Substitution, Damages, and Compensation for Anglers due to Oil Spills: The case of the Deepwater Horizon

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Abstract

Oil spills and other anthropogenic environmental disasters have economic consequences that transcend losses of business revenue and property damages. Such non-market losses include those accrued by recreational users, as well as by individuals who hold passive use value for the affected environmental resources. We use a series of random utility models to examine the substitution patterns and welfare losses experienced by recreational saltwater anglers in the Southeast U.S. due to the Deepwater Horizon oil spill. The use of a difference ratio to measure changes between pre- and post-spill preferences that allow us to discern substitution patterns in fishing season, catch, and site popularity. We also estimate monetary welfare measures for damages incurred by anglers, as well as the in-kind compensatory restoration that would be required to make anglers whole.

Keywords: recreational fishing, MRIP, Deepwater Horizon, oil spill, random utility model, compensatory restoration, welfare measure

Introduction

Oil spills and other anthropogenic environmental disasters have economic consequences that transcend business losses and property damages. Such non-market losses include those accrued by recreational users, as well as by individuals who hold passive use value for the resource in question. Measurement of the non-market economic consequences of man-made disasters is often complicated by the *ex-post* nature of such analysis, as most researchers do not have the necessary foresight to collect data before, during, and after the event (Grigalunas, et al. 1986). Researchers are thus forced to rely on counterfactuals and hypothetical scenarios to re-create what behavior and preferences would have been like in an alternate state of the world where the event does not occur. However, persistent data collection efforts such as that of the Marine Recreational Information Program (MRIP) provide opportunities for study of the non-market impacts of oil spills and other disasters in an *ex-ante*/*ex-post* fashion.

The Deepwater Horizon (DWH) oil spill presents an opportunity to use MRIP to analyze the effects of a man-made environmental disaster before, during, and after the event. On April 20, 2010, the largest oil spill in the history of the United States began off the coast of Louisiana in the Gulf of Mexico. By the time the leaks in the DWH offshore drilling rig were fully contained on July 15, surface oil had reached several areas in the Florida Gulf Coast. A large expanse of the Gulf of Mexico Exclusive Economic Zone (EEZ) had been closed to fishing, reaching 37 percent of the EEZ at the height of the spill (Figure 1). State waters throughout the Gulf were heavily impacted, resulting in closures ranging from 95 percent of state waters in Mississippi, 55 percent in Louisiana, 40 percent in Alabama, and two percent in Florida (Upton 2011). Federal and State authorities responded to the oil spill by deploying large-scale cleanup and mitigation efforts throughout the affected areas. In Florida, a massive campaign to ensure potential beach-goers and recreational anglers that coastal areas of the state were still “open for business” was also launched, and included “free-fishing days” during which the fishing license requirement was temporarily lifted.

Aside from the effects on marine ecosystems and the commercial fisheries that depend on them, the DWH spill can also be expected to have impacted recreational use of coastal and marine resources in many areas of the Gulf. Under the Oil Pollution Act, Federal, State, and Tribal authorities have standing to claim and recover losses on behalf of the public from responsible parties. Recoverable damages include both the costs of primary restoration and losses in value from the time of the incident until recovery, where losses include direct use and passive use values (Jones 1997). Recreational use of natural resources falls under the direct use value category, implying that beach-goers and anglers may be entitled to compensation for interim losses in value in the form of compensatory restoration (Mazzotta, Opaluch and Grigalunas 1994; Jones and Pease 1997; Flores and Thacher 2002; Parsons and Kang 2010). More importantly, recreational demand may offer a litmus test of whether primary restoration under Natural Resource Damage Assessment (NRDA) plans have been effective by determining whether affected locations are as desirable after restoration as they were before the oil spill.

A random utility model (RUM) of site choice is well suited to analyze situations where recreational users have alternative locations to visit (Bockstael, McConnell and Strand 1991). A RUM models human behavior based on observed choices that are assumed to be driven by the characteristics of each alternative. The RUM was introduced by McFadden (1974, 1977), who developed the conditional and nested logits. Bockstael, Hanemann and Kling (1987) used the nested logit to model recreational choices by swimmers in the Boston area and value the associated water quality attributes. Morey, Shaw and Rowe (1991) also used a nested RUM to control for the decision of whether or not to participate in recreational fishing in the Oregon coast and value the elimination of fishing opportunities at particular locations. Similarly, Greene, Moss and Spreen (1997) use a RUM of fishing in the Tampa Bay region to value the loss of access to the fishing grounds. Kaoru's (1995) nested site choice model values changes in combinations of quality for anglers in coastal North Carolina. Most recently, Thomas, Lupi, and Harding (2010) create a model of site choice using ramp access points as nests and on-water locations as the elemental sites, and use their model to value the benefits of mantaining and improving boat ramps in the Fort Myers, Florida area.

One commonality among site choice models of recreational fishing is the use of catch as a quality attribute, primarily because catch rates are policy relevant. While catch is available for the intercepted trip, it is not available for rejected sites by the same individual. McConnell, Strand and Blake-Hedges (1995) propose a two stage process in which a catch equation is estimated in the first stage and used to create a quality attribute for the alternatives used in the estimation of the site choice model, the second stage. This process gives a proxy of the angler's *ex-ante* expectation of catch and thus expected quality of the fishing experience at the chosen site. Such an approach allows variation in site attributes among alternatives at the trip level. Haab et al. (2010) follow this approach to value different sets of marine species using a series of site choice models.

The second type of RUM developed by McFadden, the conditional logit, is limited by the assumption of independence of irrelevant alternatives (IIA). The IIA assumption is violated when there is correlation of unobserved characteristics between alternatives. While the nested logit allows the researcher to establish *a priori* which alternatives are expected to be correlated with each other through the specification of nests, some problems may not be amenable to such specification or the specification may not be intuitive. The mixed or random parameters logit (Train 1998, 2003) and the latent class logit (Boxall and Adamowicz 2002) do not rely on the restrictive IIA assumption, with the added benefit that heterogeneity in the sample can be explicitly accounted for either by the estimation of distributions of the parameters in the former, or separation of the sample into latent classes in the latter.

Some problems involved in the estimation of site choice models are related to the computing power required to estimate models with many alternatives, as well as the limited scope of data collected during intercept surveys. Researchers can aggregate or eliminate sites to reduce the number of choices modeled and several studies have investigated the merits of each approach. Parsons and Needleman (1992) develop a site choice model of fishing in Wisconsin lakes to analyze the effect of aggregating recreational sites on estimates of the value of different site characteristics, and caution against the use of aggregation schemes due to the introduction of bias on welfare estimates. In a similar study, Parsons and Kealy (1992) model choices of recreational users of Wisconsin lakes engaging in different activities, and use the model to analyze the effect of using randomly drawn subsets of alternatives—rather than the complete set—to estimate the parameters of the RUM. These two studies suggest that using random draws from the alternative set may be more effective than aggregating sites as a way to ease computational requirements. These conclusions are echoed by Feather's (1994) analysis of sampling and aggregation using a site choice model of sport fishers in Minnesota. Lupi and Feather (1998) offer a pragmatic solution in which unimportant sites are aggregated, while those that are heavily visited or will be affected by policy changes are kept in their elemental form. Whitehead and Haab (2000) use a different approach by examining the use of distance and historical catch to eliminate sites that are either too far or too unproductive to warrant inclusion as a viable choice; they find results are not significantly affected by the elimination of non-viable choices determined using these criteria for marine recreational anglers in the Southeastern United States. Lastly, Hindsley, Landry, and Gentner (2011) develop a RUM for private boat-based anglers in the southeast, use it to investigate the problems inherent with on-site sampling and propose a correction method based on propensity scores that mitigates the sample selection bias.

In this study, we use Marine Recreational Information Program (MRIP) intercept data from the Southeast U.S. and follow the two stage approach proposed by McConnell, Strand and Blake-Hedges (1995) to create proxies for the *ex-ante* expectation of angler catch as a site quality index. We aggregate the 85 coastal counties into 10 zones, and allow substitution in sites as well as in time periods. While aggregation would be expected to introduce bias in welfare estimates to the extent that site quality differs within an aggregation, it is considered appropriate for examining the substitition patterns observed by marine anglers visiting the Southeast U.S. before, during and after the DWH oil spill. This is because the spill affected a very large portion of the Gulf coast such that multiple elemental sites were affected concurrently. The substitution pattern we are interested in examining is between broad areas (e.g., states) in the Gulf and South Atlantic rather than between elemental sites with equal access to primary fishing grounds (or consideration of species caught). Aggregated sites (and species) allow substitution between these two distinct areas, while keeping the dataset manageable enough to allow intra-year trip subsitution (i.e., delayed trips). Also, rather than focus solely on the monetary valuation of the oil spill's impacts on anglers, we take an approach similar to that of Parsons and Kang (2010) and also analyze avenues for compensatory restoration of the affected areas.

Site Choice RUM for DWH Impacts on Marine Anglers

The RUM is a model of choice among a set of available alternatives. In the case of recreational fishing, the RUM models the choice an individual angler makes between available fishing sites because of the attributes of the site, such as the costs of travel, the historic and expected catches of fish, and the popularity or accessibility of the fishing site, among others (Bockstael, McConnell and Strand 1991). In our case, we consider the presence of oil near the coastline, as indicated by the NOAA fishery closure maps, as an indication of site quality (e.g., Figure 1).

Following Train (2003), individual n decides to go fishing in saltwater, and must choose from among a set J available alternatives (j = 1, …, J). The utility of angler n from selecting alternative j is denoted U_{nj}. Angler n chooses the alternative that maximizes her utility. That is, site j is chosen if

$$U_{nj} > U_{nh} \forall h \neq j. \tag{1}$$

However, the angler's utility is unobservable. Instead, we observe some attributes of the fishing locations as faced by the angler (q_{nj}), with travel costs (TC_{nj}) being one of these attributes. Based on these observables, we specify a function (V_{nj}) that relates these attributes to the angler's utility, and which we refer to as indirect utility, $V_{nj}(TC_{nj}, q_{nj})$. Since there are likely to remain unobserved factors in the angler's utility function, we can express utility as being composed of a deterministic component (V_{nj}) and a stochastic component (ε_{nj}) that captures the factors that affect the angler's well-being but are not accounted for, such that

$$U_{nj} = V_{nj}(TC_{nj}, q_{nj}) + \varepsilon_{nj}, \tag{2}$$

where the joint density of the random component $\varepsilon_n = [\varepsilon_{n1}, \ldots, \varepsilon_{nJ}]$ is denoted $f(\varepsilon)$.

As previously stated, the angler chooses the alternative that yields the maximum utility form among the available set. The probability that angler n choose alternative j is thus given by

$$\begin{aligned} P_{nj} &= \Pr(V_{nj} + \varepsilon_{nj} > V_{nh} + \varepsilon_{nh} \forall j \neq h) \\ &= \Pr(\varepsilon_{nh} - \varepsilon_{nj} > V_{nj} - V_{nh} \forall j \neq h). \end{aligned} \tag{3}$$

Using the density of the stochastic terms $f(\varepsilon)$, this cumulative probability can be expressed as

$$P_{nj} = \int_{\varepsilon} I(\varepsilon_{nh} - \varepsilon_{nj} > V_{nj} - V_{nh} \forall j \neq h) f(\varepsilon_n) d\varepsilon_n, \tag{4}$$

where $I(.)$ is the indicator function that equals one when the expression in parenthesis is true and zero otherwise. Assuming that the stochastic terms are independent and identically distributed extreme value yields McFadden's (1974) conditional logit, where the probability takes the form

$$P_{nj} = \frac{e^{V_{nj}}}{\sum e^{V_{nh}}}. \tag{5}$$

The conditional logit can be estimated using maximum likelihood methods.

We specify the indirect utility function to be linear in the attributes of the alternatives to facilitate the derivation of the subsequent measures used to assess the impacts of the DWH oil spill. The utility that angler n obtains from choosing alternative j can then be expressed as

$$U_{nj} = \beta' q_{nj} + \varepsilon_{nj}, \tag{6}$$

where q_{nj} is a vector of attributes and β is a vector of model parameters. Preferences for the different attributes of available alternatives are reflected in the estimated parameters (β). Heterogeneity in preferences can be introduced by allowing a cumulative density function $f(\beta)$ for the estimated parameters. In this case, the choice probability becomes

$$P_{nj} = \int \left(\frac{e^{\beta' q_{nj}}}{\sum e^{\beta' q_{nh}}} \right) f(\beta) d\beta, \tag{7}$$

which is referred to as the mixed or random parameters logit model, and can be estimated using simulated maximum likelihood methods.

To examine the welfare impact of a change in a quality attribute across all sites, we decompose the indirect utility function explicitly into travel costs (TC_{nj}) and other attributes, so that angler n's utility from choosing alternative j is given by

$$U_{nj} = \alpha TC_{nj} + \beta' q_{nj} + \varepsilon_{nj}, \tag{8}$$

where α is interpreted as the marginal utility of income.

Now, suppose we want to evaluate the welfare impact of a proposed change in quality from the initial level of quality (q_{nj}) to an alternative level (q_{nj}^*), where

$$q_{nj}^* = q_{nj} + \Delta q. \tag{9}$$

The welfare measure for such a quality change is given by the difference in the sum of the indirect utilities across sites under both states of the world, weighted by the marginal utility of income as follows

$$W = \frac{1}{\alpha}\left[Ln\sum_{j=1}^{J}\exp\left[V_{nj}^*(TC_{nj}, q_{nj}^*)\right] - Ln\sum_{j=1}^{J}\exp\left[V_{nj}(TC_{nj}, q_{nj})\right]\right], \tag{10}$$

which, as shown by Haab and McConnell (2002), reduces to

$$W = \frac{1}{\alpha}\beta'\Delta q, \tag{11}$$

the per trip welfare measure or willingness-to-pay to prevent a decrease in quality, or conversely, to purchase an increment in a quality attribute. Accordingly, the sign of *W* depends on whether anglers perceive the quality change as an improvement or damage to the fishing experience.

Now, suppose that rather than being interested in monetary measures of compensation for quality changes, we try to find policies that could compensate anglers for these changes in-kind. That is, suppose we want to compensate anglers for a decrease in one quality attribute with a change in a second attribute. This is what is known as compensatory restoration (Jones and Pease 1997; Flores and Thacher 2002). To do so, assume that, in addition to travel costs, there are only two quality attributes, q_{n1} and q_{n2}, respectively. Angler *n*'s utility of choosing alternative *j* is then given by

$$U_{nj} = \alpha TC_{nj} + \beta_1 q_{n1} + \beta_2 q_{n2} + \varepsilon_{nj}. \tag{12}$$

If an unforeseen event were to result in a decrease in q_{n1} of Δq_1, we could find a corresponding change in q_{n2}, Δq_2, that would leave the angler as well off as before the event. To be explicit, let U_{nj} be the angler's utility before the event, and U_{nj}^{*} the utility after the event, such that

$$U_{nj}\left(TC_{nj}, q_{n1}, q_{n2}\right) = U_{nj}^{*}\left(TC_{nj}, (q_{n1} - \Delta q_1), (q_{n2} + \Delta q_2)\right) \qquad (13a)$$

$$\alpha TC_{nj} + \beta_1 q_{n1} + \beta_2 q_{n2} + \varepsilon_{nj} = \alpha TC_{nj} + \beta_1 (q_{n1} - \Delta q_1) + \beta_2 (q_{n2} + \Delta q_2) + \varepsilon_{nj}^{*}. \qquad (13b)$$

As shown by Flores and Thacher (2002), the expected amount of compensatory restoration or change in q_{n2} required to offset the change in q_{n1} reduces to

$$\Delta q_2 = \frac{\beta_1}{\beta_2} \Delta q_1. \qquad (14)$$

This relationship allows us to use the results of a random utility model that considers both the affected quality attribute and additional attributes, which can be treated as candidates for restoration activities, to find the necessary changes in attributes to compensate anglers for unforeseen losses in quality.

Data Sources and Specification of Site Attributes and Alternatives

The Marine Recreational Information Program (MRIP) conducts intercept surveys of recreational anglers throughout the year (Hicks et al., 2000). These surveys focus on the level and composition of catch to provide statistics on catch and fishing effort by species. The data is reported by two-month periods referred to as waves. For this study, we assembled the intercept datasets for years 2006 through 2010, the year in which the DWH oil spill occurred.

MRIP intercepts in the Southeast U.S. are conducted in several locations from Louisiana to North Carolina. Several authors who have worked with MRIP have used county level aggregation to define their sites (e.g., Morey, Shaw and Rowe 1991;

McConnell, Strand and Blake-Hedges 1995; Whitehead and Haab 2000; Haab, Whitehead and McConnell 2001; Haab et al. 2010; Hindsley, Landry and Gentner 2011). We aggregate further given the objective to measure the impact of the DWH oil spill, which occurred in the Gulf of Mexico, and define a set of 10 regions. The states of Lousiana, Mississippi, Alabama, Georgia, South Carolina, and North Carolina are defined as individual regions. Florida is divided into four regions: Northwest, Southwest, Florida Keys, and Florida Atlantic (Figure 2).

To include oil spill specific effects, we also include a time dimension to the available alternatives based on the waves that correspond to data collection. This allows us to include the effects of the DWH oil spill in a spatially and temporally explicit manner. The final alternative set for each angler then includes the 10 alternative sites in six possible seasons for a total of 60 available alternatives.

In a RUM of recreational fishing choices, the probability of an angler choosing a particular site to go fishing is estimated as a function of the attributes of the chosen alternative and the available alternatives. At the moment the fishing site is chosen, the angler has at best a limited expectation of what his catch will be. Furthermore, it can be expected that different anglers will catch different numbers of fish, even if they visit the same area. Given the limitations of the data being used for this analysis (i.e., lack of angler-specific information), the major site attributes considered in the analysis are travel costs to the site and the expected number of fish caught, which serves as an indicator of trip quality as experienced by the angler. Additionally, we consider proxies for the size and popularity of each alternative region, as well as indicators for trips that take place in the spring, summer, and fall, whether the fishing location is located in the Gulf of Mexico, and whether the alternative trip could have been affected by the oil spill.

The historical catch and keep rate (*HCKR*) in a given site is a good indication of the expected catch in a fishing trip to that location. However, the catch can also be expected to differ seasonally and between fishing modes. For instance, anglers fishing from a boat in mid-spring can be expected to enjoy different catch rates than anglers fishing from the shore in late summer. To calculate the historical catch and keep rate in a given site during a given year, we use the mean catch and keep rate in the previous four years, separated by fishing mode and wave. The three fishing modes considered are shore fishing, fishing from a private or rental boat, and fishing from a charter or party boat (for-hire fishing). This historical catch and keep rate, which is unique to each site, fishing mode, and wave, can then be used to predict the catch that an individual angler would experience, taking account of the mode used and the time of the year in which the trip takes place.

Another key variable that will help determine the number of fish caught and kept is the number of days an individual has fished in the last year. For an angler, experience can be an important determinant of success, as the more experienced fisher can be expected to have some knowledge regarding appropriate bait, tackle, and good fishing spots, among others, that the less experienced angler lacks. Fishing experience, in this case, is indicated by the number of days an individual has fished in the last year. However, there is an unobservable attribute, fishing avidity, which can be expected to influence both the expected catch and the number of days fished in the last year. More avid or better anglers, for one, can be expected to catch more fish than their less avid counterparts. More avid anglers can also be expected to fish more often, although the causality between fishing experience and fishing avidity may not be so straightforward. In other words, it is difficult to determine whether an individual becomes a good angler because he fishes often, or if avid anglers enjoy fishing more and therefore take more fishing trips than less avid anglers.

To deal with this endogeneity problem we use the method of instrumental variables (Greene 1997, pp. 288-295). The only angler information available is the zip code of their permanent residence, which was used to calculate the distance traveled to the site and obtain a proxy for income. Distances between each respondent's county of residence and a mid-point of the alternative site in which the intercept was conducted were calculated with Microsoft MapPoint 2004, using a Visual Basic program to calculate distances by batches. Median income was obtained from the Census Bureau's Small Area Income and Poverty Estimates. The distance traveled to the site and median household income—as well as several mathematical transformations of these variables such as the squared, cubed, and logarithmic terms—are used as instruments to predict the number of fishing trips that the respondent took during the last year. This model is referred to as the participation model.

The catch and keep rate that each angler is expected to enjoy can be estimated as a function of angler, trip, and site attributes. The predicted catch serves as an individual-specific indicator of site quality, which allows greater heterogeneity in estimation of the site choice models (McConnell, Strand and Blake-Hedges 1995). We use a negative binomial regression procedure to estimate the predicted catch and keep rate for each individual. The negative binomial was preferred over the Poisson procedure because it is better able to control for overdispersion in count data regressions (Haab and McConnell 2002). This model is used to predict the catch and keep rate of each angler for all available alternatives.

Lastly, site choice models are estimated for each fishing mode; private/rental boat, for-hire, and shore. Private and rental boat anglers may behave differently, but they are treated as a single mode during the MRIP data collection, hence dissagregation of this mode is not possible. Separating out the models both reduces the dimentionality of the model and allows for a better representation of site choice, which is expected to vary by mode. For example, site choice models could include information on individual anglers such as race, gender, employment status, boat ownership, and number of years fishing (experience). Several of these variables have been used in studies that use MRIP data in the years when economic data was collected, most notably 2000 (Whitehead and Haab 1999; Haab et al. 2001; Haab et al. 2010). Unfortunately the last Add-On MRIP Economic Survey (AMES) was conducted in 2006. In particular, not having information on income and employment status presents critical problems in travel cost models, where consideration of the value of time is especially important (Bockstael 1995).

The site choice models in this study use estimates of travel costs for all possible trips in addition to the observed trip. Thus, we created a matrix of distances between all alternative sites and all counties of residence of intercept respondents. Travel related expenses (*TravelExp*) incurred by angler *n* traveling to site *j* were calculated as twice the product of the driving distance and the standard IRS mileage rate in 2009 ($0.55/mile) as follows

$$TravelExp_{nj} = 2(0.55)D_{nj}, \tag{15}$$

where D_{nj} is the one-way distance between the angler's county of residence and the fishing site.

In order to engage in a recreational activity such as fishing, participants must not only spend some of their disposable income to pay for travel related expenses, but in many cases must give up work or other wage-earning opportunities. This opportunity cost of time must also be factored into travel cost recreational demand models for accurate measure of the value of the recreational experience. In our case, the best indication of an angler's opportunity cost of time is the median income in his or her county of residence. We estimate time related expenses (*TimeExp*) as:

$$TimeExp_{nj} = \gamma\left(\frac{MedIncome_n}{2{,}080}\right)\left(\frac{2D_{nj}}{40}\right), \tag{16}$$

where $\gamma = 0.33$ indicates the share of the value of travel time used to account for the cost of leisure time (this is the standard rate used, which was first proposed under Executive Order 11747), and $MedIncome_n$ is the median annual income in the respondent's county during the year the fishing trip took place. Median income is divided by 2,080, the number of full-time hours potentially worked in a year. The distance term is divided by 40, reflecting the assumption that road travel takes place at an average speed of 40 miles per hour (Haab et al. 2001). Total Travel Costs (*TC*) are the sum of travel and time related expenses and total travel costs are expected to be indirectly related to site choice for all modes.

Results

The empirical analysis consists of estimating models for participation (days fished in past 12 months), catch (number of fish caught and kept in intercepted trip), and site choice (by fishing mode: shore, for hire, and private/rental), and the calculation of per trip welfare measures and change in catch to compensate for the oil spill. Each analysis is summarized in turn. Descriptions of variables used in all models are reported in Table 1.

Participation Model

The predicted participation rate of each angler in the Gulf of Mexico and the South Atlantic interviewed in the MRIP intercepts was estimated using a negative binomial regression. For this regression, the dependent variable selected was *ffdays12*, the number of days the respondent went fishing in the last 12 months. The results from the participation model are shown in table 2.

The instruments perform relatively well as predictors of participation in recreational fishing, as indicated by the large number of statistically significant coefficients, although the goodness of fit is rather low. The decision to participate in recreational fishing is a complex one, and it is unlikely that a model with a high goodness of fit measure can be developed without very detailed information on individual preferences for things like outdoor activities, as well as individual attributes like age, race, income, and gender, among others. The predicted values for this regression are saved as a new variable, *pred_fdays*, which is used in the ensuing analysis.

Catch Model

A model that predicts each angler's catch as a function of the historic catch in the visited site and the time spent fishing, among others, was also estimated using a negative binomial regression (Table 3). This model's goodness of fit measure is also low, but as in the participation model the independent variables are good predictors of fishing success. In particular, the number of hours fished (*hrsf*) and the historic catch and keep rate in the site (*hckr*), are both predictors of the catch experienced by an angler, and both have a positive impact on catch, as expected. The distance from shore, as indicated by the *area1* and *area2* coefficients, as well as the fishing mode used (*mode1*, *mode2*), are also strong predictors of catch. The predicted value equation from this model is used in the ensuing analysis to create the individual-specific site-season attribute *pred_catch*, which gives an indication of the number of fish we expect each angler to catch if he had visited the alternatives that were rejected.

Site Choice Models by Fishing Mode

The estimates from the site choice models are shown in tables 4 through 6 for shore fishing, for-hire fishing, and private/rental boat fishing, respectively. To compare individual parameter estimates from the baseline condition, which we take to be the year 2009, to those from the event in year 2010, we use a difference ratio that is computed as

$$DR = \frac{(\beta_{2010} - \beta_{2009})}{|\beta_{2009}|}. \tag{17}$$

This difference ratio is a rough percentage change measure, which takes a negative value if the parameter estimate decreases in value, and a positive value is it increases. Care must be exercised when interpreting the difference ratio of parameter estimates with a negative sign, as a negative ratio implies that the parameter grows in absolute value since it becomes more negative. Difference ratios are calculated only for parameters that are statistically significant across years and are compared across modes in table 8.

The coefficients on travel costs (*TC*) are statistically significant and of the expected sign throughout the six models. Also, the coefficients remained relatively stable from the baseline year to the event year, as the largest difference ratio is that of for-hire fishing, which reflects a change of less than 6 percent. The response to travel costs is strongest for private and rental boat anglers. This relative strength of response is not surprising as those using private boats are more likely to be pulling their boats on trailers and be less eager to drive longer distances.

The coefficient on *count*, which indicates the number of anglers in the sample who visit the chosen location, serving as a proxy for the popularity of the site, is also statistically significant and of the expected sign, although not very stable across years. The positive sign indicates that anglers are more likely to visit the more popular locations, which can be an indication of good and accessible fishing grounds. All coefficients are of the same order of magnitude across the six models. The difference ratio, which ranges from 68 percent for shore anglers to 13 percent for private and rental boats, is negative for all three modes. This may indicate that popular sites were hard hit by the oil spill, and anglers may have substituted from the locations which have been traditionally favored to other, less popular locations.

Historic catch and keep rates (*hckr*) in the fishing zones are good predictors of site choice for all modes except private and rental boats. In the shore and for-hire models, the coefficient on this variable is statistically significant and positive, as expected, indicating that anglers prefer sites with higher historic catch. The difference ratio for these two modes is also negative and in the 25-30 percent range, which signals that during the oil spill anglers using these modes may have substituted towards locations with lower catch than the areas that were traditionally visited. The *hckr* coefficient was not statistically significant for private and rental boat anglers in both the baseline and event years so the difference ratio could not be calculated.

Seasonal indicators *summer*, *spring*, and *fall* all yield positive and significant parameter estimates as evidence that anglers prefer fishing during the warmer months of the year compared to the winter baseline. The difference ratios for these variables show that seasonal substitution from the baseline year to the event year was substantial. While changes in the difference ratios in the for-hire fishing model were in the 15-24 percent range, those for private and rental boats exhibit much more drastic changes that exceed 100 percent. That is, in some cases the magnitude of the coefficient in the event year is more than twice what it was in the baseline year. Using the difference ratios we can deduce that seasonal substitution was strongest for private and rental boat anglers and weakest for anglers who use the for-hire sector, with that of shore-based anglers somewhere in between.

The coefficient on the *gulf* regional indicator is statistically significant across all models. The sign, however, is positive in the shore and for-hire models and negative in the private and rental boats models. The seeming conclusion is that, on average, shore-based and for-hire anglers prefer the Gulf of Mexico, while private and rental boat anglers prefer the Atlantic coast. Surprisingly, it also appears that during 2010 anglers using all modes substituted towards the Gulf, as shown by the positive difference ratio across models. As we will see, this does not mean that anglers preferred locations affected by the oil spill.

Parsons and Needleman (1992) suggest including the number of elemental sites in each aggregate site as a variable in site choice models to control for aggregation bias. In our case, the number of elemental sites was not available. We therefore create the *size* variable as proxy for this value using the number of counties included in each of the aggregate zones in our analysis. The parameter estimate for *size* is statistically significant in the for-hire and private and rental boat models. The sign, however, is negative in the for-hire and positive in the private and rental models. While this may seem incongruous at first, there is a possible explanation. A few zones with a small number of counties may be responsible for a large portion of for-hire trips. One of these zones is the Florida Keys, which are composed of only one county, but are arguably the most important destination for guided fishing trips. Other locations with small *size* value but with important for-hire sectors are Mississippi and Alabama, which have only three and two coastal counties, respectively. Conversely, anglers pulling trailers with boats for long distances may be reluctant to fish in the Florida Keys due to the distance that must be travelled. The difference ratio is positive in both cases and in the 30 – 60 percent range, indicating that the oil spill may have driven for-hire and private and rental boat anglers to 'larger' locations than those they would have visited otherwise. The parameter estimate for the shore model in the baseline year is not statistically significant; hence we deem this aspect of that model inconclusive.

Our predicted catch index appears not to be a good predictor of site choice, as the parameter estimates are not statistically different from zero in the shore and private and rental boat models. In the for-hire model, the coefficients are significant, but the negative sign implies that anglers prefer locations in which they would catch less fish. This unlikely response to catch deems this aspect inconclusive and warrants further work on the development of this attribute for use in the present models.

The indicator of oil spill effects, *spill*, was included in both the baseline and event year models for two reasons. First and most obvious, this is the main variable of interest, as it will aid in determining whether anglers' choices were affected by the spill. Second, *spill* is included in all models to analyze the baseline preferences for the combinations of locations and seasons that were affected by the DWH spill. Ideally, the coefficient on *spill* for 2009 would not be significantly different from zero, which would imply that all attributes that make season-site combinations desirable are accounted for. This, however, is the case only in the for-hire model. In the shore-based and private and rental boats models the parameter estimate is significant and positive at a 0.05 and 0.01 level, respectively. This suggests that our models do not account for all attributes that factor into angler's choices, and furthermore, that the 2010 parameter estimates on *spill* are downward biased and do not fully capture the detrimental impact of the DWH spill on anglers. It is evident from our models, however, that the *spill* is perceived as a negative attribute in 2010, as indicated by the negative and significant parameter estimates for all event year models. The magnitude of this negative effect differs across fishing modes, with shore anglers showing the strongest aversion to alternatives affected by the DWH spill.

Welfare Measures for Oil Spill Prevention

Development of welfare measures (eqs. 10-11) for a change in a quality attribute requires the construction of a counterfactual scenario where the quality attribute would have been different. In our case, the counterfactual scenario is the complete prevention of the DWH spill. Thus we use a Δq of minus one in our calculations of welfare measures, reflecting a scenario where the oil spill did not occur.

As stated previously, our *spill* parameter estimates for the event year are downward biased, as evidenced by the positive and statistically significant coefficients in the shore and private boat models in the baseline models. We can establish a correction factor for this bias so that the entire difference between the baseline and event cases is accounted for. Specifically, we can take the difference between the parameter estimate from the event year model (β_{event}) and that from the baseline model ($\beta_{baseline}$) to be the corrected estimate of the spill impact coefficient (β_{spill}):

$$\beta_{spill} = \beta_{event} - \beta_{baseline}. \tag{18}$$

This correction yields the estimates labeled as $W_{corrected}$ in table 7. The correction increased the welfare loss estimates for the shore-based and private/rental fishing modes.

The corrected per trip welfare measures are largest for shore anglers and smallest for private and rental boat anglers. It seems intuitive that for-hire and private and rental boat anglers generally are expected to pay more for a fishing trip, thus their willingness-to-pay (WTP) to prevent an oil spill would be higher. However, the welfare measure is a direct function of the strength of the response to the oil spill, which is strongest for shore-based anglers. Hence, estimated WTP is highest for shore-based anglers at $110.19 and lowest for private and rental boats at $32.91. The corrected WTP for the for-hire sector did not, however, increase from the original estimate of $76.61 since the parameter was not statistically significant.

Compensatory Restoration

As an alternative to focusing on monetary compensation to anglers who were detrimentally affected by the DWH spill, the natural resource trustees could consider in-kind compensation through restoration programs (Jones and Pease 1997; Flores and Thacher 2002; Parsons and Kang 2010). If so, we could use models such as ours to estimate the necessary amount of restoration required to make anglers whole. Even though our model is not very rich in site attributes that could be changed through restoration programs, one attribute that stands out as a possible candidate is historic catch (*hckr*). While historic catch is not the same as fish stock, it is likely that increases in the total number of fish in an area would result in higher catches for anglers fishing in that area.

The estimated increase in historic catch necessary to compensate anglers for the DWH spill is also shown in table 7 for the three fishing modes considered. The actual increase in catch required is similar across fishing modes, which is surprising considering the large variation in monetary estimates of compensation. Private and rental boat anglers require the largest increase in catch to be whole, at an average of 0.44 to 1.68 additional fish per trip for the uncorrected and corrected measures respectively. Shore-based anglers require an average increase of 0.32 to 0.36 fish per trip, while for-hire anglers require an increase of only 0.16 fish per trip.

Discussion

A set of random utility models of site choice constructed using aggregated MRIP data allow us to examine the major substitution patterns among Southeast anglers that took place in 2010 as a result of the DWH oil spill. Furthermore, these models allow us to estimate monetary and in-kind compensation measures that would make recreational marine anglers whole. In summary, the bias-adjusted per trip welfare measures for spill prevention ranged from approximately \$32 for the private/rental boat fishing mode to \$110 for the shore-based fishing mode (the for-hire WTP was \$77/trip). Average catch would have to increase by 0.16 to 1.68 fish per trip for the for hire and private/rental modes, respectively, to fully compensate anglers for losses due to the DWH oil spill.

Estimating separate models for different fishing modes and using a difference ratio measure allows us to evaluate substitution choices across anglers due to the spill (table 8). Seasonal substitution, for instance, was strongest among anglers using private and rental boats and weakest among anglers using the for-hire sector. This may be because anglers using the for-hire sector may seek to reserve trips with a specific guide in advance of their travel dates. As such, flexibility or substitutability across seasons is likely to be low. On the other hand, boat owning anglers may be able to plan a trip relatively quickly, and are probably as likely to cancel, reschedule, or change the location of a planned trip as they are to take a previously unplanned trip on short notice. Our models are therefore capturing the relative flexibility that private boat anglers have in rescheduling or otherwise changing fishing trips relative to other modes. For-hire operators may therefore be especially hard hit by events such as oil spills since their customers are less likely to reschedule trips or more likely to cancel trips outright if conditions are bad enough to force fishery closures or severely limit fishing opportunities. Judging from these substitution patterns, it is unlikely that for-hire operators would recoup their losses at a later time in the year.

An examination of difference ratios also reveals substitution pattern away from sites in the Gulf of Mexico, which are more popular (in terms of the numbers of anglers intercepted), toward sites in the South Atlantic due to the DWH oil spill. The difference ratio for historic catch also shows that anglers in 2010 were driven towards high catch areas than they were in the baseline year. More tellingly and as expected, the presence of oil or oil residue near the coastline was perceived as a negative attribute of a trip (i.e. negative sign on the *spill* coefficient for 2010), although this detrimental effect is perceived differently by anglers using different fishing modes. In sum, the DWH spill induced changes in anglers' preferences for fishing seasons and locations, and it drove anglers to less preferable alternatives.

Our models also allowed us to develop in-kind measures of compensatory restoration in the form of increased catches. Higher average catches are traditionally provided through restoration initiatives, such as restocking or habitat enhancement programs. The relationship between fish stocks and catch is, however, not direct for all species and all fisheries that would make such an approach a sub-optimal form of compensation. Re-allocation of quotas that are distributed between commercial and recreational sectors could also be used to increase recreational catch rates, although not with certainty and not without controversy. In general, due to the relatively large fishing sites and multi-species targeting environment in the Gulf and South Atlantic, increasing stocks of specific species may not improve welfare across all anglers.

In conclusion, three issues remain with respect to our analysis of the Gulf versus Atlantic substitution patterns by marine anglers using different fishing modes. First, the conditional logit model, which we use to estimate the RUMs, relies of the IIA assumption and ignores heterogeneity in preferences. While some of this heterogeneity is explicitly accounted for by the segregation of fishing modes, we can expect heterogeneity within fishing modes as well. Using a random parameters or mixed logit model could ameliorate this problem. Second, our predicted catch measure that was used to construct compensatory restoration measures fails to capture the expected relationship between site choices and expected catches, especially by species, which may be due to colinearity with the historic catch measure. Whatever the case, improvement in this aspect of the analysis is likely to improve the overall results. Lastly, we are not able to ascertain whether the areas affected by oil have returned to their pre-spill state. Updating the models with more recent data could be used to discern the long-term effects that the DWH spill has had on marine angler site preferences in the Southeastern U.S., and whether further restoration/compensation may be warranted. It is possible that while cleanup and restoration have been effective from a biological and ecological standpoint, the Gulf coast may yet require restoration of a different type: restoring of the Gulf's image as a desirable fishing area in anglers' minds.

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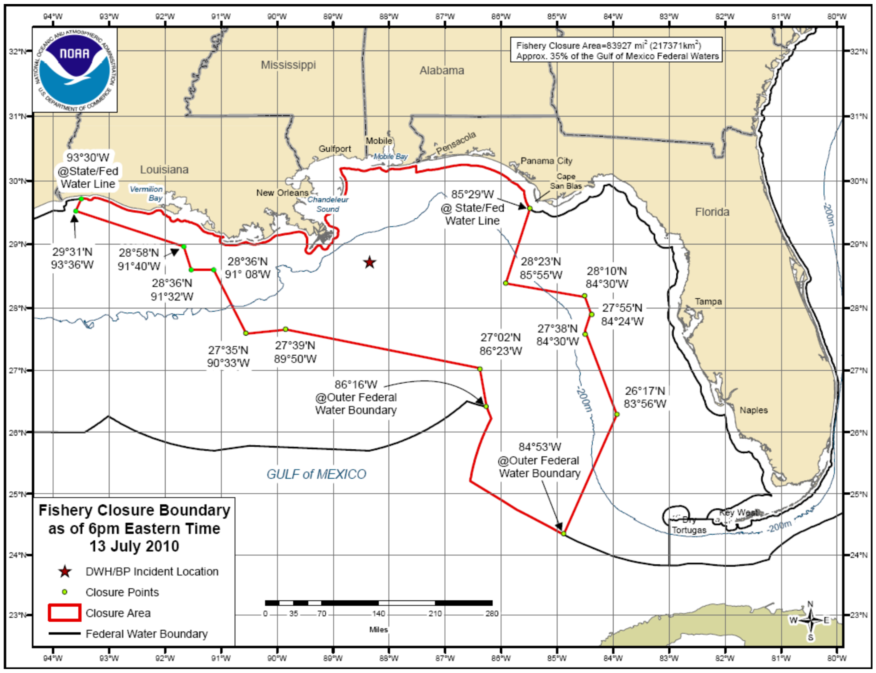

Figure 1. Federal Fishery Closure in the Gulf of Mexico in Response to the Deepwater Horizon Oil Spill, July 13, 2010

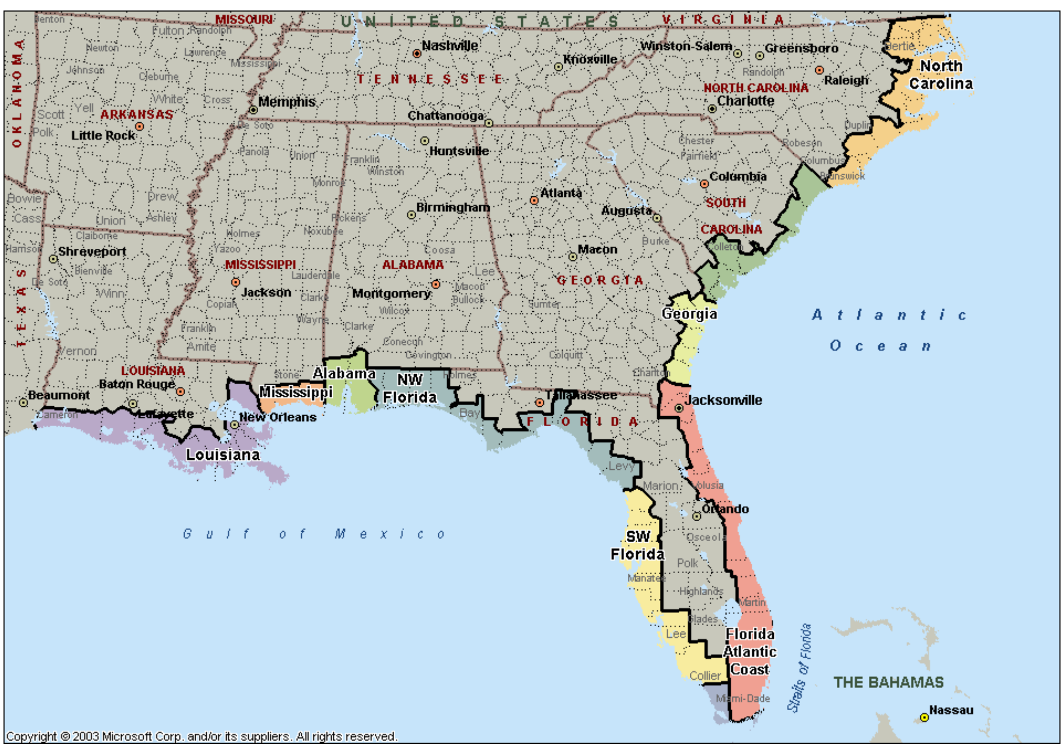

Figure 2. Ten Coastal Regions in the American Southeast

Table 1. Model Variables

Variable	Description
hrsf	Hours spent fishing during intercepted trip
ffdays12	Number of days fished in last year
med_income	Median annual income in respondent's county of residence
wavei	Dummy for wave i (i = 2^{nd}, 3^{rd}, 4^{th}, 5^{th}, or 6^{th})
mode1	Dummy for 1^{st} mode (shore fishing)
mode2	Dummy for 2^{nd} mode (for hire fishing)
mode3	Dummy for 3^{rd} mode (private or rental boat)
area1	Dummy for fishing in the ocean, close to shore
area2	Dummy for fishing in the deep ocean, offshore
area3	Dummy for fishing inland or inshore
targ	Dummy for targeting any species
rdistance	One-way istance between county of residence and zone in miles
cpue	Catch per hour for intercepted trip
hckr	Historic CPUE from previous 4 years, specific to wave and mode
inc2	med_income squared
inc3	med_income cubed
ln_inc	Natural log of med_income
dist2	Rdistance squared
dist3	Rdistance cubed
ln_dist	Natural log of rdistance
count	Number of intercepts made in the alternative zone
al	Dummy for intercepts made in Alabama
fl	Dummy for intercepts made in Florida
ga	Dummy for intercepts made in Georgia
la	Dummy for intercepts made in Louisiana
ms	Dummy for intercepts made in Mississippi
nc	Dummy for intercepts made in North Carolina
sc	Dummy for intercepts made in South Carolina
west	Dummy for respondents from the Western United States
southwest	Dummy for respondents from the Southwestern United States
midwest	Dummy for respondents from the Midwestern United States
northeast	Dummy for respondents from the Northeastern United States
southeast	Dummy for respondents from the Southeastern United States
pred_fdays	Predicted participation in number of days fished in last year
pred_catch	Predicted catch and keep rate
TC	Round trip travel cost to site
spill	Dummy for oil spill effects on intercept zone
summer	Dummy for May-August alternative
spring	Dummy for March-April alternative
fall	Dummy for September-October alternative
gulf	Dummy for Gulf of Mexico alternative
size	Number of counties in the aggregate region

Table 2. Negative Binomial Participation Model of Days Fished in the Last 12 Months

Variable	Coef.	Std. Err.	Z	P>|z|
mode1	0.2032	0.0137	14.79	0
mode2	-1.4253	0.0270	-52.71	0
area1	0.0357	0.0134	2.67	0.008
area2	0.0439	0.0208	2.11	0.035
med_income	0.0003	1.18E-5	25.69	0
inc2	-4.68E-09	2.01E-10	-23.32	0
inc3	2.18E-14	1.08E-15	20.25	0
rdistance	-0.0059	0.0002	-35.37	0
dist2	4.03E-06	1.38E-07	29.2	0
dist3	-6.37E-10	2.80E-11	-22.73	0
ln_dist	0.1744	0.0135	12.92	0
targ	0.4958	0.0108	45.77	0
wave2	-0.1839	0.0235	-7.84	0
wave3	-0.2595	0.0225	-11.51	0
wave4	-0.3629	0.0227	-16.01	0
wave5	-0.1979	0.0231	-8.57	0
wave6	-0.1670	0.0251	-6.77	0
hckr	-0.4088	0.0603	-6.78	0
al	0.0506	0.0414	1.22	0.221
fl	0.5823	0.0328	17.77	0
ga	-0.0752	0.0444	-1.69	0.091
la	-0.0751	0.0347	-2.16	0.030
ms	0.5454	0.0439	12.42	0
nc	0.2189	0.0455	4.81	0
count	-3.63E-07	1.95E-06	-0.19	0.852
southwest	-0.2292	0.0630	-3.63	0
northeast	-0.2025	0.0344	-5.89	0
west	-1.5542	0.1101	-14.06	0
midwest	0.0229	0.0417	0.55	0.584
constant	-3.1087	0.2295	-13.54	0
Model statistics:				
LR chi2(26)	25,651.39			0.0
Pseudo R-squared	0.043			
Observations	72,312			

Table 3. Negative Binomial Predicted Catch Model of Fish Caught and Kept

Variable	Coef.	Std. Err.	Z	P>|z|
targ	0.4644	0.0301	15.43	0
mode1	-0.1450	0.0344	-4.22	0
mode2	0.1237	0.0563	2.2	0.028
area1	0.1326	0.0321	4.13	0
area2	0.5022	0.0470	10.69	0
hrsf	0.2064	0.0074	27.96	0
hckr	3.2048	0.1248	25.69	0
pred_fdays	0.0003	0.0009	0.4	0.689
count	-1.48E-06	1.95E-06	-0.76	0.448
med_income	-8.49E-06	1.23E-06	-6.91	0
constant	-2.0486	0.0894	-22.93	0
Model statistics:				
LR chi2(10)	4,366.05			0
Pseudo R-squared	0.0354			
Observations	72,312			

Table 4. Conditional Logit Model of Shore Fishing Site Choice

	Baseline (2009)		Event (2010)		Difference
Variable	Coef.	Z	Coef.	Z	Ratio
TC	-0.0075**	-105.62	-0.0077**	-109.51	-0.028
count	0.0005**	55.65	0.0002**	30.12	-0.681
pred_catch	0.0324	0.15	0.8165**	3.58	NS
hckr	3.1090**	18.82	2.3390**	15.21	-0.248
spill	0.0809*	2.33	-0.7643**	-21.29	NS
summer	0.6104**	29.1	1.0566**	51.88	0.731
spring	0.4338**	17.29	0.5447**	21.6	0.256
fall	0.5403**	23.1	0.9216**	40.18	0.706
gulf	0.2751**	11.43	0.3589**	14.77	0.304
size	-0.0033	-1.03	0.0839**	25.73	
Model statistics:					
Log L	-50,215.12		-55,597.64		
Pseudo R^2	0.3357		0.3722		
Cases	18,463		21,628		

Notes: The models included 60 alternatives (10 sites with 6 waves each). Single and double asterisks indicate statistical significance at the 0.05 and 0.01 levels, respectively. NS indicates that the ratio cannot be calculated since one or both of the coefficients were not statistically significant at the 0.05 level.

Table 5. Conditional Logit Model of For-hire Fishing Site Choice

	Baseline (2009)		Event (2010)		Difference
Variable	Coef.	Z	Coef.	Z	Ratio
TC	-0.0032**	-77.42	-0.0030**	-78.32	0.058
Count	0.0007**	39.2	0.0005**	47.52	-0.270
pred_catch	-1.1299**	-12.44	-0.8246**	-13.55	0.270
hckr	2.0011**	8.87	1.3800**	7.66	-0.310
spill	0.0404	1.21	-0.2275**	-6.63	NS
summer	0.9391**	33.09	1.0760**	41.07	0.146
spring	0.6517**	21.1	0.8056**	27.96	0.236
fall	0.5539**	17.38	0.6427**	21.31	0.160
gulf	0.5106**	17.31	0.7578**	27.16	0.484
size	-0.0336**	-11.15	-0.0227**	-8.09	0.325
Model statistics:					
Log L	-41,738.15		-45,776.29		
Pseudo R^2	0.1386		0.1618		
Cases	11,835		13,338		

Notes: The models included 60 alternatives (10 sites with 6 waves each). Single and double asterisks indicate statistical significance at the 0.05 and 0.01 levels, respectively. NS indicates that the ratio cannot be calculated since one or both of the coefficients were not statistically significant at the 0.05 level.

Table 6. Conditional Logit Model of Private and Rental Boat Fishing Site Choice

	Baseline (2009)		Event (2010)		Difference
Variable	Coef.	Z	Coef.	Z	ratio
TC	-0.0125**	-137.92	-0.0124**	-138.59	0.005
count	0.0003**	65.28	0.0002**	57.92	-0.132
pred_catch	0.0990	1.29	-0.117	-1.65	NS
hckr	-0.4840**	-3.68	0.2434	1.94	NS
spill	0.3017**	12.24	-0.1077**	-4.18	-1.357
summer	0.4679**	32.06	0.8114**	53.41	0.734
spring	0.1824**	10.49	0.4093**	22.67	1.245
fall	0.3184**	18.55	0.7760**	45.21	1.437
gulf	-0.4419**	-22.26	-0.1041**	-5.51	0.765
size	0.0280**	11.19	0.0474**	18.01	0.696
Model statistics:					
Log L	-91,034.67		-90,805.36		
Pseudo R^2	0.3879		0.4061		
Cases	36,327		37,346		

Notes: The models included 60 alternatives (10 sites with 6 waves each). Single and double asterisks indicate statistical significance at the 0.05 and 0.01 levels, respectively. NS indicates that the ratio cannot be calculated since one or both of the coefficients were not statistically significant at the 0.05 level.

Table 7. Predicted Welfare and Catch to Mitigate Marine Angler Losses due to the Deepwater Horizon Oil Spill

	Per trip welfare measures for spill prevention		Per trip change in catch for full compensation	
	W	$W_{corrected}$	Δq	$\Delta q_{corrected}$
Shore	\$99.64	\$110.19	0.3267	0.3613
For Hire	\$76.61	\$76.61	0.1649	0.1649
Private	\$8.66	\$32.91	0.4426	1.6820

Table 8. Substitution Patterns: Comparison of Difference Ratios Across Fishing Modes

		Difference Ratio		
Variable	Attribute	Shore	For-Hire	Private/Rental
TC	Cost	-0.0276	0.0581	0.0049
count	Site Popularity	-0.6812	-0.2699	-0.1322
pred_catch	Predicted Catch	-	0.2702	-
hckr	Historic Catch	-0.2477	-0.3104	-
summer	Season	0.7310	0.1457	0.7341
spring	Season	0.2557	0.2362	1.2445
fall	Season	0.7057	0.1603	1.4372
gulf	Gulf of Mexico	0.3044	0.4840	0.7645
size	Area Size	-	0.3245	0.6964