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Gauging the Value of Short-Term Site Closures in a Travel-Cost RUM Model of Recreation Demand With a Little Help from Stated Preference Data

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16 Gauging the value of short-term site closures in a travel-cost random utility model of recreation demand with a little help from stated preference data

George R. Parsons and Stela Stefanova

Introduction

Random utility models of recreation demand are well suited for valuing closure of sites and changes in the characteristics of sites such as an improvement in water quality or increase in fish catch. In these applications the welfare effects are realized through site substitution or the choice of taking no trip on a given choice occasion. Parameter estimates from the models are used to measure the decline in utility implied by substitution along these lines and the coefficient on a trip cost variable, in turn, is used to monetize the change in utility.

The models, however, ignore the possibility of substitution across choice occasions within a given season in response to a site closure or change in site quality. 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.[1]

We have designed and estimated a random utility maximization (RUM) model that accounts for substitution over time and use it to gauge the value of short-term closures. The model combines revealed and stated preference data and is applied to beach use on the Texas Gulf coast. The data were gathered by a phone survey in 2001. Respondents were asked to report information on trips to 65 beaches during the year.[2]

As part of the survey, all respondents visiting the Padre Island National Seashore (14 percent 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. Our approach does not use a dynamic choice model over a season. Instead, it offers a practical alternative; we believe a strong alternative given the limitations of our simple SP follow-up choice question. Part of our motivation for pursuing this topic was the large number of respondents who reported that they would "make up" a lost trip by visiting Padre later, leading us to wonder if conventional RUM analysis might be missing a key behavioral response to a closure and hence measuring welfare loss inaccurately.

The SP questions are shown in Figure 16.1. If a person responded "Definitely Will" or "Very Likely" or "Likely" to the follow up question we assume that they will take a make-up trip. There are drawbacks to this question format. First, instead of "closure," it uses the wording "...if you had not been able to visit..." which, in principle, could be due to reasons other than a closure. If people took a broad enough interpretation, such as being sick or the traffic being bad, there may be a great deal of latitude in our response data, and that is a reason for caution. Furthermore, even if respondents are thinking in terms of closure, the assumed reason for the closure could vary in the minds of the respondents. Oil spill? Red tide? Other? If behavioral responses are sensitive to the reason for the closure this will lead to even more latitude in the response data. Second, it does not mention how long Padre will be closed. The length of closure will affect the amount of time available during the balance of the season for a make-up trip, when during the balance of the season make-up trips would be possible, and even how many trips may be affected. We, in effect, assume a single day closure in our modeling strategy. Third, the construction of the follow-up question is

[IF ANSWER TO QUESTION 5 IS PADRE ISLAND NATIONAL SEASHORE, ASK] If you had not been able to visit Padre Island National Seashore on that day, would you have visited another Gulf Coast beach?

1	Yes →	Which Beach?
_____		RECORD NUMBER CORRESPONDING WITH SITES ON THE SITE DEFINITION SHEET
_____		OTHER [PLEASE SPECIFY]
2	No	
3	Not sure	

[IF ANSWER TO QUESTION 5 IS PADRE ISLAND NATIONAL SEASHORE, ASK] Would you try to visit Padre Island National Seashore later in the season to "make up" for the lost trip? [PROBE IF NECESSARY]

1	DEFINITELY WILL
2	VERY LIKELY
3	SOMEWHAT LIKELY
4	UNLIKELY
5	DEFINITELY WILL NOT
6	DON'T KNOW

Figure 16.1 Padre Island stated preference closure questions.

such that everyone is asked if they would take a make-up trip to Padre, even if they choose another site in the first question. Only a small fraction choose both and we treated them as choosing another site only. Fourth, with any stated preference response data, what people say they will do and what they actually do can be quite different things. In the recreation demand field there is some evidence that people overstated their expected number of trips for a season when asked at the beginning of a season. We may have a similar optimistic overstatement in our make-up trip data. So, our data clearly come with some caveats, and we urge the reader to keep these in mind when interpreting or using our results.

We find that accounting for delayed trips to Padre reduces the estimated welfare loss by about 70 percent. In the next two sections we present our model and study design. Then, we turn to a short presentation of the data and the results.

A repeated discrete choice model

We use a repeated discrete-choice model to analyze our trip data. Each day of the season is treated as a separate choice occasion. On each choice occasion a person decides to take a trip to the beach or not (stage one) and, if yes, which beach to visit (stage two). We estimate the model sequentially, stage 2 first and then stage 1.[3]

Stage 1 is a simple random utility model of site choice in which an individual faces C sites.[4] Each site i is assumed to give an individual utility $U_i = \beta x_i + \beta_{tc}(y - tc_i) + \varepsilon_i$ where x_i is a vector of site characteristics at site i, y is income, tc_i is the trip cost of reaching site i, and ε_i is a random error. An individual is assumed to visit the site with the highest utility, so his or her trip utility on a given choice occasion is $V = \max\{\beta x_1 + \beta_{tc}(y - tc_1) + \varepsilon_1, \ldots, \beta x_C + \beta_{tc}(y - tc_C) + \varepsilon_C\}$. Treating site choice as the outcome of a stochastic process, an individual's expected maximum trip utility is $E(V) = E(\max\{\beta x_1 + \beta_{tc}(y - tc_1) + \varepsilon_1, \ldots, \beta x_C + \beta_{tc}(y - tc_C) + \varepsilon_C\})$.

We estimate the parameters of site utility and, in turn, the expected utility of a trip using two different models: standard (fixed parameter) logit and mixed (random parameter) logit. These models are well known and documented–see Train (2009, Chapters 3 and 6). In both models the expected maximum utility of a trip takes the familiar log-sum form $E(V) = \ln \Sigma_{i \in C} e^{\beta x_i + \beta_{tc}(y - tc_i)}$. In the mixed logit model, the log-sum is a simulated mean over the estimated distribution for the random elements in β (see Parsons and Massey 2003). The mixed logit model allows for a more general pattern of site substitution than the fixed parameter model.

Stage 2 introduces a no-trip alternative on each choice occasion which is assumed to give an individual utility $U_0 = \delta_z z + \varepsilon_0$, where z is a vector of individual characteristics believed to influence the number of trips taken in a season. In our application, z includes education, employment status, age, and so forth. Using no-trip utility and the site utilities, we model an individual's choice of taking a trip or not. An individual is assumed to choose the greater of no-trip and trip utility on each choice occasion. This outcome is referred to as a person's

choice occasion utility, defined as $COU = \max\{U_0, V\}$, where V is defined above. Again, treating trip choice as the outcome of a stochastic process, an individual's expected utility on a choice occasion is $E(COU) = E\{\max(U_0, V)\}$. In our logit models $E(COU) = \ln\{e^{\delta_z z} + e^{\delta_{EV} E(V)}\}$, where $E(V) = \ln \Sigma_{\in C} e^{\beta x_i + \beta_{tc}(y - tc_i)}$.[5]

Now, consider a conventional analysis of site closure using revealed preference (RP) data only. Let C_2 be the set of Padre Island sites and C_1 the set of all other sites. The expected utility of a trip declines with the closure of the C_2 Padre sites from $E(V^{open}) = \ln \Sigma_{i \in \{C_1, C_2\}} e^{\beta x_i + \beta_{tc}(y - tc_i)}$ to $E(V^{cls}) = \ln \Sigma_{i \in \{C_1\}} e^{\beta x_i + \beta_{tc}(y - tc_i)}$, and the *welfare loss per choice occasion* for the closure is

$$W = \left(\ln\left(e^{\delta_z z} + e^{\delta_{EV} E(V^{open})}\right) - \ln\left(e^{\delta_z z} + e^{\delta_{EV} E(V^{cls})}\right)\right) / \beta_{tc} \tag{16.1}$$

The expression in the numerator is the change in expected utility due to the loss of the C_2 Padre sites. The loss is monetized by dividing by the coefficient on trip cost (β_{tc}). Since the expected utility allows for no-trip and trip utility, it allows for individuals to respond to closures by visiting other sites or staying home.[6]

Incorporating delayed trips to closed sites using stated preference data

The per-choice occasion measure W in equation (16.1) relies exclusively on RP data and is the conventional way to value closures. The difficultly with this measure is that it does not allow for substitution across time periods.

Suppose a site is closed for a short time–say a week or even days. If there is little change in total visitation to the site over the season when compared to past seasons, the argument may be made that people merely delay their trips to the closed site until later in the season and that the true welfare loss may be lower than the RUM model would suggest, maybe much lower if delaying trips involves little disutility.

In an effort to capture the effect of substituting a delayed trip until later in the season as a response to a site closure in a RUM model, we designed a survey question in which we simply asked people who had visited a site on Padre Island what they would have done on this day if Padre had been closed. The stated preference responses were classified into three groups:

i visit another site,
ii stay home and make up for the lost trip with a trip later in the season when the site is reopened, or
iii stay home without making up the trip later.

Responses (i) and (iii) are accounted for in a conventional revealed preference analysis. Response (ii) adds the dimension of substituting a later trip.

Our analysis of closure proceeds as follows. An individual's choice set if Padre is open is $\{C_1, C_2\}$. Again, C_1 is the set of all non-Padre sites, and C_2 is the set of Padre sites. The choice set when Padre is closed when using the RP data only is C_1. The choice set when Padre is closed using the RP-SP data combined is instead $\{C_1, C_2^*\}$ where C_2^* 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 may also visit Padre later in the season.

To analyze the welfare implications of accounting for delayed trip substitution, let site utility for Padre site j be $U_j = \alpha_j + \beta x_j + \beta_{tc}(y - tc_j) + \varepsilon_j$ and the site utility for a delayed trip to the same site be $U_j^* = \alpha_j^* + \beta x_j + \beta_{tc}(y - tc_j) + \varepsilon_j$. These site utilities differ only by their constants, α_j and α_j^*. The parameters β and the site characteristics are the same in the two time periods. A person essentially enjoys the same trip; it is simply delayed. We assume there is some decline in utility for having to delay the trip so $\alpha_j^* < \alpha_j$ and $U_j^* < U_j$.

In the formulation accounting for delayed trips then, the expected utility of a trip declines with the closure of the C_2 Padre sites from $E(V^{open}) = \ln(\Sigma_{i \in \{C_1\}} \exp\{\beta x_i + \beta_{tc}(y - tc_i)\} + \Sigma_{i \in \{C_2\}} \exp\{\alpha_j + \beta x_j + \beta_{tc}(y - tc_j)\})$ to $E(V^{cls*}) = \ln(\Sigma_{i \in \{C_1\}} \exp\{\beta x_i + \beta_{tc}(y - tc_i)\} + \Sigma_{j \in \{C_2\}} \exp\{\alpha_j^* + \beta x_j + \beta_{tc}(y - tc_j)\})$. The second term on the right hand side of the second expression is the expected trip utility of a delayed trip thereby allowing for delayed substitution. The *welfare loss per choice occasion* for closure then becomes

$$W^* = \left(\ln\left(e^{\delta_z z} + e^{\delta_{EV} E(V^{open})}\right) - \ln\left(e^{\delta_z z} + e^{\delta_{EV} E(V^{cls*})}\right)\right) / \beta_{tc} \tag{16.2}$$

This is the same form as equation (16.1) with $E(V^{cls*})$ used in place of $E(V^{cls})$.[7]

To compare the measures of welfare empirically we first estimate a *Business-As-Usual Model* using only RP data. The results are used to estimate a business-as-usual welfare loss, W, shown in equation (16.1). Then, we estimate a new *RP-SP Model*. The results from this model give us estimates of α_j^* which, along with the business-as-usual parameter estimates, allow us to estimate a new measure of welfare loss, W^*, in equation (16.2). The difference, $W - W^*$, is an approximation of the overstatement due to ignoring delayed trip substitution.

The new *RP-SP Model* is estimated as though Padre is closed. The choices reported by Padre visitors in their SP responses are used in estimation instead of the actual choices made when Padre is open. For those who do not visit Padre when it is open, we assume their choices are unchanged in the event of the Padre closure and enter those choices accordingly in the data. We constrain all parameters in the *RP-SP Model* to be the same as in the *Business-As-Usual Model*, except for the alternative specific constants, α_j, on the Padre sites. This keeps the choice structure constant but allows us to estimate the discount assigned to delaying a trip to Padre. We divide Padre into four separate sites and allow for scale difference in the SP versus RP data. The next section discusses the data used to estimate the models.

Data

We gathered our survey data in 2001 by a phone-mail-phone survey from May through September–the peak season for beach visits. Texas residents living

within 200 miles of the Gulf of Mexico were sampled by random digit dialing and recruited to participate in a series of follow-up surveys 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. All our welfare analysis is adjusted to account for the stratification. The initial survey was conducted in May and given to the adult member of the household (> 17 years old) with the most recent birthday. English and Spanish versions of the survey were offered. Basic demographic information was gathered on each respondent in the initial phone survey. The follow-up surveys were confined to reporting beach trips. About 60 percent of the respondents stayed on through all of the follow-up surveys.

Those who agreed to participate in the follow-up survey received a mail packet that included a map of the coast, a list of 65 beaches, a calendar to help record trips from May through September, and a decorative magnet of the state of Texas for posting the calendar. Individuals were then contacted monthly by phone to report trips in the previous month. The calls were made monthly to reduce the difficulty of recall. Respondents reported 2692 trips over the five-month period to the 65 beaches.[8]

Of the 884 respondents who completed the survey, 14 percent had made at least one trip to the Padre Island National Seashore. If they reported having made a trip to Padre, they were asked what they would have done if Padre had been closed. These responses formed our SP data. Table 16.1 shows the breakdown for each category of response – 19 percent chose to visit another site in the same time period, 5 percent chose to stay at home and not make-up the trip later, and 76 percent chose to make up the trip later.

The second part of our data set covers the characteristics of the sites. 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 and Bay Access Guide* and a two-week field trip to the coast. The delineation of beaches was intended to be as the public generally perceived the boundaries.

The beach characteristic data came from several sources: interviews with beach managers at the city, county, and state levels; the *Access Guide* mentioned above; other independent travel guides; field trips to each of the beaches; and on-line maps of the area. The variables used for site characteristics in our model are presented in Table 16.2 along with descriptive statistics.

Table 16.1 Stated preference responses for adjustment to Padre Island closure

Option	*% of SP responses (adjusted for stratification)*
Visit another beach now	19
Visit Padre later	76
Stay home	5

Table 16.2 Site characteristics for 65 beaches in choice set

Beach characteristics		*Number of beaches*	*Mean or % of beaches*
Beach length (miles)		–	5.35
Yes/No dichotomous variables:			
Gulf access	Beach is located on the Gulf	48	74
State park	Beach is part of a state park	4	6
Remote	Must leave major road to visit beach	22	34
Vehicle-free	Vehicles disallowed on beach	26	40
Manual clean	Beach is routinely manually cleaned	33	51
Machine clean	Beach is routinely machined cleaned	36	55
Restroom	Restrooms located at beach	37	57
Lifeguards	Lifeguards at beach	17	26
Concession	Concession located at beach	15	23
No fishing	Not listed as a fishing area in *2002 Texas Beach and Bay Access Guide*	3	5
No swimming	Not listed as a swimming area in *2002 Texas Beach and Bay Access Guide*	6	9
Red tide history	Beach has a recent history of red tide according to local beach managers	12	18
Advisory/closure history	Beach has a recent history of closures and/or advisories according to local beach managers	11	17

Travel cost was calculated at 36.5 cents per mile plus any fee paid to use a beach. Time cost is valued at one-third of household income divided by 2000 as a proxy for a person's wage. Distances and times to beaches were calculated using *PC Miler*. Average trip cost of reaching a chosen site was $56. The average cost to all sites was $182. Accounting for stratification, about 30 percent of all trips were less than 30 miles one-way. About 50 percent were less than 50 miles, and 80 percent were less than 100 miles. It is also interesting to note that only 4 percent of all trips were taken to the beach closest to a person's home and only about 36 percent were taken to one of the five closest beaches. All beaches within 300 miles of an individual's home were included in the choice set.

Table 16.3 shows the individual characteristics used in the second stage model. We have no strong priors on how these will predict visitation, but have included characteristics that have typically been used in past analyses–age, education, work status, ownership of recreational equipment, and so forth. Finally, Table 16.4 is a frequency distribution of trips to four Padre Island sites used in our closure analysis.

Coefficient and welfare estimates

The results for our *Business-As-Usual Model*, which uses only RP data, are shown in Table 16.5 for the standard and mixed logit models. In the mixed model we allow *Vehicle Free Access* and seven geographic variables (*Gulf Access*, *Remote*, and *five Region Constants*) to have random coefficients. These represented the lines along which we felt there would be important shared unobserved characteristics. In all cases we assume that the parameters are normally distributed. The model was estimated using 100 Halton draws.

The results work more or less as expected. The coefficient on trip cost is negative and significant.[9] All else constant, people prefer a beach closer to home. Variables that predict a higher probability of visiting a site with significance, all else constant, include *Gulf Access*, *Vehicle Free*, *Beach Length*, and *Manual* and

Table 16.3 Individual characteristics for 884 people

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
Retired	9
Spanish	9
Female	60
Own fishing equipment	49
Own pool	24
Own coastal property	7

Table 16.4 Frequency distribution of trips to Padre Island sites

Option	*% of Padre trips (adjusted for stratification)*
Padre 1: North Beach	64
Padre 2: Malaquite Beach	14
Padre 3: South Beach	19
Padre 4: Shell Beaches/Mansfield Cut	3

Table 16.5 Business-as-usual model: parameter estimates for site utility

Variable	*Logit*	*Mixed logit*	
		Fixed coefficients	
Trip cost	–0.02 (–22.08)[1]	–0.03 (–17.95)	
Beach length	0.27 (8.66)	0.27 (8.53)	
State park	0.20 (0.75)	0.25 (0.95)	
Manual clean	0.78 (6.01)	0.77 (5.87)	
Machine clean	0.80 (7.13)	0.89 (7.06)	
Restroom	–0. 06 (–0.50)	–0.05 (–0.44)	
Lifeguards	–0.04 (–0.40)	–0.03 (–0.11)	
Concessions	–0.01 (–0.10)	–0.04 (–0.37)	
No fishing	–0.26 (–2.21)	–0.28 (–2.31)	
No swimming	–0.98 (–4.38)	–0.99 (–4.20)	
Red tide history	–1.95 (–5.86)	–1.84 (–5.39)	
Advisory/closure history	–0.63 (–2.99)	–0.61 (–2.85)	
Constant for Padre 1	2.80 (12.49)	3.04 (11.64)	
Constant for Padre 2	–0.27 (–0.86)	0.04 (0.12)	
Constant for Padre 3	1.80 (6.38)	2.11 (6.75)	
Constant for Padre 4	0.06 (0.12)	0.50 (0.94)	
		Random Coefficients	
		Mean	*Std. dev.*
Gulf access	0.53 (3.77)	0.58 (4.06)	0.003 (0.004)
Vehicle-fFree	0.99 (10.27)	1.01 (9.92)	0.002 (0.004)
Remote	0.15 (1.49)	–0.02 (–0.14)	0.98 (2.56)
Region 1	0 (Fixed)	0 (Fixed)	0.002 (0.002)
Region 2	0.97 (3.42)	1.02 (3.45)	0.02 (0.04)
Region 3	2.15 (4.73)	2.13 (4.48)	0.004 (0.015)
Region 4	0.82 (2.18)	0.83 (2.05)	0.03 (0.05)
Region 5	1.24 (3.69)	1.30 (3.53)	1.45 (5.02)
Region 6	–0.14 (–0.36)	–0.39(–0.79)	1.76 (3.78)
Log likelihood	–3926	–3912	
Number of people	561	561	
Number of choices	2692	2692	

Note
1 t-statistics in parentheses.

Machine Cleaning. Variables that predict a lower probability with significance include *No Fishing*, *No Swimming*, *Red Tide History*, and *Advisory/Closures History*. Variables having little significance in predicting site choice include *Remote*, *Restroom*, *Lifeguard*, *Concessions*, and *State Park*. The regions run from north to south with *Region 1* being the northernmost. *Region 6*, located in the south near Brownsville, is the excluded region. The regions with the largest coefficients are 2, 3, and 5. These are beach areas near Galveston, Freeport, and Corpus Christi. These are near the largest population centers and are popular beaches. Padre Island is located in *Region 5*. The standard deviation estimates in the mixed logit model are largest, relative to their means, for *Remote*, *Region 5*, and *Region 6*. This suggests that substitution among sites within these geographic areas is strongest, at least in a stochastic sense.

If there were any surprises, it was that the man-made characteristics like *Restroom*, *Lifeguard*, and *Concessions* seemed to play a small role in site choice. It was also somewhat surprising that *Vehicle Free Access* was positive, large, significant, and had a small estimated standard deviation in the mixed logit. We had expected a large standard error signaling large substitution (or perhaps population heterogeneity) among these sites.

The parameter estimates for no-trip utility in the *Business-as-Usual Model* in the standard and mixed logit form are shown in Table 16.6. The coefficients imply that trips increase, all else constant, with education, having children in the household, being younger, and speaking Spanish. Also, men are more likely to take trips than women. And finally, the coefficient on expected trip utility (also reported in Table 16.6 alongside the no-trip parameters) is positive and significant in both regressions as expected.

Table 16.6 Business-as-usual model: parameter estimates for no-trip utility

Variable	*With logit site choice*	*With mixed logit site choice*
Intercept	8.36 (29.20)[1]	7.69 (27.87)
Log(Age)	–0.27 (4.01)	–0.27 (3.94)
Female	0.21 (5.07)	0.20 (4.97)
Work fulltime	0.00 (0.09)	0.01 (0.19)
Spanish	–0.47 (6.98)	–0.48 (7.07)
Retired	0.06 (0.74)	0.06 (0.75)
Children under 17	–0.18 (4.18)	–0.17 (4.10)
Graduate school	–0.12 (1.61)	–0.11 (1.49)
College	–0.30 (6.15)	–0.29 (6.06)
High school	0.21 (4.23)	0.22 (4.09)
Own coastal property	–0.00 (0.02)	–0.00 (0.04)
Own fishing equipment	–0.17 (4.26)	–0.17 (4.10)
Own pool	0.03 (0.55)	0.03 (0.63)
Coefficient on expected trip utility (δ_{EV})	0.74 (28.73)	0.62 (28.88)
Log likelihood	11983.86	11999.62

Note
1 t-statistics in parentheses.

The parameter estimates from Tables 16.5 and 16.6 provide the information we need to calculate W–our business-as-usual welfare loss. Using equation (16.1), the value for the closure of all four beaches on the Padre Island National Seashore is $0.054 per choice occasion in the standard logit model and $0.038 per choice occasion in the mixed logit model.[10] The lower values in the mixed logit reflect that model's ability to account better for substitution across sites. This is driven by the large standard error on *Region 5*, which suggests that other sites in the Corpus Christi area are good substitutes for the Padre sites.

Now let's turn to our estimates of the *RP-SP Model*. These are needed to calculate the new welfare measure W^* which accounts for delayed trip substitution. The *RP-SP Model* is estimated assuming that the Padre Island National Seashore is closed. All the RP choices for the Padre Island visitors are replaced with their SP choices. For respondents who did not visit Padre Island when it was open, we assume their choices are unchanged. We constrained the parameters on all of the site characteristics to be the same with and without closure, but allowed the Padre Island constants to change. This keeps the behavioral model constant and allows us to isolate the effect of a delayed trip to Padre Island.

Table 16.7 Revealed and stated preference model: parameter estimates on site utility[2]

Variable	*Logit*	*Mixed logit*	
		Fixed coefficients	
Constant for Padre 1	2.46 (17.23)[1]	–2.66 (–17.65)	
Constant for Padre 2	–0.89 (–2.74)	–0.62 (–1.88)	
Constant for Padre 3	1.67 (7.61)	1.95 (8.65)	
Constant for Padre 4	–1.38 (–1.46)	–0.97 (–1.03)	
		Random coefficients	
		Mean	*Std. dev.*
Gulf Access	n/a	–	0.06 (0.10)
Vehicle Free	n/a	–	0.01 (0.02)
Remote	n/a	–	0.96 (5.08)
Region 1	n/a	–	0.01 (0.007)
Region 2	n/a	–	0.03 (0.04)
Region 3	n/a	–	0.002 (0.01)
Region 4	n/a	–	0.01 (0.02)
Region 5	n/a	–	1.52 (8.31)
Region 6	n/a	–	1.59 (3.59)
Log likelihood	–3906		–3893
Number of people	561		561
Number of choices	2692		2692

Notes
1 Estimates for all coefficients except the alternative specific constants for Padre sites and all random coefficients are constrained to equal the estimates in the RP model shown in Table 16.5.
2 t-statistics in parentheses.

The *RP-SP Model* results are shown in Table 16.7 and include only the coefficients that vary from the *Business-As-Usual Model.* Following Brownstone *et al.* (2000) we estimated a scaling parameter on the SP choices relative to the RP choices using a normal mixing distribution for a dummy variable on the SP choices with zero mean. We found no significant scale difference in the data sets. We also estimated separate standard deviations on all the parameters with mixing distributions expecting somewhat larger variability in *RP-SP Model.* As shown, the coefficients estimates are reasonably close in the two models. This may be due to the similarity of the SP and RP choices and limited number of observations affected. As expected, the coefficients on the Padre Island constants fall in the *RP-SP Model* relative to the *Business-As-Usual Model*. This captures the decline in utility that comes with having to delay a trip. The per choice occasion value for a closure of all Padre sites, W^*, is \$0.016 in the logit model and \$0.011 in the mixed logit model. These are about 30 percent of the value estimated when delayed trips are not taken into account, so the implication of ignoring delayed trip substitution, if the SP data are believed, is not trivial. The standard and mixed logit differences from the *Business-As-Usual Model* are about the same. These results are, of course, driven by the larger number of respondents reporting that they would make-up their lost trip with a trip later in the season.

Conclusions

Applications of the Travel Cost RUM Model to value short-term site closures sometimes leads to controversy over the handling of substitution between time periods in the same season. In cases where there is a short-term closure of a site (closes and opens within the same season) but the number of the trips to the site over the entire season shows little change compared with past seasons, the argument is sometimes made that people are merely substituting future trips for lost current trips. Since the conventional RUM Model does not account for substitution across time periods and indeed forces substitution to another site or staying home, the argument is sometimes made that it may lead to an overstatement of loss because the model disallows what may be the best substitute for many individuals–delaying a trip to the closed site.

We explored this potential overstatement in a model of beach use in Texas with an SP question posed to all respondents who had visited the Padre Island National Seashore–14 percent of our sample. The question simply asked visitors what they would have done if Padre had been closed. The responses allowed for staying home, visiting another site, or taking a trip later in the season to Padre to "make-up" for the lost Padre trip. About 75 percent of the respondents chose to make-up the trip later, suggesting the potential for a significant overstatement if ignored. We found that estimated losses were about 70 percent lower when delayed trips were incorporated in the model.

The implication, if the SP data are believed, is that the conventional estimates of loss using RUM models of recreation demand may consistently lead to overstatement. In our application it is rather large. The results would no doubt vary across different resources and settings. In general, the greater the likelihood of substitution to other sites or staying home, the more reliable the conventional RUM analysis. Also, the longer the period of closure, the less likely there will be substitution within the same season.

As noted earlier, our analysis is somewhat speculative. There is considerable room for improvement in our SP question, need for validation with actual trip data before and after a closure, and a desire for validation with an explicit dynamic model. At this stage, we hesitate to draw strong conclusions. Nevertheless, our findings suggest that further inquiry may be in order.

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Notes

1 If people delay trips across seasons, the argument may be extended further. We would expect the replacement value of trips delayed that long would be substantially diminished.
2 For another application using these data, see Parsons *et al.* (2009).
3 Morey *et al.* (1993) introduced the repeated discrete-choice model to recreation demand.
4 For some examples of the random utility model applied to beach recreation see Lew and Larson (2008), Whitehead *et al.* (2010), Murray *et al.* (2001), and Parsons and Massey (2003).
5 This formulation nests the model by trip and no-trip and introduces δ_{EV} as a coefficient on the log-sum (or inclusive value) for trip.
6 See Hanemann (1999) or Haab and McConnell (2002) or for more on welfare analysis in the context of RUM models of recreation demand.
7 The Padre constants α_j are subsumed in the parameter vector β in the previous section.
8 We collapse six Padre Island sites into four, leaving 63 sites in our final analysis.
9 In estimation y drops out of $\beta_{tc}(y-tc)$ and β_{tc} is estimated as a negative coefficient on tc.
10 Per choice occasion values are averaged over all respondents–non-participants and participants visiting any site.

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