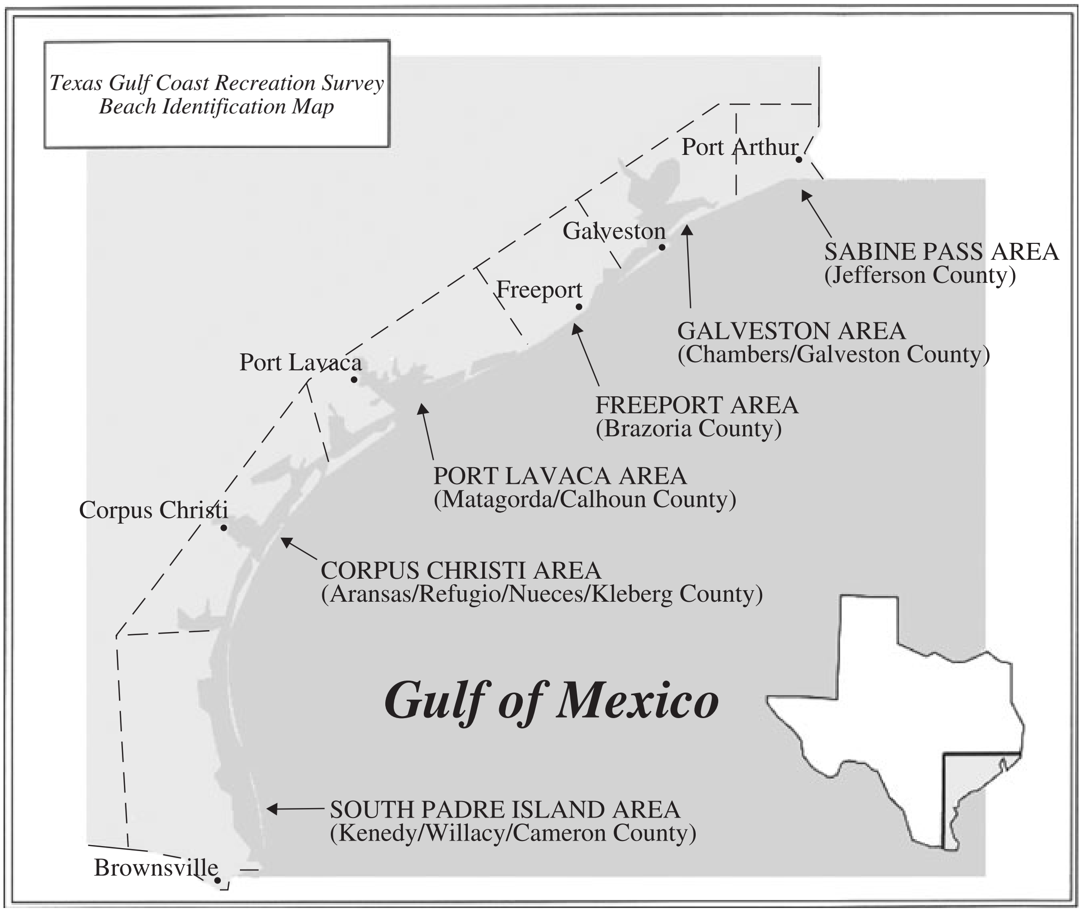
A. Coefficient Estimates

Our estimation results are shown in Table 2. For the most part, the results are as expected. The terms "mean" and "dispersion" here refer to and φ discussed in Section II. Our mixed coefficients include the six regional dummies (mimicking nests), *PADRE*, all characteristics used in our policy analysis, and *CONCESSIONS*.

We discuss the non-mixing coefficients first. The mean coefficient on *TRIP COST*, the centerpiece of the travel cost RUM model, is negative and significant as expected—an individual's probability of visiting the site declines as trip cost increases. *LOG LENGTH* is included to scale the sites by size and is positive and significant also as expected. Our two environmental quality variables *CLOSURE* and *REDTIDE* are both negative and significant. *GULF COAST*, *STATE PARK*, and *REMOTE* are all positive but only *GULF COAST* is significant.

Now let us consider the coefficients with mixing. The management variables with positive and significant *means* (in order by size of coefficient estimate) are *VEHICLE FREE*, *MACHINE CLEANING*, *MANUAL CLEANING*, and *REST ROOMS*. The model strongly implies that the probability of taking a trip to a site will increase with the presence of these characteristics. Among these variables, only *MANUAL CLEANING* has a large and significant coefficient estimate on its *dispersion* term relative to its mean. *LIFEGUARDS* and *CONCESSIONS* have negative *mean* estimates, but both have

FIGURE 1
Six Regions on the Texas Gulf Coast



large estimates for dispersion—substitution is strong among sites that share these characteristics.[5] We also interacted *VEHICLE FREE* with Ownership of Surf Fishing Equipment to allow for a difference in preferences for vehicle-free access across the fishing and non-fishing populations. Both groups prefer beaches without vehicles, but the non-fishing population has a stronger preference.

B. Compensatory Restoration

We consider five attributes for potential use in compensatory restoration projects: *MACHINE CLEANING*, *MANUAL CLEANING*, *VEHICLE FREE*, *RESTROOMS*, and *LIFEGUARDS.* We also consider waiving beach fees on Padre Island as compensation in one of our scenarios. We assume any compensatory restoration action that takes place commences 2 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. We also assume Padre is closed for one season.

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 gain associated with introducing

5. In a nested logit model, this result is equivalent to finding a small inclusive value coefficient and a negative or near zero value on the constant shared by sites in the nest.

TABLE 2
Estimation Results for Mixed Logit Model

Variables	Mean of Coefficient (μ) Estimate	Mean of Coefficient (μ) *t* Statistic	Dispersion of Coefficient (φ) Estimate	Dispersion of Coefficient (φ) *t* Statistic
TRIP COST	−0.04	−14.1	—	—
LOG LENGTH	0.30	8.8	—	—
GULF COAST	0.79	4.8	—	—
STATE PARK	0.38	1.2	—	—
REMOTE	0.12	1.1	—	—
VEHICLE FREE	1.18	8.9	0.01	0.0
VEHICLE FREE × own surf fishing equipment	−0.49	−3.3	—	—
MANUAL CLEANING	0.65	3.6	1.38	2.9
MACHINE CLEANING	1.14	7.0	0.32	0.4
RESTROOMS	0.35	3.3	0.02	0.1
LIFEGUARDS	−0.01	−0.1	2.28	4.2
CONCESSIONS	−0.72	−3.2	2.27	2.5
REDTIDE	−2.11	−5.4	—	—
CLOSURE	−0.86	−3.6	—	—
PADRE	−2.69	−1.8	7.57	5.2
SABINE PASS	—	—	1.58	1.4
GALVESTON	2.87	2.5	2.68	5.2
FREEPORT	3.11	2.7	0.10	0.2
PORT LAVACA	2.34	2.0	0.16	0.2
CORPUS CHRISTI	2.86	2.5	2.05	5.5
SOUTH PADRE ISLAND	2.89	2.3	0.69	0.5
Log-likelihood	−3955.41			
Number of trips	2692			
Number of people	561			
Average number of sites	54			

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) attribute will require the fewest years. Future years are discounted at a real rate of 3%. We assume that preferences as estimated in our model 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. We use the two measures of alignment discussed in Section III: (1) the mean absolute difference of compensation and loss per person (D in Equation [5]) and (2) the coefficient from a linear regression of compensation on loss constrained to go through the origin. Finally, based on the individual projects' Kaldor-Hicks rankings and alignment rankings, we select combinations of projects that are likely to be desirable for compensatory restoration. These allow compensatory restoration to involve more that one site and more than one site characteristic simultaneously.

Table 3 lists the actions at individual beaches by the 25 projects with the fewest number of years required to compensate fully 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 2 years after the Padre closure. Machine cleaning on Malaquite Beach on the Padre Island National Seashore has the second largest impact requiring 7.7 years before reaching full compensation. The next three projects in order of effectiveness are providing vehicle-free access at Bolivar Flats in Galveston for 7.7 years, machine cleaning on Galveston Island State Park for 8.8 years, and vehicle-free access on Crystal Beach in Galveston for 9 years. When we array all the Kaldor-Hicks projects, the beaches where

TABLE 3
Summary of Top 25 Individual Projects by Time Required to Pass Kaldor-Hicks Test

1 Project ID	2 Region	3 Beach Name	4 Project	5 Years Required to Meet Kaldor-Hicks	6 Mean Absolute Difference between Compensation and Loss (2001$)	7 Coefficient Estimate on Regression of Compensation on Loss
1	G	Fort Crockett	Machine cleaning	6.41	42	0.15
2	CC	PINS Malaquite Beach	Machine cleaning	7.65	4.8	0.87
3	G	Bolivar Flats	No vehicle	7.68	42	0.15
4	G	Galveston Island SP	Machine cleaning	8.82	42	0.16
5	G	Crystal Beach	No vehicle	9.01	42	0.15
6	G	Galveston's Western Beach	Manual cleaning	10.19	42	0.17
7	CC	Port Aransas Park	No vehicle	10.23	12	1.06
8	CC	J.P. Luby Park	No vehicle	10.53	15	1.52
9	G	Fort Crockett	Manual cleaning	10.82	43	0.15
10	G	High Island Beach	No vehicle	11.49	43	0.10
11	G	Fort Travis Beach	No vehicle	12.85	42	0.15
12	CC	PINS North Beach	No vehicle	13.36	3.6	0.90
13	CC	PINS North Beach	Machine cleaning	13.57	3.6	0.90
14	G	Texas City Dike	No vehicle	13.81	42	0.14
15	G	Bolivar Flats	Manual cleaning	14.03	43	0.14
16	G	Caplen Beach	No vehicle	14.68	43	0.14
17	G	Galveston Beach Pocket Park #3	Manual cleaning	14.83	42	0.16
18	G	Gilchrist Beach	No vehicle	15.10	43	0.12
19	G	Crystal Beach	Manual cleaning	15.15	43	0.14
20	CC	PINS North Beach	Lifeguard	15.72	6.5	0.83
21	G	Pointe San Luis	No vehicle	16.58	40	0.19
22	CC	PINS Malaquite Beach	Lifeguard	18.14	8.9	0.83
23	G	High Island Beach	Manual cleaning	18.86	44	0.10
24	CC	North Beach (Corpus Christi Beach)	Machine cleaning	18.92	19	1.21
25	CC	PINS South Beach	Lifeguard	20.65	6.4	0.84

CC, Corpus Christi; G, Galveston; PINS, Padre Island National Seashore.

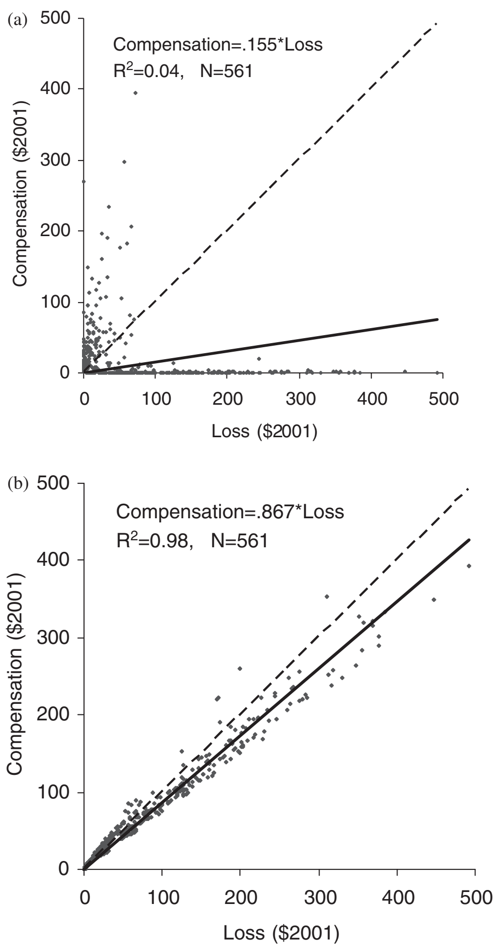
compensation is most effective are those located near large population centers and those where beach use is highest—Galveston and Corpus Christi.

Although each project listed in Table 3 passes our Kaldor-Hicks test, how well they align compensation with damages on an individual-by-individual basis may vary significantly. Certainly, compensatory projects that affect beaches close to or on Padre Island and beaches that have characteristics similar to Padre are more likely to align compensation effectively. Columns 6 and 7 in Table 3 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 coefficient estimate for the regression of compensation on loss (without a constant term) for each project. Perfect alignment in this case would give a coefficient estimate of 1.0. This would mimic a 45-degree line in compensation (y-axis)—loss (x-axis) space. The larger the deviation from 1.0, the poorer the alignment.

As shown, the projects outside the Corpus Christi region have much higher absolute differences and much lower coefficient estimates (deviations from the 45-degree line) 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

FIGURE 2

(A) Scatter Plot of Compensation versus Loss for Fort Crockett Beach in Galveston for Machine Cleaning Compensatory Restoration Project (Solid Line = Fitted; Dashed Line = 45 Degree Line). (B) Scatter Plot of Compensation versus Loss for Malaquite Beach Machine Cleaning Compensatory Restoration Project (Solid Line = Fitted; Dashed Line = 45 Degree Line)



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 correlation coefficient of 0.15. This stands in stark contrast with Malaquite Beach, which has an absolute difference of only $3.63 and a correlation coefficient of 0.87. Figures 2A and 2B show scatter plots of compensation versus loss for the Malaquite and Fort Crockett beach projects along with fitted lines and a "perfect compensation 45-degree line."

Now consider some combinations of projects with short payback periods and favorable alignment. To obtain favorable alignment, we focused on project combinations using Corpus Christi area beaches only. For Padre Island, we only consider projects on the three northernmost beaches where use is heaviest.

First, we consider three *machine cleaning projects*:

Clean A: Machine Cleaning on 2 non-Padre Beaches → *Corpus Christi* and *Magee Beaches*

Clean B: Machine Cleaning on 3 Padre Beaches → *North, Malaquite,* and *South Beaches*

Clean C: Clean A & Clean B

Second, we consider three *vehicle-free access projects*:

Vehicle A: Vehicle Free on 2 non-Padre Beaches → *Port Aransas Park* and *JP Luby Park Beaches*

Vehicle B: Vehicle Free on 2 Padre Beaches → *North* and *South Beaches*

Vehicle C: Vehicle A & Vehicle B

Last, we consider three *Padre only projects*:

Padre A: Machine Cleaning on 3 Padre Beaches → *North*, *Malaquite*, and *South Beaches* & Lifeguards on 2 Padre Beaches → *North* and *Malaquite Beaches*

Padre B: Padre A & No Entrance Fee on 2 Padre Beaches → *Malaquite* and *South Beaches*

Padre C: Padre B & Vehicle Free on 2 Padre Beaches → *North* and *South Beaches*

Table 4 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 complete. All these have a mean absolute difference of about $6 (where the annual loss 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—the scatter plots are similar to Figure 2B. Clean C has the best compensation to loss alignment (mean absolute difference of $3.41 and coefficient of 0.97) and the years until

TABLE 4
Candidate Bundled Projects for Compensatory Restoration

Project	Years Required to Meet Kaldor-Hicks	Mean Absolute Difference between Compensation and Loss ($)	Coefficient Estimate on Regression of Compensation on Loss
Padre C	2.55	$6.12	0.82
Padre B	3.23	5.98	0.83
Clean C	3.72	3.41	0.97
Padre A	3.76	6.02	0.83
Vehicle C	3.86	6.34	1.13
Clean B	4.88	4.16	0.88
Vehicle A	5.69	12.27	1.28
Vehicle B	8.94	3.67	0.89
Clean A	10.79	18.24	1.21

Clean A: Machine Cleaning on 2 non-Padre Beaches → *Corpus Christi* and *Magee Beaches*

Clean B: Machine Cleaning on 3 Padre Beaches → *North, Malaquite,* and *South Beaches*

Clean C: Clean A & Clean B

Vehicle A: Vehicle Free on 2 non-Padre Beaches → *Port Aransas Park* and *JP Luby Park Beaches*

Vehicle B: Vehicle Free on 2 Padre Beaches → *North* and *South Beaches*

Vehicle C: Vehicle A & Vehicle B

Padre A: Machine Cleaning on 3 Padre Beaches → *North, Malaquite,* and *South Beaches* & Lifeguards on 2 Padre Beaches → *North* and *Malaquite Beaches*

Padre B: Padre A & No Entrance Fee on 2 Padre Beaches → *Malaquite* and *South Beaches*

Padre C: Padre B & Vehicle Free on 2 Padre Beaches → *North* and *South Beaches*

compensation is complete is 3.72, only slightly longer than two of the Padre project bundles.

The cost of the projects, which we do not take up explicitly here but presumably would be the subject of negotiation in any NRDA, would vary widely, not just across project types (vehicle free versus cleaning) but also across the same project at different beaches. Some beaches will require more frequent 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 to hundreds of thousands of dollars.[6] As noted earlier, 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, high. Lifeguard costs are apt to be less beach dependent. At $15/hour, ten lifeguards for a beach would cost about $1,200/day ignoring equipment, shelter, training, and perhaps other associated costs. Finally, the fee for entry to all but North Beach on Padre Island is $10 for a weekly pass. The expense 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 4, and in any cases generated from a RUM model, we would expect some ground truthing of the results. Are these feasible? Are there 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. In addition, it is important to note that when considering the candidate projects passing the Kaldor-Hicks test, some of the projects 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 because 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

6. For example, Denise Malan writes that "Port Aransas oversees maintenance on 7 1/2 miles of beach, and removes sargassum on 3 1/2 miles of that for four months a year, at a cost of as much as $500,000 for heavy years." (Caller-Times on Oct. 21, 2007)

well. If Pigouvian-like incentive structures are a goal (or one goal) for compensatory restoration projects, this is an 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.

VI. CONCLUSION

We presented a method using the travel cost random utility model to conduct a value-to-value compensatory restoration analysis. In an application to beach use on the Texas Gulf Coast and a closure of the Padre Island National Seashore, we showed how a mixed logit model could be used to identify and compare compensatory restoration projects using beach attributes. We screened candidate projects using a Kaldor-Hicks criterion—the value of the restoration had to be at least as large as the loss due to a closure. We then compared projects in terms of number of years they needed to be in place to pass a Kaldor-Hicks test and their success at aligning compensation with individuals actually suffering losses. We used two indexes to measure success of alignment—the mean absolute difference of compensation and loss and an ordinary least square regression of compensation on loss. Low-mean absolute differences and a "fit" with a coefficient near one were taken as good indicators of alignment. These seemed to work quite well in identifying projects with good alignment. Not surprisingly, these were projects on or near the site experiencing the hypothetical closure. The projects that worked best in our case were machine cleaning and providing vehicle-free access on beaches.

Our method is easily transferable to other areas. However, there are a number of limitations. First, if one seeks restoration projects that do not involve attributes of the estimated model, the model cannot be used. For example, providing parking space at an inland location could not be analyzed in our model. Stated preference data on attributes outside the set of observable attributes could be used to overcome this limitation. If candidate restoration projects were known in advance, these could be directly incorporated into the data gathering effort. Second, if current beach management is less than optimal (beneficial projects are not being undertaken), the burden of compensatory restoration on responsible parties will be lessened because they can use these "cheap and easy" means of compensation to satisfy their obligation. This may be an undesirable outcome from an incentive perspective. Third, ground truthing of each project is required. Are there physical, political, or other constraints that prevent the projects recommended from the model? If so, other suggested projects should be considered. Finally, our analysis only considers day-trip users. We miss compensation for overnight trips, nonuse value, and any congestion effects that might ensue at sites where restoration is taking place and other external effects that might be induced by restoration.

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