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Abstract

In this study we assess the ability of the Marine Recreational Fishery Statistics Survey (MRFSS) to support single-species recreation demand models. We use the 2000 MRFSS southeast intercept data combined with the economic add-on. We determine that the MRFSS data will support only a few species-specific recreation demand models. Considering species of management interest in the southeast, we focus on dolphin, king mackerel, red snapper and red drum. We examine single-species recreational fishing behavior using random utility models of demand. We explore mixed logit (i.e., random parameter) logit and finite mixture (i.e., latent class logit) models for dealing with angler heterogeneity. We compare these to the commonly used conditional and nested logit models in terms of the value of catching (and keeping) one additional fish. Mixed logit models illustrate that the value of catch can be highly heterogeneous and, in some cases, can include both positive and negative values. The finite mixture model generates value estimates that were some times strikingly different than conditional, nested and mixed logit models. Preference heterogeneity is significant within the MRFSS data. We find evidence that single-species models outperform multiple species models and recreational values differ.

Introduction

Efficient and effective management is needed to accomplish an economically and biologically sustainable level of harvest in marine fisheries. Many marine fish species are overfished and are desired by both commercial fishermen and recreational anglers. As a result, fisheries managers must consider changes in allocations of the total allowable catch between the commercial and recreational sectors. The efficient allocation is that which equalizes the marginal value of the last fish caught (harvested) across sectors. This paper addresses two issues when measuring the marginal value of recreation catch: angler heterogeneity and species-specific values. We focus our attention on U.S. federally managed species and the Marine Recreational Fishery Statistics Survey (Hicks et al., 1999).

Much of the past marine recreational fishing demand research in the journal (e.g., Schuhmann 1998, Whitehead and Haab 1999, Whitehead 2006, Gentner 2007) and gray literature (e.g., McConnell and Strand 1994; Hicks et al. 1999; Haab, Whitehead, and McConnell 2001) ignores differences among anglers. Each of these studies assumes that homogeneous anglers make decisions about trip benefits, costs and constraints in the same way. It is likely that there exists heterogeneity among anglers with regard to how they might react to trip benefits, costs and constraints. Angler preferences are likely to vary substantially and this has potential implications for how they might value changes in fisheries regulations. For example, Kim, Shaw and Woodward (2007) incorporate income differences in their site choice model. Consequently, econometric models that allow for heterogeneity may yield better predictions of fishing behavior and changes in economic value.

Recent advancements in econometrics have allowed researchers to investigate heterogeneous preferences with random parameter models and finite mixture models. Each of these methods possesses its own advantages and have been applied in a number of different settings. The mixed logit provides modeling flexibility (Train 1998). The mixed logit model can approximate any random utility based behavioral model, and allows for more flexible patterns of substitution between alternatives than the standard logit based models. In addition, the mixed logit model allows for random preference variation across individuals in the sample. In the context of recreational fishing, the mixed logit allows the researcher to estimate different economic values of changes in fishing quality for each angler type based on characteristics of the angler.

The mixed logit model estimates a distribution of parameter estimates, and therefore a distribution of economic value measures and preferences. In contrast, finite mixture models can be used to estimate separate parameter estimates for individuals who possess similar preferences, declared a different "type" within the population (Boxall and Adamowicz 2002). Motivation for different types of anglers in a recreational fishery can easily be made by noting that there exist a number of different objectives (catch-and-release, partial retention, subsistence targeting). Each of these objectives can easily combine to represent a different type of angler. Therefore, a model that can be used to determine the number of types within the recreational fishery, the anglers who are contained in each type and the preferences for a representative angler within each type may be extremely advantageous.

For marine recreational fishing, management actions are typically directed at a specific species. Many studies of saltwater fishing have employed species aggregations (e.g., Bockstael, McConnell, and Strand 1999; Green, Moss, Spreen 1997; Schuhmann 1998; Whitehead and Haab 1999 in the journals and McConnell and Strand 1994; Hicks et al. 1999; and Haab, Whitehead, and McConnell 2001 in the gray literature). These approaches assume that an aggregate species model can roughly approximate changes in welfare resulting from species-specific changes. If the goal of the analysis is to measure changes in value due to changes in the conditions of a single species, it may be important to develop a species-specific model.

The choice of target species and how to incorporate substitute species in a marine setting, where many species may be sought, is an important modeling decision. To accurately assess angler values for marine recreational fishing, modeling of target species and the existence of substitutes is critically important. If anglers are assumed to target a species complex, when in fact they are targeting only one species, then estimates of angler preferences and economic values for fishing quality may be biased due to aggregation over species. The degree of aggregation bias increases as species become less substitutable.

We develop species-specific demand models for: (1) dolphin and big game in the south Atlantic (Florida), (2) mackerel and small game in the south Atlantic and Gulf of Mexico, (3) red drum and seatrout in the south Atlantic and Gulf of Mexico and (4) snapper-grouper in the Gulf of Mexico. For each species we develop a series of models where anglers are assumed to choose a mode of fishing (private boat, shore, or party/charter), a single target species and species groups and a recreation site. We explore methods for dealing with differences in angler heterogeneity in recreation demand modeling. We compare these techniques to the commonly used conditional and nested logit models. The rest of this paper is organized as follows. In the next two sections we describe the random utility model and data. Then we present results from conditional logit, nested logit, mixed logit and finite mixture models. In the final section we discuss the results, offer some conclusions and make some suggestions for future research.

Random Utility Models

Anglers will tend to choose fishing modes, target species and sites that provide the most utility. Consider an angler who chooses from a set of *j* recreation sites. The individual utility from the trip is decreasing in trip cost and increasing in trip quality:

$$(1) \qquad u_i = v_i(y - c_i, q_i) + \varepsilon_i$$

where *u* is the individual indirect utility function, *v* is the nonstochastic portion of utility, *y* is the per-trip recreation budget, *c* is the trip cost, *q* is a vector of site qualities, *ε* is the error term, and *i* is a member of *s* recreation sites, *s* = 1, … , *i* , … *J*. The random utility model assumes that the individual chooses the site that gives the highest utility

$$(2) \qquad \pi_i = \Pr(v_i + \varepsilon_i > v_s + \varepsilon_s \;\; \forall\, s \neq i)$$

where *π* is the probability that site *i* is chosen. If the error terms are independent and identically distributed extreme value variates then the conditional logit site selection model results

(3) $$\pi_i = \frac{e^{v_i}}{\sum_{s=1}^{J} e^{v_s}}$$

The conditional logit model restricts the choices according to the assumption of the independence of irrelevant alternatives (IIA). Intuitively, imposing IIA on the choice patterns means that the researcher thinks that the relative probability of an angler choosing site A over site B is independent of the attributes of all other sites. While not entirely unrealistic in the case of unrelated sites, many times some sites can be thought of as closely related groups. This is often one motivation for the use of the nested logit model wherein sets of similar sites are grouped into nests. Within each nest, IIA still holds, but across nests, the strict substitution patterns implied by IIA are relaxed, thereby reducing one potential source of researcher induced bias.

Consider a two-level nested model. The site choice involves a choice among M groups of species-mode nests, $m = 1, \ldots, M$. Within each nest is a set of J_m sites, $j = 1, \ldots, J_m$. When the nest chosen, n, is an element in M and the site choice, i, is an element in J_n and the error term is distributed as generalized extreme value the site selection probability in a two-level nested logit model is

(4) $$\pi_{ni} = \frac{e^{v_{ni}/\theta}\left[\sum_{j=1}^{J_n} e^{v_{nj}/\theta}\right]^{\theta-1}}{\sum_{m=1}^{M}\left[\sum_{j=1}^{J_m} e^{v_{mj}/\theta}\right]^{\theta}}$$

where the numerator of the probability is the product of the utility resulting from the choice of nest n and site i and the summation of the utilities over sites within the chosen nest n. The denominator of the probability is the product of the summation over the utilities of all sites within each nest summed over all nests. The dissimilarity parameter, $0 \leq \theta \leq 1$, measures the degree of similarity of the sites within the nest. As the dissimilarity parameter approaches zero the alternatives within each nest become less similar to each other when compared to sites in other nests. If the dissimilarity parameter is equal to one, the nested logit model collapses to the conditional logit model where $M \times J_m = J$.

While encouraging, the nested logit model still requires the researcher to specify the nesting structure of the choices. It is the researcher's responsibility to specify mutually exclusive groups of sites for each nest. At times this is intuitive. For example, distinct geographic division may make the nests obvious. But at other times, the nesting structure of the sites is not as straightforward. Mis-specified nests can lead to biased parameter estimates and biased welfare measures.

Further, both the conditional and nested logit models assume that angler preferences are homogeneous. That is, the marginal utility of a change in any of the site attributes is the same for all individuals sampled. The additional utility gained from a decrease in travel cost to a site is the same regardless of the other characteristics of the angler. A wealthy angler and a poor angler both benefit equally from a one fish increase in the targeted catch rate. A well-specified model will allow for preference heterogeneity across anglers and for flexible substitution patterns between sites.

The mixed logit allows for more flexibility in the substitution pattern between alternatives and allows for preference heterogeneity across individuals. In this paper we apply some of the simpler forms of the mixed logit to the four species (group) choice models. Typically, the deterministic indirect utility component for individual *j* and site *i* is assumed to be linear in a vector of individual and alternative specific variables:

(5) $$v_i = x_{ih}\beta$$

Where the vector x_{ih} may contain variables that vary by alternative only (e.g. catch rates) or vary by alternative and individual (e.g. travel cost), but does not contain variables that vary only by individual. Algebraically, individual specific variables drop out of equation (3) unless they are interacted with alternative specific dummy variables—a level of complication we have chosen to avoid for the purposes of this paper.

For the conditional (and nested) logit models, the parameter vector β is assumed to be constant across individuals. Imposing preference homogeneity may result in a mis-specified utility function and inaccurate estimates of the value of changes in the independent variables. To allow for preference heterogeneity, we will assume that individual angler preferences randomly vary according to a prespecified population distribution such that:

(6) $$\beta_{ih} = \tilde{\beta} + \eta_{ih}$$

where $\tilde{\beta}$ is an unknown, but constant locational parameter for preferences, and η is an individual and alternative specific random error component for preferences that is independently and (not necessarily identically) distributed across alternatives and identically (but not necessarily independently) distributed across individuals.

Incorporating (6) and (5) into (3) gives a new conditional expression for the choice probability for a specific individual

$$(7) \qquad \pi_{ih}|\eta_{ik} = \frac{e^{x_{ih}\tilde{\beta}+\eta_{ih}}}{\sum_{s=1}^{J} e^{x_{ih}\tilde{\beta}+\eta_{jh}}}$$

The choice probability in (7) is conditional on a specific value or realization of the preference error term, η_{ik}. However, to the researcher the most we can know, or assume, is the form of the distribution for η_{ik} up to an unknown parameter vector γ. Assuming that the density function is $f(\eta|\gamma)$, the probability in (7) must be integrated over all possible values of η_{ik} to eliminate the conditioning:

$$(8) \qquad \pi_{ih} = \int_{\eta_{ih}} \pi_{ih}|\eta_{ih}\partial f(\eta_{ih}|\gamma) = \int_{\eta_{ih}} \frac{e^{x_{ih}\tilde{\beta}+\eta_{ih}}}{\sum_{s=1}^{J} e^{x_{ih}\tilde{\beta}+\eta_{jh}}}\partial f(\eta_{ih}|\gamma)$$

Ideally, the integration problem in (8) would be such that the probability has a closed form expression as a function of the unknown parameters β and γ. Unfortunately this is not the case. Closed form expressions for equation (8) do not exist for common distributions (normal, uniform, log normal) and estimation of the parameters in (8) requires simulation of the integral.

The most common way to simulate the probability is to repeatedly draw from the multivariate distribution of η_{ik}, calculating the integrand in (8) at each draw and then averaging over the draws to find an estimate of π_{ih} conditional on β and γ (Train 2003). Using maximum likelihood algorithms to search over the possible space of β and γ (and simulating the probability vector for each possible value of β and γ) will yield simulated maximum likelihood estimates of the utility function and the preference heterogeneity parameters.

The finite mixture model allows the data to reveal the presence of angler heterogeneity. In much the same way that it is difficult to justify the assumption of parameter homogeneity, in these models heterogeneity is driven by the data and assumed to be related to socioeconomic factors that sort anglers into tiers. However, this sorting is really a construct for motivating the model, since an angler with a set of socioeconomic characteristics will receive different probability weights for each tier than anglers with different characteristics. Consequently, rather than assume completely random heterogeneity as in the mixed logit model, this model provides more structure to the form of heterogeneity.

In the finite mixture site choice model, a vector of individual specific characteristics (Z_i) is hypothesized to sort angler types into T tiers each having potentially different site choice preference as denoted by the preference parameters (β^t) over site specific characteristics (X_k) where there are $i \in I$ anglers, $k \in K$ sites, and $t \in T$ tiers.

From the researchers' perspective, neither tier membership nor site-specific indirect utility functions are fully observable. Assuming that angler i is in tier t, the indirect utility of choosing site j is

(9) $$V(X_{ij}, \beta^t \mid i \in t) = X_{ij}\beta^t + \varepsilon_{ijt}$$

Following standard practices in random utility models (assuming that ε_{ikt} is distributed as i.i.d. GEV I), the probability of observing individual *i* choosing site *j* given membership in tier *t* can be written as

$$(10) \qquad P(j \mid X_{ij}, \beta^t, i \in t) = \frac{e^{X_{ij}\beta^t}}{\sum_{k \in K} e^{X_{ik}\beta^t}}.$$

Tier membership is also unknown to the researcher. Consequently, we specify the probability of tier membership given a vector of socio-demographic information (Z_i). We construct this probability using common logit probabilities as in the site choice models above:

$$(11) \qquad P(i \in s \mid Z_i, \delta^s) = \frac{e^{Z_i\delta^s}}{\sum_{t \in T} e^{Z_i\delta^t}}$$

Notice that in this specification, the socio-demographic variables (Z_i) do not vary over tiers, but rather the tier parameters (γ_t) varies by tier.

Equations (10) and (11) can be constructed for every individual *i*, tier *t* to calculate the overall probability of an observed choice as

$$(12) \qquad P_i(j) = \sum_{t \in T} P(i \in t \mid Z_i, \delta^t) \times P(j \mid X_{ij}, \beta^t, i \in t)$$

In effect, using the tier probabilities in (11) the estimator mixes the tier-specific site choice models to estimate an overall probability of visiting site *j*.

Welfare Measurement

Welfare analysis is conducted by specifying a functional form for the site utilities. It is typical to specify the utility function as linear:

(13)
$$\begin{aligned} v_{ni}(y-c_{ni},q_{ni}) &= \alpha(y-c_{ni})+\beta' q_{ni} \\ &= \alpha y-\alpha c_{ni}+\beta' q_{ni} \\ &= -\alpha c_{ni}+\beta' q_{ni} \end{aligned}$$

where α is the marginal utility of income. Since αy is a constant it will not affect the probabilities of site choice and can be dropped from the utility function.

The inclusive value, *IV*, is measured as the natural log of the summation of the nest-site choice utilities:

(14)
$$\begin{aligned} IV(c,q;\alpha,\beta) &= \ln\left(\sum_{m=1}^{M}\left[\sum_{j=1}^{J_m} e^{v_{mj}/\theta}\right]^{\theta}\right) \\ &= \ln\left(\sum_{m=1}^{M}\left[\sum_{j=1}^{J_m} e^{(-\alpha c_{mj}+\beta' q_{mj})/\theta}\right]^{\theta}\right) \end{aligned}$$

Hanemann (1999) shows that the choice occasion welfare change from a change in quality characteristics is:

(15) $$WTP=\frac{IV(c,q;\alpha,\beta)-IV(c,q+\Delta q;\alpha,\beta)}{\alpha}$$

where willingness-to-pay, *WTP,* is the compensating variation measure of welfare. Haab and McConnell (2003) show that the willingness-to-pay for a quality change (e.g., changes in catch rates) can be measured as

$$(16) \qquad WTP(\Delta q \mid ni) = \frac{\beta_q \Delta q}{\alpha}$$

The welfare measures apply for each choice occasion (i.e., trips taken by the individuals in the sample).

Welfare measures in a finite mixture model follow closely the formulation found in standard conditional logit models. First, consider one of the T tiers estimated in the model. Since the choice probability in each tier follows from the standard conditional logit, we can write the willingness-to-pay for a policy change conditional on membership in tier t as

$$(17) \qquad WTP(X, \tilde{X}, \beta^t \mid i \in t) = \frac{\ln\left(\sum_{k \in K} e^{x_{ik}^t \beta^t}\right) - \ln\left(\sum_{k \in K} e^{\tilde{X}_{ik}^t \beta^t}\right)}{\beta_{tc}^t}$$

where X and $\tilde{X}$ are the pre and post site specific amenities vectors. The signing convention above corresponds to an improvement in site characteristics when moving from X to $\tilde{X}$.

To extend the welfare measure across tiers, the tier probabilities must be incorporated in order to find the unconditional CV for each individual as follows

$$(18) \qquad WTP(X, \tilde{X}, \beta, \delta) = \sum_{t=1}^{T} \left(\frac{e^{Z_i \delta^t}}{\sum_{j \in T} e^{Z_i \delta^j}} \right) \left[\frac{\ln\left(\sum_{k \in K} e^{X_{ik}^t \beta^t}\right) - \ln\left(\sum_{k \in K} e^{\tilde{X}_{ik}^t \beta^t}\right)}{\beta_{tc}^t} \right]$$

which is found by weighting each tier-specific tier CV with the corresponding probability of being in that tier.

The 95% confidence intervals for willingness-to-pay are calculated using the asymptotic procedure adapted from Krinsky and Robb (see Haab and McConnell 2002 for a detailed explanation). The confidence intervals are calculated by taking 1000 independent draws from a multivariate normal distribution with mean equal to the estimated parameter vector for each model and variance covariance matrix equal to the corresponding estimated variance covariance matrix. At each draw, willingness-to-pay is calculated to give 1000 draws from the empirical distribution of willingness-to-pay. Sorting the resulting empirical draws in ascending order and choosing the 2.5^{th} and 97.5^{th} percentile observations yields a consistent estimate of the desired confidence interval.

Data Description

The 2000 Marine Recreational Statistics Survey (MRFSS) southeast intercept data is combined with economic add-on data to characterize anglers and their spatial fishing choices (Hicks et al. 1999). The MRFSS data is collected with an onsite survey which is prone to endogenous stratification and avidity bias. Hindsley, Landry and Gentner (2011) address the issues with the MRFSS data with two empirical methods in a conditional logit model. They find that failing to correct for these features of the data can lead to significant overestimates of willingness to pay. Our primary purpose in this paper is a within sample comparison of econometric models and within this context our comparison of willingness to pay estimates from alternative models is valid. However, since we ignore these important sampling issues, the willingness to pay estimates presented should not be used for policy analysis unless the upward bias is explicitly considered.

Measures of fishing quality for individual species and aggregate species groups are calculated using the MRFSS creel data. We focus on charter/head boat and private/rental boat hook-and-line day trip anglers. In the 2000 MRFSS intercept there are 70,781 anglers interviewed from Louisiana to North Carolina. The 2000 intercept add-on data included 42,051 of the intercepted anglers. Twenty-eight percent of these anglers have missing data on their primary target species. We exclude one percent who do not use hook and line gear. We also exclude 33 percent of the anglers that self-reported a multiple day trip or who live greater than 200 miles from the nearest site. Estimation of consumer surplus values for overnight trips tends to produce upwardly biased estimates of consumer surplus (McConnell and Strand, 1999). After deleting cases with missing values on other key variables we are left with 18,709 anglers in our sample. Of these anglers, 11,257 report targeting a species and are available for analysis.

The theory behind random utility models is that anglers make fishing choices based on the utility (i.e., happiness) that each alternative provides. Anglers will tend to choose fishing modes, target species and sites that provide the most utility for the least cost. The angler target, mode and site selection decision depends on the costs and benefits of the fishing trip. Fishing costs include travel costs. Travel costs are equal to the product of round trip travel distance and an estimate of the cost per mile. In addition, a measure of lost income is included for anglers who lost wages during the trip. Benefits of the fishing trip include catch rates.

Travel costs are computed using distances calculated with PCMiler by the NMFS. Travel costs are split into two separate variables depending on the ability of the angler to trade-off labor and leisure. Ideally, travel costs would represent the full opportunity costs of taking an angling trip in the form of foregone expenses and foregone wages associated with taking an angling trip. Because not all anglers can trade-off labor and leisure at the margin, we allow for flexibility in modeling these tradeoffs. For anglers that can directly trade-off labor and leisure at the wage rate (those that indicate they lost income by taking the trip), travel costs are defined as the sum of the explicit travel cost (i.e., round trip distance valued at $0.30 per mile) and the travel time valued at the wage rate. Travel time is calculated by dividing the travel distance by an assumed 40 miles per hour for travel. For anglers that do not forego wages to take a trip, travel cost is simply defined as the explicit travel cost. All charter boat anglers are assigned the average charter boat fee for the east coast of Florida ($107.06) obtained from Gentner, Price and Steinbeck (2001).

We measure catch rate with the historic targeted harvest (hereafter, catch is synonymous with harvest). Five year (1995-1999) targeted historic catch rates per day are calculated using MRFSS data in each county of intercept to measure site quality. We also include the log of the number of MRFSS intercept sites in each county to control for site aggregation bias (Parsons and Needleman 1993). Since the sites are defined as the counties of travel destination, measurement error arises in the travel cost variable to the extent that the cost of boat travel to the fishing site varies across the county of boat launch. Measurement error arises in the catch rate variable to the extent that the fishing site is not within the vectors of the offshore boundaries of the county of boat launch.

We focus our empirical efforts on recreational species with management interest in the southeastern U.S. Twenty-percent of anglers that report targeting a specific species target red drum. Six percent target dolphin, six percent target king mackerel, four percent target Spanish mackerel, and two percent target red snapper. In Table 1 we summarize the four data sets employed.

In the dolphin and big game model we focus on dolphin and big game boat trips taken on the Atlantic coast of Florida. We also include the Gulf of Mexico trips taken from Monroe County (i.e., Florida Keys). Eighty-three percent of 823 anglers target dolphin relative to other big game.[2] There are 12 county level fishing sites in the dolphin and big game model. Each of these counties is comprised of a varying number of MRFSS intercept sites. Anglers choose among two modes and two target species. Eleven percent (n = 87) of all anglers target dolphin and choose among 8 county alternative sites in the party/charter mode. Seventy-three percent (n = 598) of dolphin target anglers choose among 10 county alternative sites in the private/rental mode. Fourteen percent (n = 136) of all anglers target big game and choose among 16 county/mode alternative sites in the combined party/charter and private/rental boat mode.

After the 2000 MRFSS add-on data was collected a 20” size limit regulation for dolphin was imposed by the South Atlantic Fishery Management Council. We investigate the effect of size limits by sorting the historic catch rate into fish greater than or equal to

[2] The big game species included are: atlantic tarpon, billfish family, blackfin tuna, cobia, little tunny, sailfish, swordfish, tuna genus, wahoo, and yellowfin tuna.

20” and less than 20”. A household production model is used to predict the number of big (>20”) and small (<20”) dolphin.[3]

In the mackerel and small game model we focus on king mackerel, Spanish mackerel and small game private boat trips taken in the south Atlantic and Gulf of Mexico. Thirty-two percent of the sub-sample of 1526 are king mackerel target anglers, 17 percent of the anglers target Spanish mackerel and 51 percent target small game

[3] A negative binomial model is used to estimate expected catch rates at each site for the relevant species for each angler by mode (McConnell, Strand and Blake-Hedges, 1995). The dependent variable in each model is the number of fish caught and kept per trip. Independent variables are the mean historic catch and keep rate at each site, years fished, boat ownership, charter mode, days fished during the past two months, hours fished and survey wave. A necessary condition for using predicted catch as an independent variable in the recreation demand models is that catch varies with mean historic catch rate across site. Otherwise, predicted catch does not vary across site and is not helpful in explaining site selection. Therefore, only 6 of 11 catch models are candidates for using predicted catch in travel cost models (the results can be found at http://econ.appstate.edu/marfin or upon request). Only predicted catch in the dolphin and big game models helps explain site selection behavior in expected ways. Other predicted catch coefficients are either statistically insignificant or wrong signed in the site selection models. While further analysis with other catch rate models (e.g., zero inflated negative binomial) might lead to models that could provide support for policy analysis of bag limits, this extension is beyond the scope of the current paper.

species.[4] There are 51 county level fishing sites from North Carolina to Louisiana in the mackerel model. Anglers choose across three target species. A number of county/species alternatives have empty cells which leaves 104 alternatives. Since many king mackerel target anglers have Spanish mackerel as a secondary target, and vice versa, we include the historic catch rate for both species as independent variables for both types of trips.

In the red drum and seatrout model we use 4353 red drum and spotted seatrout private/rental boat trips taken in the south Atlantic and Gulf of Mexico. Forty-six percent of these angler trips target red drum. There are 58 county level fishing sites from North Carolina to Louisiana in the red drum and seatrout model. Anglers choose across two species. Only a few county/species alternatives have empty cells which leave 110 choices.

In the snapper-grouper model we use 1086 red snapper, groupers and "other snappers" boat trips taken in the Gulf of Mexico. Twenty-two percent target red snapper, 67% target shallow water groupers, and 11% target other snapper species.[5] Snapper-

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[4] The small game species are: common snook, sand seatrout, seatrout genus, florida pompano, striped bass, bonefish, mackerel genus, bluefish, silver seatrout, permit, greater amberjack, great barracuda, drum family, ladyfish, weakfish, irish pompano, jack family, lookdown, tarpon family and fat snook.

[5] The grouper species are: gag, red grouper, black grouper, grouper genus and unidentified groupers. The other snapper species are: amberjack genus, Atlantic spadefish, black sea bass, blackfin snapper, crevalle jack, gray snapper, gray triggerfish,

grouper anglers choose across two modes, three species and 28 counties in the Gulf of Mexico. Many mode/species/county alternatives have empty cells which leave 71 alternatives.

Empirical Results

Variable descriptions can be found in Table 2.[6] We present the conditional logit, nested logit, mixed logit and finite mixture model results using the dolphin (Table 3), mackerel (Table 4), red drum (Table 5) and red snapper (Table 6) data. We present estimation results for mixed logits with a normally distributed travel cost parameter and with a uniformly distributed travel cost parameter. We also attempted mixed logit models with random travel cost and catch rate variables. Because these fully mixed models proved difficult to estimate, convergence was difficult to achieve using standard software packages and those that were estimated produced implausible results for several cases, we focus our attention on the models that randomize the travel cost parameters only.[7]

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silver seatrout, snapper family, vermilion snapper, white grunt, yellowtail snapper and Atlantic thread herring.

[6] Data summaries can be found in Haab et al. (2009).

[7] For example, the big game catch parameter is distributed normally with a mean of -15 and a standard deviation of 23. The 2.5th and 97.5th percentiles are -61 and 30. Using the mean travel cost parameter this would imply a 95% interval for willingness-to-pay for a one fish increase in catch of (-$533.24, $264). The problem is magnified if an individual in the tail of the TC distribution (small value) corresponds to either tail of the catch rate

Models were also attempted with log-normally distributed parameters but the fat upper tail of the log-normal distribution resulted in models for several species groups that would not converge. As a result we do not report the log-normal results here.[8]

The socio-demographic variables defining the finite mixture probabilities are comprised of years fished, boat ownership, and the number of days fished within the past two months. Although the number of tiers for the finite mixture model is endogenous, in practice it is necessary to pre-specify T and then utilize selection criteria to determine the optimal number of tiers. To conduct this selection process we utilized the corrected Akaike and Bayesian Information Criteria (MacLachlan and Peel, 2000). The selection criteria begins by specifying T=1 (a standard multinomial logit model) and then increasing T until the selection criteria indicate that the number of tiers is over-fitting the data. We normalize on the first tier and estimate T-1 sets of tier-specific parameters. Consequently, all reported finite mixture results are interpreted relative to tier 1. For example, suppose a positive coefficient is found on years fished for tier *j*: as income increases the respondent is more likely to be of type *j* than type 1.

Although the selection criteria indicated that our estimation algorithm for dolphin and big game, mackerel and small game and snapper-grouper should exceed two, we

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distribution. For example, an individual in the travel cost distribution one standard deviation above the mean (TC parameter = -.052) would have a 95% WTP interval of (-$1,169.02, $578.94) for one additional fish. Therefore, we focus our attention on the welfare estimates from the models that randomize the travel cost parameters only.

[8] Other parameter distributions could prove to be more successful.

elected to stop at two because we were unable to obtain reliable welfare estimates when T exceeded two. This was similarly true for the red drum and seatrout model when T exceeded three. This said, the criteria illustrate the largest marginal increases in our statistical fit result when T=2. Therefore, although our test statistics do suggest that we should increase the number of tiers, our results are capturing a majority of the heterogeneity present within the data.

The basic logit results indicate that the models are adequate depictions of marine recreational angling behavior (Tables 3-6). The model likelihood ratio statistics indicate that all parameters are jointly significantly different from zero in all of the conditional and nested logit models. The likelihood that an angler would choose a fishing site is negatively related to the trip cost and positively related to the catch rates. In three of the four nested logit models the parameter estimate on the inclusive value is statistically different from zero and one which indicates that the nested model is more appropriate than the conditional logit. In the mackerel nested logit model the parameter estimate on the inclusive value is statistically different from zero but not statistically different from one which indicates that the model fit is statistically the same as the conditional logit model at the p=.01 level.

It is apparent that mixing of the travel cost coefficient is appropriate in the dolphin model (Table 3). The statistical significance of the standard deviation parameter in the normal mixing model (s) and the scale parameter in the uniform mixing model (s) implies that either model would be preferred in a statistical test relative to the conditional logit. The parameter signs are as expected with the travel cost parameter having a negative mean and catch rates having a positive effect on site choice probabilities.

In the finite mixture model the travel cost parameters are negative and significant across both tiers. Those in tier 2 are more responsive to travel costs than tier 1. When the travel cost coefficients are weighted by the mean probability of tier participation the travel cost coefficient is similar to that estimated in the conditional logit model and the distributional range of the mixed logit estimates. The catch coefficients are all positive and statistically significant for tier 1, whereas only the small dolphin catch coefficient is positive for the second tier and big dolphin and big game are both negative and statistically significant. Relative to anglers in tier 1, anglers in tier 2 seem to prefer small dolphin relative to big dolphin and big game. Although this result may seem counterintuitive, it is important to keep in mind that an angler's "true" preferences are a mixture of the two types. Given the high probability of an angler's preferences being dominated by tier 1 (77% on average) this still results in positive valuations for big dolphin and big game, but just at a lower marginal rate than if their preferences were completely captured by tier 1.

The final set of coefficients uses the individual-specific data to sort anglers into tier 1 and tier 2 in a probabilistic sense. Relative to tier 1, an individual is more likely to be in tier 2 if they own their own boat and have fished more in the past two months than those in tier 1. However, more experienced anglers, as measured by the number of years spent fishing, are more likely to be in tier 1 and then tier 2.[9]

In Table 4 we present the mackerel and small game models. In all models, Spanish mackerel catch has a negative effect on choice. Recall that since many king mackerel target anglers have Spanish mackerel as a secondary target we include the historic catch rate for both species as independent variables for both types of trips. This result suggests that sites with a high ratio of Spanish mackerel to king mackerel are avoided. The log of the number of interview sites is positively related to the site choice.

The travel cost only mixing models provide estimates that coincide with expectations. Higher travel costs negatively influence site choice and higher catch rates positively affect site choice—except for Spanish mackerel. King mackerel catch rates are statistically insignificant in the normal mixed model. The king mackerel catch rate becomes statistically significant in the uniformly mixed model, but the spread of the distribution is implausibly large.

In both tiers of the finite mixture model anglers seek sites with higher catch rates with the exception of king mackerel. The travel cost parameters are very similar to the mixed logit parameter estimates which are substantially larger than the conditional logit estimates. In addition, the lack of statistical significance in both tiers for king mackerel is consistent with the broad parameter distribution within the mixed logit models. The most notable difference between the three models is the large negative coefficient for Spanish mackerel in both the conditional logit and mixed logit models, whereas it is positive and

[9] Fishing experience could also be serving as a proxy for age and/or income.

statistically significant for tier 1. This suggests that the finite mixture model is differentiating anglers based on their targeting preferences.

Focusing on the probability of tier participation variables, anglers with fewer years of fishing experience and more days fished in the last two months are more likely to be within the second tier. Combining this information with the tier-specific parameter estimates illustrates that more experienced anglers value small game and Spanish mackerel catch.

In the red drum models the likelihood that an angler would choose a fishing site is negatively related to the trip cost and positively related to the targeted catch rates. The log of the number of interview sites is positively related to the site choice. The travel cost only mixed logit models is statistically different from the conditional logit. The red drum and seatrout model is the only model for which we were able to reliably estimate the tier specific parameters beyond two tiers. This is most likely due to the large sample size for this model relative to the other models estimated. The catch coefficients for the two species illustrate that all three tiers value red drum catch and that tiers 1 and 3 value seatrout catch as well. Comparing the catch coefficients within each tier illustrates that all three tiers prefer red drum catch over seatrout, but tier 2 possesses the largest difference across species. Combining these results illustrates that tier 2 represents those individuals that solely value drum and tier 3 represents those anglers who fish for drum and seatrout Once again, the finite mixture results appear to be sorting anglers based on their species catch preferences. Anglers who have fished more in the last two months are more likely to be in tier 2. Less experienced anglers are more likely to be in tier 3 relative to tier 1. In addition, all three tiers have a relatively high probability mass within the angler population.

In the snapper-grouper models the likelihood that an angler would choose a fishing site is negatively related to the trip cost and positively related to the targeted catch rates. The mixed logit models return to the pattern of the mackerel and dolphin models with the travel cost only model providing plausible parameter estimates and statistically different results from the conditional logit. Both tiers in the finite mixture model illustrate that anglers chose closer, less costly sites. The first tier anglers are more likely to fish in counties with more interview sites, whereas second tier anglers tend to fish in counties with fewer sites. With the earlier results we readily identify whether or not the segmentation was determined by the tier's species preferences, this is not the case with the snapper-grouper model. Both tiers possess positive and statistically significant coefficients for grouper, snapper and red snapper. Although, the coefficients for grouper and red snapper are larger in tier 2, the larger negative coefficient on travel costs does not allow us to readily interpret these coefficients. We need to turn to the tier-specific marginal valuations, discussed shortly, for the different species to determine whether or not the finite mixture model is sorting by targeting strategy. The tier participation probabilities illustrate that anglers who have fished a lot in the past two months and who own a boat are more likely to be in tier 2, whereas those with more experience are likely to be in tier 1.

In Table 7 we present the root mean squared error (RMSE) of the predicted probability of site visitation across all sites for each of our models. The RMSE is a goodness of fit statistic, the lower the measure the better the predictive ability of the model.

$$RMSE = \frac{\sqrt{\sum_{i=1}^{K}(S_i^p - S_i^a)^2}}{K} \qquad (19)$$

where S_i^p is the predicted share averaged over the sample, S_i^a is the observed share of visits to site i, and K is the number of sites.

Considering each species in turn, the preference heterogeneity models provide a much better fit for the dolphin data. In the mackerel and small game models the mixed logit model performs about as well as the conditional logit and nested logit models. The finite mixture model RMSE is about 7 percent lower than the others. The predictive ability of red drum and seatrout models is virtually indistinguishable. In the snapper-grouper models, the RMSE of the nested logit, mixed logit and the finite mixture models are 14 percent, 11 percent and 53 percent lower than that of the conditional logit models.

Welfare Estimates

The willingness-to-pay values for one additional fish are presented in Table 8. For initial comparison purposes we present the midpoint estimate from the mixed logit and finite mixture models. With the mixed logit we present the normal distribution which leads to greater willingness-to-pay values relative to the uniform mixing distribution, although the differences are not statistically significant.

The willingness-to-pay values for big dolphin have a wide range with a low of

$40 and a high of $412. Confidence intervals on willingness-to-pay from the conditional logit and nested logit models indicate that these estimates are convergent valid[10]. Willingness-to-pay from the mixed logit model is significantly lower than willingness-to-pay from the conditional and nested logit models. On the other hand, willingness-to-pay from the finite mixture model is significantly higher than willingness-to-pay from the conditional and nested logit models. A similar pattern of results is found for small dolphin and big game. The value of big game catch is not significantly different from zero in the mixed logit model.

The willingness-to-pay values for king mackerel have a much more narrow range relative to dolphin with all confidence intervals overlapping each other. However, the preference heterogeneity model estimates are at the low end of the range and not significantly different from zero. The only estimate of the value of Spanish mackerel catch that is not negative and significantly different from zero is from the finite mixture model. The values of small game catch from the conditional logit, nested logit and mixed logit models are convergent valid. The value of small game catch from the finite mixture model is significantly larger than the others.

In contrast to the preceding results, the willingness-to-pay values for red drum are very similar with a narrow range and overlapping confidence intervals. We conclude that each model is convergent valid. The seatrout results are similar with only the finite

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[10] Willingness-to-pay estimates are convergent valid if they are statistically equivalent. Convergent validity lends confidence to the use of the nonmarket valuation estimates in policy analysis.

mixture model estimate having a non-overlapping confidence interval.

Red snapper willingness-to-pay values have a range of $84 with the preference heterogeneity estimates within this range. Confidence intervals for the conditional logit, mixed logit and the finite mixture model all overlap. The willingness-to-pay for red snapper from the nested logit model is significantly lower than the others. The pattern of willingness-to-pay for grouper is similar to that of red snapper. Willingness-to-pay values for snappers converge for the (a) conditional logit and mixed logit model and (b) nested logit and finite mixture model.

Comparing species-specific willingness-to-pay values to the species aggregate values we find important differences. Willingness-to-pay for big dolphin is significantly larger than small dolphin but not significantly different from big game catch (in three of four models). The confidence interval for king mackerel willingness-to-pay values overlap with small game values in only one of four models. Red drum and spotted seatrout willingness-to-pay values are not statistically different. In all models, red snapper willingness-to-pay values are statistically different from snapper values. In two of four models, red snapper willingness-to-pay values are statistically different from grouper values. These results suggest that aggregate species models could lead to biased willingness-to-pay estimates.

In Table 8 we present the midpoint estimate from the mixed logit and finite mixture models which obscures some of the gains from estimating these models. For the mixed logits, we also consider the willingness-to-pay for the individual who falls at the 5^{th} and 95^{th} percentile of the travel cost distribution. In the finite mixture models we consider the willingness-to-pay values across tiers. Note, however, given that each individual possesses a continuous probability of being in each tier the "true" representation of each angler is a mixture of all of the tiers.

The distributional range of values in the mixed logit models for three of the four models is large. In the dolphin and big game models the willingness-to-pay values range from $16 to $524 for big dolphin, $10 to $340 for small dolphin and $15 to $329 for big game. The range is almost as dramatic in the mackerel and small game model with values ranging from $0 to $37 (small game), $3 to $263 (king mackerel) and -$3 to -$239 (Spanish mackerel). In the snapper-grouper model, red snapper values range from $76 to $226, grouper values range from $50 to $149 while snapper values range from $15 to $43. The red drum model exhibits relative homogeneity with willingness-to-pay ranging less than $1 on either side of the mean.

In the dolphin and big game finite mixture model anglers in tier 1 place a much higher marginal value on big dolphin and big game fish than tier 2, whereas tier 2 places a higher marginal value on small dolphin. Willingness-to-pay for catch in the mackerel and small game model is highest in tier 1 with anglers valuing only small game and Spanish mackerel. The second tier is particularly puzzling since none of the species are valued positively by anglers.

In the red drum and seatrout model the more experienced anglers of Tier 1 possess the highest marginal value for both species. Tier 2 anglers possess a slightly lower marginal value for red drum but have a negative value for sea trout. In the less experienced Tier 3, anglers possess positive values for both species, but the values are less than one-forth of those for Tier 1. Furthermore, the estimates for tier 3 are the closest to the marginal valuation estimates for the conditional and mixed logit models than the other two tiers. Given that this tier possesses the highest distributional mass suggests that this group is driving the mean welfare estimates under the conditional and mixed logit models.

The tier participation probabilities in the snapper-grouper model illustrate that more avid anglers and those who own a boat are more likely to be in Tier 2, whereas those with more experience are likely to be in Tier 1. Tier 1 anglers possess much higher values for all three species. This is consistent with our other tier-specific welfare estimates where the more experienced anglers have larger values for the species than less experienced anglers. Therefore, the finite mixture model is again sorting anglers according to their species valuation preferences.

Conclusions

This research estimates conditional, nested, mixed logit and finite mixture models and outlines the advantages of each model using the conditional logit as the consistent reference point using the MRFSS data. Mixed logit and finite mixture models are increasingly utilized in the environmental and resource economics literature because they facilitate the investigation of the preference heterogeneity within the subject pool. To date, these methods are rarely compared, however they are both usually compared to the standard conditional logit model that provides their foundation.

We determine that the MRFSS data will support only a few species-specific recreation demand models. Nevertheless, we find evidence to suggest that development of single species target models are an important consideration when modeling marine recreational fishing demand. Confidence intervals for single species can be non-overlapping with related species aggregates. Including the catch of important recreational species in species aggregates can lead to biased estimates of willingness-to-pay for catch for these species.

The results from preference heterogeneity models illustrate that welfare distributions can be highly heterogeneous and in some cases span across both the negative and positive realm, even when the conditional logit estimates generate a mean estimate that is firmly footed in the positive realm. This is due to a high degree of preference heterogeneity in the MRFSS data.

In two of our four models, our analysis does little to lead to definitive conclusions about preferred welfare estimates for policy analysis. Considering the dolphin and big game model, preference heterogeneity models generate (1) welfare estimates that differ by an order of magnitude and (2) improved predictive ability relative to traditional models. The finite mixture model is the best model for king mackerel in terms of predictive ability but generates a negative welfare measure. In the other two models our results provide evidence that leads to defensible conclusions. Each of our red drum and seatrout models are convergent valid. In the case of red snapper, the finite mixture model outperforms the others and the willingness-to-pay for red snapper is convergent valid with that from the mixed logit and the conditional logit. In both cases we note, however, that the limitations of the conditional logit model do not seem to detract from its performance with these data.

The finite mixture model exploits the preference heterogeneity to determine different types of anglers within the MRFSS data set. Although, the finite mixture model does not estimate parameter distributions in many models it was able to unravel some of the latent heterogeneity by partitioning anglers into types that depend on their species targeting preferences and their levels of experience within the fishery. Although this facilitates the type classification, it generated welfare estimates that are strikingly different than the conditional, nested and mixed logit models. This suggests that caution should be used when electing to use welfare estimates from finite mixture models to guide policy because different specifications may generate a substantially diverse profile of welfare measures.

Combined, our results indicate that preference heterogeneity is significant within the MRFSS data and that the welfare estimates empirically generated are highly dependent on the model specification utilized. Given that the nested logit, mixed logit and finite mixture model estimates are built on the foundation of the conditional logit model and are statistically superior, it may be necessary to combine the welfare estimates to determine the entire range of possible welfare estimates that may exist within this heterogeneous population. For example, consider the recreational vs. commercial fishing allocation issue for red snapper. The recreational value per catch should be conducted with the best estimate available, in the $102-$123 range. If the results indicate that more catch should be allocated to the recreational sector then the lower nested logit value, $39, could be used in sensitivity analysis.

This research is the first to estimate the complete gamut of preference heterogeneity models utilizing the same data set within the marine recreational fishing literature. Our results are not sufficient to suggest that preference heterogeneity models are preferred to the more traditional conditional logit and nested logit models. However, preference heterogeneity is present in these data. Future research should continue with the MRFSS and other recreational fishing data to develop empirical methodologies so that more complete and reliable welfare profiles can be estimated.

In particular, additional effort should be employed in order to determine if the unreliable catch coefficients found for big game and mackerel are manifest in other data. If not, measurement error resulting from the thin MRFSS catch data, or due to the lack of correlation between boat launch and fishing sites, may be the culprit. In addition, methods such as those proposed by Hindsley, Landry and Gentner (2011) to address endogenous stratification and avidity bias should be employed with preference heterogeneity models in order to determine if the wide range in estimates is exacerbated by sampling problems. Further analysis of these data with other catch rate models such as the zero inflated negative binomial should be explored in order to support policy analysis of bag limits.

Finally, one of our goals is to make our comparisons within the context of the traditional recreation demand model used by the National Marine Fisheries Service. Relaxation of these constraints could improve upon the results presented here. Potential extensions are including distance from shore (more than three miles vs less than three miles) as an additional site feature and consider an intertemporal model to consider seasonal variation across survey waves.

Table 1. Data sets used for each of the four logit models							
Dataset	Single Species		Species Groups		Mode(s)	Number of Sites	Number of Alternatives
1	Dolphin (n=685)		Big Game (n=138)		Private Boat, Charter/Head Boat	12	34
2	King mackerel (n=484)	Spanish mackerel (n=257)	Small Game (n=785)		Private Boat	50	104
3	Red Drum (n=1993)	Spotted Seatrout (n=2360)			Private Boat	58	110
4	Red Snapper (n=239)		Snappers (n=122)	Groupers (n=725)	Private Boat, Charter/Head Boat	28	71

Table 2. Variable Descriptions

Variable	Description
Big game	Big game fish aggregate catch and keep per trip
Charter	=1 if party/charter mode, 0 otherwise
Boat owner	=1 if boat owner, 0 otherwise
Days fished	Days fished in last 2 months
Grouper	Grouper aggregate catch and keep per trip
King mackerel	King mackerel catch and keep per trip
Pr_big dolphin	Predicted dolphin catch and keep > 20” per trip
Pr_small dolphin	Predicted dolphin catch and keep < 20” per trip
Red drum	Red drum catch and keep per trip
Red snapper	Red snapper catch and keep per trip
Seatrout	Seatrout catch and keep per trip
Sites	Number of MRFSS intercept sites in each county site
Small game	Small game aggregate fish catch and keep per trip
Spanish mackerel	Spanish mackerel catch per trip
Snappers	Aggregate other snappers catch per trip
Travel cost	Travel cost of a fishing trip
Years fished	Fishing experience (in years)

Table 3. Dolphin and Big Game Logit Models						
			Mixed Logit		Finite Mixture Model	
Variable	Conditional Logit	Nested Logit	Normal	Uniform	Tier 1	Tier 2
Travel cost	-0.04	-0.057	-0.12	-0.16	-0.01	-0.20
	-26.85[a]	-22.68	-16.71	-14.09	-6.88	-11.49
SD (Travel cost)			0.08	-0.17		
			9.38	-12.69		
Pr_big dolphin	4.91	5.83	4.31	4.52	5.94	-0.69
	11.21	10.18	8.55	8.96	6.19	-0.77
Pr_small dolphin	0.66	0.62	0.43	0.39	0.29	2.99
	12.28	7.64	6.79	6.31	4.08	6.19
Big Game	2.36	4.68	-0.05	0.14	2.98	-9.39
	2.02	2.62	-0.06	0.17	2.94	-4.08
Ln(Sites)	-0.05	-0.059	-0.22	-0.23	-0.23	-0.07
	-1.13	-1.19	-3.88	-3.97	-2.10	-0.86
IV		0.40				
		10.51				
Constant						0.36
						-1.47
Days fished						24.56
						6.33
Years fished						-1.78
						-2.19
Boat owner						1.09
						4.60
Log-Likelihood	-1811	-1748			-1308	
Alternatives	34	34	34	34	34	
Cases	823	823	823	823	823	

[a]t-statistics

Table 4. Mackerel and Small Game Logit Models						
			Mixed Logit		Finite Mixture Model	
Variable	Conditional Logit	Nested Logit	Normal	Uniform	Tier 1	Tier 2
Travel Cost	-0.04	-0.04	-0.08	-0.11	-0.02	-0.20
	-37.93[a]	-32.53	-26.33	-21.20	-16.46	-15.38
SD (Travel cost)			-0.04	-0.11		
			-13.00	-21.00		
Small game	0.12	0.14	0.07	0.06	0.47	-0.18
	4.36	4.46	-2.48	2.00	7.00	-3.18
King mackerel	0.78	1.05	0.52	0.35	-0.61	-0.50
	2.47	2.97	1.53	1.02	-0.81	-0.99
Spanish mackerel	-0.4	-0.34	-0.47	-0.51	0.40	-1.74
	-4.57	-3.67	-5.15	-5.59	3.27	-7.11
Ln(Sites)	0.66	0.66	0.63	0.62	0.97	-0.02
	14.65	14.66	12.84	12.08	11.14	-0.22
Inclusive Value		0.89				
		17.27				
Constant						0.95
						4.63
Days fished						2.69
						3.33
Years fished						-1.86
						-3.58
Boat owner						-0.15
						-0.82
Log-Likelihood	-4062	-4060			-3588	
Alternatives	104	104	104	104	104	
Cases	1562	1562	1562	1562	1562	

[a]t-statistics

Table 5. Red Drum and Seatrout Logit Models							
			Mixed Logit		Finite Mixture Model		
Variable	Conditional Logit	Nested Logit	Normal	Uniform	Tier 1	Tier 2	Tier 3
Travel cost	-0.04	-0.04	-0.05	-0.07	-0.01	-0.08	-0.21
	-67.63[a]	-67.48	-54.00	-67.00	-25.74	-12.99	-15.33
SD (Travel cost)			0.03	0.07			
			26.00	32.50			
Red drum	0.45	0.45	0.65	0.73	0.46	2.39	1.66
	6.94	6.16	6.74	7.46	4.58	9.58	4.71
Seatrout	0.28	0.32	0.35	0.38	0.36	-0.32	1.54
	13.66	12.85	11.42	11.94	12.56	-1.12	12.58
Ln(Sites)	0.55	0.55	0.479	0.445	0.38	1.59	-0.44
	19.75	19.63	15.97	14.35	7.21	10.25	-4.06
Inclusive value		0.57					
		6.10					
Constant						-0.59	0.00
						-2.73	0.02
Days fished						2.06	1.78
						2.06	2.98
Years fished						-0.90	-0.53
						1.60	-1.72
Boat owner						0.02	0.05
						0.11	0.45
Log-Likelihood	-12,468	-12,460			-11,525		
Alternatives	110	110	110	110	110		
Cases	4353	4353	4353	4353	4353		

[a]t-statistics

Table 6. Snapper-Grouper Logit Models						
			Mixed Logit		Finite Mixture Model	
	Conditional Logit	Nested Logit	Normal	Uniform	Tier 1	Tier 2
Travel cost	-0.04	-0.1	-0.04	-0.08	-0.02	-0.34
	-29.91[a]	-26.91	-40.00	-20.25	-15.57	-11.33
SD (Travel cost)			-0.01	0.08		
			-5.00	11.00		
Snappers	0.89	0.83	0.88	0.88	0.22	0.95
	10.21	8.71	6.62	6.03	4.41	5.93
Groupers	3.27	3.11	3.02	2.22	2.25	13.90
	27.41	15.83	21.40	12.12	18.78	13.05
Red snapper	4.43	3.82	4.59	4.85	2.71	3.71
	21.76	13.93	23.09	24.39	14.64	7.57
Ln(Sites)	0.98	0.72	0.914	0.924	1.65	-0.25
	17.02	11.76	17.92	17.43	14.96	-1.70
Inclusive value		0.14				
		14.79				
Constant						-0.54
						-2.99
Days fished						2.05
						1.79
Years fished						-0.26
						-0.43
Boat owner						1.37
						7.46
Log-Likelihood	-2377	-2028			-1903	
Alternatives	71	71	71	71	71	
Cases	1086	1086	1086	1086	1086	

[a]t-statistics

Table 7. Root Mean Square Error				
	Conditional Logit	Nested Logit	Mixed Logit[a]	Finite Mixture Model
Dolphin and Big Game[d]	0.0537	0.0508	0.0233	0.0188
Mackerel and Small Game	0.0106	0.0106	0.0105	0.0098
Red Drum and Seatrout	0.0088	0.0088	0.0087	0.0088
Snapper-Grouper	0.0187	0.0160	0.0176	0.0134

[a]Normal Distribution

Table 8. Willingness-to-pay for One Additional Fish Caught and Kept				
	Conditional Logit	Nested Logit	Mixed Logit[a]	Finite Mixture Model[b]
Pr_big dolphin	$123 (100, 147)[c]	$103 (81, 126)	$37 (27, 48)	$412 (272, 606)
Pr_small dolphin	$17 (14, 19)	$11 (8, 14)	$4 (3, 5)	$23 (13, 35)
Big Game	$40 (2, 115)	$81 (18, 142)	-0.50 (-14, 13)	$202 (55, 340)
King mackerel	$19 (3, 35)	$25 (9, 41)	$6 (-3, 15)	-$23 (-83, 41)
Spanish Mackerel	-$10 (-14, -6)	-$8 (-13, -4)	-$6 (-8, -4)	$13 (4, 24)
Small Game	$3 (2, 4)	$3 (2, 5)	$1 (0, 2)	$19 (13, 25)
Red drum	$13 (9, 16)	$12 (9, 16)	$12 (8, 16)	$22 (16, 27)
Seatrout	$8 (7, 9)	$9 (7, 10)	$7 (5, 8)	$12 (10, 14)
Red snapper	$123 (113, 134)	$39 (33, 45)	$114 (103, 127)	$102 (87, 121)
Grouper	$91 (85, 96)	$32 (28, 36)	$75 (66, 85)	$98 (88, 110)
Snapper	$25 (20, 30)	$9 (7, 11)	$22 (15, 29)	$9 (6, 13)

[a]Normal Distribution
[b]Mean willingness-to-pay.
[c]95% confidence interval in parentheses.

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