Angler Heterogeneity and the Species-Specific Demand for Recreational Fishing in the Southeast United States

Final Report
Marine Fisheries Initiative (MARFIN) Grant
#NA06NMF4330055

Timothy Haab
Department of Agricultural, Environmental,
and Development Economics
The Ohio State University
Columbus, OH 43210
haab.1@osu.edu

Robert Hicks
Department of Economics
The College of William and Mary
Williamsburg, VA 23187
rob.hicks@wm.edu

Kurt Schnier
Department of Economics
Andrew Young School of Policy Studies
Georgia State University
Atlanta, GA 30303
kschnier@gsu.edu

John C. Whitehead
Department of Economics
Appalachian State University
Boone, NC 28608
whiteheadjc@appstate.edu

December 29, 2008 (Revised September 1, 2009)

Angler Heterogeneity and the Species-Specific Demand for Recreational Fishing in the Southeast United States

Executive Summary

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 several methods for dealing with angler heterogeneity, including mixed logit (i.e., random parameter) logit and finite mixture (i.e., latent class logit) models. We compare these techniques to the commonly used conditional and nested logit models in terms of the value of catching (and keeping) one additional fish.

The conditional and nested logit models estimated illustrate that accounting for mode and species substitution possibilities has a potentially large impact on economic values. Failure to account for substitution possibilities appropriately will, in general, lead to economic values that are upwardly biased.

Mixed logit models allow the estimation of a distribution of economic values, relative to point estimates (with standard errors). Our models illustrate that the value of catch can be highly heterogeneous and, in some cases, can include both positive and negative values. The high degree of preference heterogeneity in the MRFSS data set calls into question the results from the conditional and nested logit models.

The finite mixture model exploits the preference heterogeneity to determine different types of anglers. The finite mixture model is able to determine latent heterogeneity by partitioning anglers into types that depend on their species targeting preferences and their levels of fishing experience. Latent partitioning generated value estimates that were some times strikingly different than conditional, nested and mixed logit models. This suggests that further caution should be used when using value estimates because different specifications may generate a substantially diverse range of value measures.

Our results indicate that single species modeling is important as the willingness-to-pay for changes in catch rates are significantly different across species. Preference heterogeneity is significant within the MRFSS data and that the value estimates are dependent on the model specification. 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 models' value estimates to determine the entire range of possible values that may exist within this heterogeneous population.

Table of Contents

1. Introduction

Efficient and effective management for recreational fisheries is needed to accomplish an economically and biologically sustainable level of harvest in marine fisheries. According to the National Marine Fisheries Service (NMFS), in 2001 there were 15 to 17 million marine recreational anglers, taking over 86 million fishing trips and harvesting over 189 million fish weighing almost 266 million pounds. In addition, over 254 million fish were caught and released. Marine recreational fishing has significant economic effects on coastal areas and non-coastal areas where market goods related to this activity are produced. To develop fishery management plans and evaluate the impacts of resulting regulations on marine recreational anglers and fisheries, the NMFS collects data on the number and socio-economic characteristics of participants, total number of fishing trips, and the number, size, and weight of recreational harvest through its Marine Recreational Fishing Statistical Survey (MRFSS).

Marine recreational fishing demand models often assume that anglers are targeting either a species complex (e.g. all coastal migratory pelagic) or a specific species (e.g. king mackerel). These models artificially impose constraints on the tradeoffs anglers face with regard to targeting behavior especially in the presence of common management tools such as bag or size limits. Because current fishery regulations are directed at single species and species groups, management must be formulated in ways that capture the likely behavioral responses by anglers. If in response to management, anglers switch target species or significantly alter effort geographically, effective recreational fisheries management should take this behavior into account. If not, then fishing effort displaced by management could cause recreational over-fishing elsewhere or for other species.

We examine species targeting behavior using random utility models of recreation demand. By focusing on several key species in the southeast United States, this research extends the recreational demand methodology to specifically address targeting behavior by anglers. We explore several methods for dealing with differences in angler heterogeneity in recreation demand modeling, including random parameter (i.e., mixed) logit and latent class logit (i.e., finite mixture) models. We compare these techniques to the commonly used conditional and nested logit models.

This research helps to identify the extent to which angler heterogeneity impacts the economic value of marine recreational fishing. When managers tighten regulations (e.g., bag and size limits), recreational anglers are likely to respond in several ways: (1) by decreasing their recreational fishing activity or stopping it altogether, (2) continue targeting the same species but choose fishing areas with less stringent regulations, (3) continuing to fish but release more fish to comply with regulations and (4) targeting other species of fish. The reaction is likely to result in a loss of economic value because the angler can no longer behave as they were before the regulation was changed. We focus on deriving results that will facilitate the ability of fishery managers to gauge the effects of common management tools for different species across different types of anglers. Our modeling efforts focus on species substitution reactions to regulations.

Past MRFSS-based marine recreational fishing demand research ignores differences among anglers (McConnell and Strand, 1994; Hicks, Steinbeck, Gautam, Thunberg, 1999; Haab, Whitehead, and McConnell, 2001). Each of these studies assume that all 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. An angler focused on taking home the maximum amount of fish may react differently to bag limit decreases than a catch-and-release angler. The latter may change behavior little if any and may not care about regulations at all. Consequently, econometric models that allow for heterogeneity may yield better predictions of fishing behavior and changes in economic value.

Targeting Behavior

For marine recreational fishing, management actions are typically directed at a specific species. In order to examine the benefits or costs of management actions it is necessary to measure value based on species-specific changes. The MRFSS data can be problematic when trying to characterize fishing quality on a species by species basis. Consider the southeast United States (North Carolina to Louisiana) for the year 2000. There were 425 unique species caught by recreational anglers sampled by the MRFSS. Of these, 15 species account for 82% of the targeting activity by anglers and some 38% of the catch.

This paucity of data for some species is further exacerbated if random utility models of recreation demand are employed. In their simplest form, these models assume that anglers choose from among a set of recreation sites. In order to model this choice, the researcher needs data for all sites considered by the individual. The basic data required includes travel cost and measures of expected fishing quality for each site. To characterize fishing quality historical catch data is needed across at least two strata: species and sites. Other studies have stratified on species, sites, time of the year, and the mode of fishing. Because data are missing for many of these strata, most studies have aggregated across species to reduce the dimensionality of the problem, thereby reducing data requirements.

For the reasons listed above, many studies of saltwater fishing have employed species aggregations (Bockstael, McConnell, and Strand, 1999; Green, Moss, Spreen, 1997; Haab and Hicks, 1999). 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 is important to develop a species-specific model.

Most models of marine recreational fishing demand have focused on species groups, or when possible, a particular species of fish when characterizing fishing quality. The choice of target species and how to incorporate substitute species in a marine setting, where many species may be sought, is an important choice. To accurately assess angler values for marine fishing in a recreational demand setting, 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.

The importance of targeting behavior is further magnified when the recreation demand model is intended to capture the impacts due to commonly used management tools such as bag and size limits, or seasonal closures. These policies are typically designed on a species by species basis, and therefore some anglers may be more willing and able to substitute to other species.

Preference Heterogeneity

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 they have been applied in a number of different settings. The mixed logit model provides modeling flexibility. 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 and common management tools for each angler type based on characteristics of the angler.

Whereas the mixed logit model estimates a distribution of parameter estimates, and therefore a distribution of economic value measures and preferences, finite mixture models can be used to estimate separate parameter estimates for individuals who possess similar preferences, declared a different "type" within the population. 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.

Based on data support 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 (2) 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 target species group, and a recreation site. To alleviate the independence of irrelevant alternatives (IIA) restrictions inherent in the conditional logit model we vary our assumptions concerning the behavior of anglers. Specifically, we develop four models for each of the species. In each model anglers target individual species and can substitute to other species or species groups. Models 1 and 2 are the standard conditional logit and nested logit models. Model 3 allows for heterogeneity of preferences through the use of a mixed logit model. Model 4 allows for heterogeneity of preferences through the use of a finite mixture model. In all, we estimate 16 random utility models.

The rest of this report is organized as follows. In the next two sections we describe the data and conditional logit and nested logit models. Then we present mixed logit and latent class logit models. In the final section we discuss the results, offer some conclusions and make some suggestions for future research.

2. Data Description

The 2000 MRFSS southeast intercept data is combined with the economic add-on data to characterize anglers and their spatial fishing choices. Measures of fishing quality for individual species and aggregate species groups are calculated using the MRFSS creel data. We focus on shore, charter 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 and that 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 target a species.

In Table 2-1 we present descriptions of variables used in this report. In Table 2-2 we compare those anglers who target species with those who do not. On average, targeting anglers have 23 years of fishing experience and fish 9 days every two months.[1] Sixty-eight percent of targeting anglers are boat owners. Only 14 percent fish from shore and 8 percent fish from party/charter boats. Fifty-nine percent of targeting anglers are intercepted on a Gulf of Mexico trip.

Non-targeting anglers have 19 years of fishing experience and fish 7 days every two months. Fifty-three percent of targeting anglers are boat owners. Thirty-three percent fish from shore and 8 percent fish from party/charter boats. Sixty-seven percent of targeting anglers are intercepted on a Gulf of Mexico trip.

In a binary logistic regression analysis we consider the factors that influence targeting behavior (Table 2-3). Anglers are more likely to report targeting a species if they are more experienced, more avid and boat owners. Anglers intercepted in Waves 5 and 6 are more likely to report targeting a species. Anglers are less likely to target a species if they are fishing from the shore. Gulf of Mexico anglers are also less likely to report targeting a specific species. Additional targeting anglers are excluded from subsequent analysis based on feasible and logical substitute species and modes for each of the primary species (e.g., we exclude shore anglers that target grouper). Final sample size for the four models is 7788 targeting anglers. In the remainder of this report we focus on targeting anglers.

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

[1] See the supporting website for more details: http://econ.appstate.edu/marfin.

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. For simplicity 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 and keep rates per day are calculated using MRFSS data in each county of intercept to measure site quality. The random utility models exploit the empirical observation that anglers tend to choose fishing alternatives with relatively low fishing trip costs and relatively high chances at fishing success. 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).

Data Summary

Considering species of management interest in the southeast, twenty-percent of the 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.

<u>Dolphin and Big Game</u>

In the dolphin and big game model we focus on dolphin and big game boat trips taken on the Atlantic coast of Florida (Table 2-4). 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] Dolphin anglers have 20 years of fishing experience and fish an average of 7 days each wave. Sixty-five percent are boat owners. Thirteen percent of the trips are charter trips. Big game anglers have 22 years of experience and fish 11 days each wave. Sixty-nine percent are boat owners and 17 percent are charter boat trips. Dolphin and big game anglers fish an average of 5 hours each day.

---

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

There are 12 county level fishing sites in the dolphin and big game model.[3] 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.

With 823 anglers and 34 alternatives there are 27,982 cases. In Table 2-5 we present the means of the independent variables summed over the number of site choices within each target and mode category. 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 20" and less than 20". A household production model, described below, is used to predict the number of big (>20") and small (<20") dolphin.

Travel costs for dolphin target trips party/charter trips are about twice that of private/rental trips since they include the charter fee. Predicted big dolphin catch per day is 0.19 for party/charter mode trips and 0.18 for private/rental mode trips. Predicted small dolphin catch per day is 1.15 and 0.28 for party/charter and private/rental mode trips. The historic catch rate of big game fish per day is 0.13 for party/charter and private/rental mode trips. The average number of MRFSS interview sites ranges from 33 to 39 for dolphin and is 76 for big game.

<u>Mackerel and Small Game</u>

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 (Table 2-6). Thirty-two percent of the sub-sample of 1526 are king mackerel target anglers who have 22 years of fishing experience and fish an average of 9 days each wave. Eighty percent are boat owners. Forty percent of boat trips are in the Gulf of Mexico. Seventeen percent of the anglers target Spanish mackerel and have 25 years of fishing experience and fish an average of 8 days each wave. Seventy-nine percent are boat owners. Forty-nine percent of the private boat trips are in the Gulf of Mexico. Fifty-one percent target small game species.[4] Small game target anglers have 24 years of experience and fish 11 days each wave. Eighty-one percent are boat owners and 64 percent fish in the Gulf of Mexico. Hours fished ranges from 4 to 5 per day.

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. Twelve percent of all angler

---

[3] The full frequency distribution of all dependent variables is available at http://econ.appstate.edu/marfin.

[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.

trips take place in Alabama, 64% take place in Florida, 2% in Georgia, 1% in Louisiana, 4% in Mississippi, 14% in North Carolina and 4% in South Carolina. For king mackerel 17% of all targeted trips take place in Alabama, 61% take place in Florida, 6% in Georgia, 1% in Louisiana, less than 1% in Mississippi, 7% in North Carolina and 7% in South Carolina. Fifteen percent of all targeted Spanish mackerel trips take place in Alabama, 44% take place in Florida, 2% in Georgia, 0% in Louisiana, 1% in Mississippi, 32% in North Carolina and 5% in South Carolina.

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. Summed over alternatives, the average travel cost for Gulf of Mexico and South Atlantic private/rental boat trips ranges from $240 to $278 across the four types of choices (Table 2-7). Small game targeted catch per day is 1.41 fish in the Gulf and 0.27 fish in the South Atlantic. King mackerel targeted catch per day is 0.08 fish in the Gulf and 0.09 fish in the south Atlantic. Spanish mackerel targeted catch per day is 0.32 fish in the Gulf and 0.28 fish in the South Atlantic. The average number of MRFSS intercept sites in each county ranges from 20 to 24.

Red Drum and Seatrout

In the red drum and seatrout model we focus on 4353 red drum and spotted seatrout private/rental boat trips taken in the south Atlantic and Gulf of Mexico (Table 2-8). Forty-six percent of these angler trips target red drum. Red drum anglers have 22 years of experience and fish 9 days each wave. Eighty-two percent own a boat. Sixty-two percent fish in the Gulf of Mexico. Spotted seatrout anglers have 24 years of experience and fish 8 days each wave. Eighty-one percent own a boat. Seventy-five percent fish in the Gulf of Mexico.

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. For red drum 2% of all targeted trips take place in Alabama, 61% take place in Florida, 2% in Georgia, 29% in Louisiana, 1% in Mississippi and North Carolina and 4% in South Carolina. Four percent of all targeted spotted seatrout trips take place in Alabama, 45% take place in Florida, 7% in Georgia, 33% in Louisiana, 4% in Mississippi, 1% in North Carolina and 5% in South Carolina.

The average travel cost over all alternatives for private/rental boat trips ranges from $260 for red drum trips and $264 for spotted seatrout trips (Table 2-9). Red drum targeted catch per day is 0.32 fish. Spotted seatrout targeted catch per day is 0.95 fish. The average number of MRFSS intercept sites in each county is about 18 for each species.

Snapper-Grouper

In the snapper-grouper model we focus on 1086 red snapper, shallow water groupers and "other snappers" boat trips taken in the Gulf of Mexico (Table 2-10). Twenty-two percent target red snapper, 67% target shallow water groupers, and 11% target other snapper species.[5]

Red snapper anglers have 24 years of experience and fished an average of 6 days over the two months prior to the intercepted trip. Sixty percent are boat owners. Thirty-five percent of the red snapper anglers fish from charter boats. Shallow water grouper anglers have 21 years of experience and fished an average of 7 days over the two months prior to the intercepted trip. Sixty-five percent are boat owners. Twenty-one percent fish from charter boats. Other snapper anglers have 23 years of experience and fished an average of 9 days over the two months prior to the intercepted trip. Seventy-nine percent are boat owners. Eleven percent fish from charter boats. Anglers fish an average of 4 to 5 hours per day.

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 choices. For red snapper targeted trips 51% take place in Alabama, 32% take place in Florida, 9% in Louisiana and 9% in Mississippi. One percent of all targeted grouper trips take place in Alabama, 99% take place in Florida and 0% in Louisiana and Mississippi. Seven percent of all targeted other snappers trips take place in Alabama, 89% take place in Florida, 3% in Louisiana and 1% in Mississippi.

Over all alternatives the average travel cost for party/charter boat trips is $317 and $183 for private/rental boat trips (Table 2-11). Other snappers targeted catch per day is 0.004 fish on party/charter trips and 0.03 on private/rental trips. Grouper targeted catch per day is 0.04 fish on party/charter trips and 0.06 fish on private/rental trips. Red snapper targeted catch per day is 0.02 fish on party/charter trips and 0.02 fish on private/rental trips. The average number of MRFSS intercept sites in each county is 27 for party/charter trips and 19 for private/rental trips.

Predicted Catch Models

Poisson and negative binomial models are 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 negative binomial model represents a generalization of the standard Poisson model and relaxes the equality between the mean and variance assumption of the Poisson. If overdispersion is present in the reported cach rates (i.e., unequal mean and variance) then the Poisson model will be misspecified and result in inefficient predictions of expected catch rates.

In contrast to Haab, Whitehead and McConnell (2001) who estimate a single catch rate model pooled over all species, we estimate catch rate models for individual species. The dependent variable in each model is the number of fish caught and kept per trip.

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

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.

With the dolphin data we estimate models for dolphin greater than 20” and dolphin less than 20” for anglers that target dolphin (Table 2-12). For anglers that target big game species we estimate a similar model with aggregate big game catch as the dependent variable. The big game model is estimated with the Poisson distribution. For dolphin target anglers, catch per trip is positively correlated with mean historic catch rates. Anglers in the fifth wave tend to catch more dolphin longer than 20” per trip. Anglers in the third, fourth and fifth wave tend to catch more dolphin less than 20” in length per trip. No coefficients are statistically significant in the big game model.

With the king mackerel data we estimate models for anglers targeting king mackerel, Spanish mackerel and the small game species aggregate (Table 2-13). Catch per trip is positively correlated with mean historic catch rate for king mackerel and small game. King mackerel and small game catch is greater in the Gulf of Mexico relative to the south Atlantic. Small game catch increases with fishing experience and is greater in waves 4 and 5.

With the red drum data we estimate catch models for anglers who target red drum and spotted seatrout (Table 2-14). Both species’ catch rates are positively correlated with mean historic catch rate and fishing experience. Boat owners catch more red drum. Anglers who fish more during the past two months catch more of both fish. More spotted seatrout are caught during wave 6.

With the red snapper data we estimate catch models for anglers who target red snapper, the grouper aggregate and the other snappers aggregate (Table 2-15). Only a few coefficients are statistically significant and none of these appear in the snapper-grouper model.

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. Predicted catch is estimated as in McConnell, Strand and Blake-Hedges (1995), with linear hours fished instead of the natural log of hours fished, and included in preliminary demand models. 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. These results are likely due to outliers. For example, some infrequently visited sites have high catch rates. Using these to predict catch generates unrealistically high predicted catch rates at infrequently visited sites.

Table 2-1. Variable Descriptions

Variable	Description
Big game	Big game fish aggregate catch and keep per trip
Charter	=1 if party/charter mode, 0 otherwise
Boatown	=1 if boat owner, 0 otherwise
Ffdays2	Days fished in last 2 months
Grouper	Grouper aggregate catch and keep per trip
Gulf	=1 if Gulf of Mexico trip, 0 otherwise
Hrsf	Hours fished on intercepted trip
King mackerel	King mackerel catch and keep per trip
Mean	Mean historic catch and keep rate by species/site/mode
Pr_big	Predicted dolphin catch and keep > 20” per trip
Pr_small	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
Shore	=1 if shore mode, 0 otherwise
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
Travcost	Travel cost of a fishing trip
Yearfish	Fishing experience (in years)

Table 2-2. Comparison of Targeting and Non-Targeting Anglers

	Targeting		Not-Targeting	
Variable	Mean	Std	Mean	Std
Yearfish	22.71	14.98	19.32	15.06
Ffdays2	8.91	9.94	7.20	8.68
Boatown	0.68	0.47	0.53	0.50
Shore	0.14	0.34	0.33	0.47
Charter	0.08	0.27	0.08	0.27
Gulf	0.59	0.49	0.67	0.47
Cases	11,257		7452	

Table 2-3. Determinants of Targeting Behavior (Binary Logit Model)

Variable	Coeff.	t-stat
Constant	0.3216	6.29
Yearfish	0.0113	10.56
Ffdays2	0.0242	13.15
Boatown	0.0953	2.49
Shore	-1.2027	-26.85
Charter	-0.07	-1.16
Wave4	-0.0415	-0.99
Wave5	0.2106	4.92
Wave6	0.2482	5.37
Gulf	-0.3401	-10.43
Model $\chi 2$ [df]	1622.16[9]	
Cases	18,709	

Table 2-4. Characteristics of Dolphin and Big Game Targeting Anglers

	Dolphin		Big Game	
Variable	Mean	StdDev	Mean	StdDev
Yearfish	20.42	13.94	22.03	14.78
Ffdays2	7.11	7.23	10.59	9.36
Boatown	0.65	0.48	0.69	0.46
Charter	0.13	0.33	0.17	0.38
Hrsf	5.18	2.09	5.36	2.82
Cases	685		138	

Table 2-5. Summary of Determinants of Mode/Target Site Choice for the Dolphin and Big Game Models

	Dolphin				Big Game	
	Party/Charter		Private/Rental		Party/Charter and Private/Rental	
Variable	Mean	StdDev	Mean	StdDev	Mean	StdDev
Travcost	178.53	51.59	82.91	60.36	117.11	75.65
Pr_big	0.19	0.13	0.18	0.11	0.00	0.00
Pr_small	1.15	1.96	0.28	0.19	0.00	0.00
Big game	0.00	0.00	0.00	0.00	0.13	0.13
Sites	38.50	41.13	32.80	38.20	76.00	61.95
Cases	6584		8230		4115	
Alternatives	8		10		16	

Table 2-6. Characteristics of Mackerel and Small Game Targeting Anglers

	King Mackerel		Spanish Mackerel		Small Game	
Variable	Mean	StdDev	Mean	StdDev	Mean	Std
Yearfish	21.70	14.30	24.47	15.34	24.15	14.07
Ffdays2	9.03	8.79	7.61	8.72	11.27	11.31
Boatown	0.80	0.40	0.79	0.41	0.81	0.39
Gulf	0.40	0.49	0.49	0.50	0.64	0.48
Hrsf	4.60	2.13	4.16	1.96	4.76	1.97
Cases	484		257		785	

Table 2-7. Summary of Determinants of Mode/Target Site Choice for the Mackerel and Small Game Models

	Gulf of Mexico				South Atlantic			
	Small Game		King and Spanish Mackerel		Small Game		King and Spanish Mackerel	
Variable	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Travcost	265.75	177.58	239.80	155.92	278.75	171.67	254.46	145.67
Small	1.41	1.69	0.00	0.00	0.27	0.39	0.00	0.00
King	0.00	0.00	0.08	0.12	0.00	0.00	0.09	0.10
Spanish	0.00	0.00	0.32	0.37	0.00	0.00	0.28	0.55
Sites	19.82	12.45	20.67	14.96	24.33	14.78	22.41	15.18
Cases	33,572		45,780		27,468		51,884	
Alternatives	22		30		18		34	

Table 2-8. Characteristics of Red Drum and Seatrout Targeting Anglers

	Red Drum		Spotted Seatrout	
Variable	Mean	StdDev	Mean	StdDev
Yearfish	22.48	14.71	23.85	15.27
Ffdays2	9.04	8.87	7.52	7.48
Boatown	0.82	0.38	0.81	0.39
Gulf	0.62	0.48	0.75	0.43
Hrsf	4.46	1.77	4.35	1.74
Cases	1993		2360	

Table 2-9. Summary of Determinants of Mode/Target Site Choice for the Red Drum and Seatrout Models

	Red Drum		Spotted Seatrout	
Variable	Mean	StdDev	Mean	StdDev
Travcost	260.36	161.78	263.92	164.64
Drum	0.32	0.35	0.00	0.00
Trout	0.00	0.00	0.95	0.84
Sites	18.50	13.68	18.02	13.59
Cases	235,062		243,768	
Alternatives	54		56	

Table 2-10. Characteristics of Snapper-Grouper Anglers

	Red Snapper		Groupers		Snappers	
Variable	Mean	StdDev	Mean	StdDev	Mean	StdDev
Yearfish	23.62	13.88	20.82	13.84	23.19	15.18
Ffdays2	6.00	7.64	6.65	6.98	9.23	9.6
Boatown	0.60	0.49	0.65	0.48	0.79	0.41
Charter	0.35	0.48	0.21	0.41	0.11	0.32
Hrsf	4.27	1.91	5.10	2.06	4.43	2.15
Cases	239		725		122	

Table 2-11. Summary of Determinants of Mode/Target Site Choice for the Snapper-Grouper Models

	Party/Charter		Private/Rental	
Variable	Mean	StdDev	Mean	StdDev
Travcost	317.29	142.83	183.49	143.04
Snapper	0.004	0.11	0.03	0.24
Grouper	0.04	0.26	0.06	0.15
Red snapper	0.02	0.16	0.02	0.12
Sites	27.59	27.49	18.80	13.33
Cases	29,322		47,784	
Alternatives	27		44	

Table 2-12. Negative Binomial Household Production Models: Dolphin and Big Game

	Dolphin ≥ 20"		Dolphin < 20"		Big Game (Poisson)	
Variable	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Intercept	-3.346	-5.382	-3.418	-3.956	0.077	0.869
Mean	2.651	2.433	3.823	3.898	-0.161	-0.493
Yearfish	-0.002	-0.225	-0.007	-0.570	0.001	0.438
Boatown	0.377	1.365	0.294	0.765	-0.068	-1.280
Charter	0.247	0.624	-0.101	-0.170	0.117	1.292
Ffdays2	0.023	1.439	-0.001	-0.052	0.002	0.654
Hrsf	0.032	0.557	-0.061	-0.729	0.005	0.659
Wave 3	0.655	1.426	1.798	2.554	-0.077	-1.336
Wave 4	0.139	0.284	2.155	2.969	0.003	0.049
Wave 5	1.149	2.269	2.432	3.101	0.028	0.423
Dispersion	3.462	4.029	11.540	6.434	0.262	16.601
Cases	685		685		138	

Table 2-13. Negative Binomial Household Production Models: Mackerel and Small Game

	King Mackerel		Spanish Mackerel		Small Game	
Variable	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Intercept	-2.654	-4.968	-1.214	-1.214	-5.201	-5.446
Mean	4.398	2.918	0.804	1.513	1.639	3.657
Yearfish	0.000	-0.026	-0.004	-0.255	0.041	3.441
Boatown	0.287	0.991	0.576	1.154	0.341	0.776
Ffdays2	0.016	1.331	0.022	0.961	-0.025	-1.595
Hrsf	0.014	0.261	0.030	0.249	0.107	1.128
Wave 4	-0.142	-0.524	-0.108	-0.244	1.282	2.338
Wave 5	-0.062	-0.191	-0.198	-0.398	0.810	1.834
Wave 6	-0.338	-0.996	0.382	0.775	0.424	0.793
Gulf	0.569	2.501	-0.530	-1.445	0.987	2.039
Dispersion	1.550	3.194	5.915	5.490	15.569	7.377
Cases	484		257		785	

Table 2-14. Negative Binomial Household Production Models: Red Drum and Seatrout

	Red Drum		Seatrout	
Variable	Coeff.	t-ratio	Coeff.	t-ratio
Intercept	-3.463	-11.800	-2.448	-8.748
Mean	2.812	13.797	0.796	13.084
Yearfish	0.008	2.026	0.010	2.605
Boatown	0.446	2.733	0.115	0.802
Ffdays2	0.011	1.551	0.028	3.623
Hrsf	0.088	2.618	0.187	5.662
Wave 4	-0.015	-0.088	-0.167	-1.077
Wave 5	0.015	0.095	0.142	0.900
Wave 6	-0.007	-0.040	0.557	3.486
Gulf	0.251	1.560	-0.226	-1.563
Dispersion	2.828	10.324	5.494	17.761
Cases	1993		2360	

Table 2-15. Negative Binomial Household Production Models: Snapper-Grouper

	Red Snapper		Groupers		Snappers	
Variable	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Intercept	0.104	0.136	-2.326	-5.157	-1.845	-1.313
Mean	0.252	0.552	0.311	0.906	0.195	0.548
Yearfish	-0.006	-0.554	0.012	1.570	0.029	1.173
Boatown	-0.209	-0.694	0.321	1.297	0.402	0.515
Charter	-0.336	-0.997	0.859	3.019	1.127	0.880
Ffdays2	-0.003	-0.147	0.016	1.080	-0.002	-0.064
Hrsf	0.001	0.006	0.098	1.885	-0.047	-0.216
Wave 3	-0.290	-0.858	-0.402	-1.237	0.739	0.896
Wave 4	-0.135	-0.389	0.034	0.124	1.987	2.240
Wave 5			-0.396	-1.445	1.544	1.469
Dispersion	3.202	5.105	4.236	6.182	7.148	4.311
Cases	239		725		122	

3. Conditional and Nested Random Utility Models

Nested random utility models (NRUM) allow for sequential choices. For example, in the standard NMFS travel cost marine recreational fishing model anglers are assumed to choose (1) target species and fishing mode and (2) fishing sites based on their attributes (McConnell and Strand, 1994; Hicks, Steinbeck, Gautam, Thunberg, 1999; Haab, Whitehead, and McConnell, 2000). The species-mode-site choice NRUMs developed here are based on the standard NMFS recreation demand model. First, the angler chooses among fishing modes (e.g., shore, charter boat, and private/rental boat fishing) and various species. Conditional on the mode-species choice from the first stage decision, the angler chooses the fishing site. The MRFSS fishing access sites are aggregated to the county level (i.e., zones) due to limited observations at some sites.

The theory behind the NRUM 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. The utility function depends on the costs and benefits of the fishing trip. 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:

(3-1) $$u_i = v_i(y - c_i, q_i) + \varepsilon_i$$

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

(3-2) $$\pi_i = \Pr(v_i + \varepsilon_i > v_s + \varepsilon_s \;\; \forall\, s \neq i)$$

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

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

The conditional logit model restricts the choices according to the assumption of the independence of irrelevant alternatives (IIA). The IIA restriction forces the relative probabilities of any two choices to be independent of other changes in the choice set. For example, if a quality characteristic at site *j* causes a 5% decrease in the probability of visiting site *j* then the probability of visiting each of the other *k* sites must increase by 5%. This assumption is unrealistic if any of the *k* sites are better substitutes for site *j* than the others.

The nested logit model relaxes the IIA assumption. The nested logit site selection model assumes that recreation sites in the same species-mode nest are better substitutes than recreation sites in other species-mode nests. Choice probabilities for recreation sites within the same nest are still governed by the IIA assumption.

Consider a two-level nested model. The site choice involves a choice among M groups of species-mode nests, m = 1, … , M. Within each nest is a set of J_m sites, j= 1, … , 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:

$$(3\text{-}4)\qquad \pi_{ni} = \frac{e^{v_{ni}/\theta}\left[\sum_{j=1}^{J_n} e^{v_{nj}/\theta}\right]^{\theta-1}}{\sum_{m=1}^{M}\left[\sum_{j=1}^{J_m} e^{v_{mj}/\theta}\right]^{\theta}}$$

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, $0 \le \theta \le 1$, 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 $M \times J_m = J$.

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

$$(3\text{-}5)\qquad \begin{aligned} v_{ni}(y - c_{ni}, q_{ni}) &= \alpha(y - c_{ni}) + \beta' q_{ni} \\ &= \alpha y - \alpha c_{ni} + \beta' q_{ni} \\ &= -\alpha c_{ni} + \beta' q_{ni} \end{aligned}$$

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 next step is to recognize that the inclusive value is the expected maximum utility from the cost and quality characteristics of the sites. The inclusive value, IV, is measured as the natural log of the summation of the nest-site choice utilities:

$$(3\text{-}6)\qquad \begin{aligned} IV(c, q; \alpha, \beta) &= \ln\left(\sum_{m=1}^{M}\left[\sum_{j=1}^{J_m} e^{v_{mj}/\theta}\right]^{\theta}\right) \\ &= \ln\left(\sum_{m=1}^{M}\left[\sum_{j=1}^{J_m} e^{(-\alpha c_{mj} + \beta' q_{mj})/\theta}\right]^{\theta}\right) \end{aligned}$$

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

$$(3\text{-}7) \quad WTP = \frac{IV(c,q;\alpha,\beta) - IV(c,q+\Delta q;\alpha,\beta)}{\alpha}$$

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

$$(3\text{-}8) \quad WTP(\Delta q \mid ni) = \frac{\beta_q \Delta q}{\alpha}$$

The welfare measures apply for each choice occasion (i.e., trips taken by the individuals in the sample). If the number of trips taken is unaffected by the changes in trip quality, then the total willingness-to-pay is equal to the product of the per trip willingness-to-pay and the average number of recreation trips, $\bar{x}$.

In this chapter and the rest of the report 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 2.5th and 97.5th percentile observations yields a consistent estimate of the desired confidence interval.

Results

The conditional and nested logit models are estimated using the full information maximum likelihood PROC MDC in SAS. The nested logit routine estimates the two stages of choice jointly. In the models that follow we estimate conditional and nested logit models for each species in order. Each species data leads to a different nesting structure. The dolphin data supports estimation of the welfare impacts of size since size limit regulations were put into place after data collection.

<u>Dolphin and Big Game</u>

The dolphin data considers 823 dolphin and big game anglers and 34 choices. The model likelihood ratio statistic indicates that all parameters are jointly significantly different from zero in both the conditional and nested logit models. The nested logit specification that best fit the data employs mode/species nests as described in Section 2 (Table 2-4). In the nested logit model the parameter estimate on the inclusive value is statistically different from zero and one which indicates that the nested model is more appropriate then the conditional logit. In both logit models the likelihood that an angler would choose a county fishing site is negatively related to the trip cost and positively related to the catch rates. The log of the number of interview sites is not related to the site choice in either model.

The trip cost coefficient in the conditional logit model is 30% lower in absolute value relative to the trip cost coefficient in the nested logit models. This will reduce the welfare measures of catch obtained from the nested logit model relative to the conditional logit model, holding catch rate coefficients constant. The effects of the predicted big and small dolphin catch and big game catch on choice are 16% larger, 6% smaller and 50% larger in the nested logit model relative to the conditional logit. This effect will increase the welfare measures of catch obtained from the nested logit model relative to the conditional logit model.[6]

In Table 3-2 we present the willingness-to-pay for one additional fish caught and kept per trip. These values are similar across models with a 28% difference, at most, for big dolphin and big game. There is a 45% difference for predicted small dolphin. Dolphin greater than 20” is a highly valuable catch. In the nested logit model an additional big dolphin is worth $102 per trip, about 20% higher than big game. An additional small dolphin is worth only $11 per trip.

The 95% confidence intervals for predicted big dolphin and big game catch willingness-to-pay overlap in both conditional and nested logit models. Predicted small dolphin catch willingness-to-pay overlaps with big game catch in the conditional logit model due to the imprecise measurement of big game willingness-to-pay. From this analysis we conclude that there is little reason, in terms of willingness-to-pay estimation, to focus on a single species (big) dolphin and big game model relative to a model that includes dolphin in the big game aggregate species.

Mackerel and Small Game

The mackerel data considers 1562 mackerel and small game anglers and 104 species/site alternatives (Table 3-3). The model likelihood ratio statistics indicate that all parameters are jointly significantly different from zero in both the conditional and nested logit models. The nested logit specification that best fit the data includes four nests as described in Section 2 (Table 2-5). In the nested logit model the parameter estimate on the inclusive value is statistically different from zero but not statistically different from

---

[6] We considered additional function forms for the catch variables. These are discarded for various reasons. The square root conditional logit model suggests that dolphin smaller than 20” are worth more than dolphin greater than 20”. The square root nested logit model contains a negative and statistically significant coefficient for big game catch. The quadratic conditional logit and nested logit models suggest negative values for big dolphin catch. Additional model results mentioned throughout the report and others can be found at http://econ.appstate.edu/marfin.

one which indicates that the model fit is statistically the same as the conditional logit model at the p=.01 level.

In the logit models the likelihood that an angler would choose a county fishing site is negatively related to the trip cost and positively related to the king mackerel and small game catch rate. 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 trip cost coefficients in the conditional logit model is not statistically different from the trip cost coefficient in the nested logit models. The coefficient on king mackerel catch is 35% larger in the nested logit model relative to the conditional logit. This effect will increase the welfare measures of catch obtained from the nested logit model relative to the conditional logit model. In Table 3-4 we present the willingness-to-pay for one additional fish caught and kept per trip. These values are similar with only 8% and 31% differences for small game and king mackerel catch.

In the conditional logit model, the willingness-to-pay for small game and king mackerel are not significantly different. However, there are significant differences in the nested logit model. This suggests that there are empirical gains to pursuing a single-species mackerel and small game model relative to including king mackerel in the small game aggregate.

<u>Red Drum and Seatrout</u>

The red drum data considers 4353 red drum and spotted seatrout target anglers and 110 species/site alternatives (Table 3-5). The model likelihood ratio statistics indicate that all parameters are jointly significantly different from zero in all logit models. The nested logit structure that fit the data includes 2 species nests (red drum and spotted seatrout) as described in Section 2 (Table 2-6). In the nested logit model 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.

The likelihood that an angler would choose a county 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 trip cost coefficients in both models are not statistically different. The catch coefficients are not statistically different.

In Table 3-6 we present the willingness-to-pay for one additional fish caught and kept per trip. These values are similar with only 2% and 12% differences for red drum and spotted seatrout catch. The 95% confidence intervals from each model overlap which suggests there is little reason, in terms of willingness-to-pay estimation, to disaggregate red drum and spotted seatrout catch.

Snapper-Grouper

There are 1086 snapper-grouper anglers and 71 choices (Table 3-7). The model likelihood ratio statistic indicates that all parameters are jointly significantly different from zero in each of the four models. In each of the models the likelihood that an angler would choose a county fishing site is negatively related to the trip cost and positively related to the catch rate. The log of the number of interview sites is positively related to the site choice.

The nested logit specification that fit the data best includes 2 mode nests as described in Section 2. This indicates that each of the species-site choice alternatives are good substitutes. In the mode-species/sites nested logit model 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. The inclusive values are closer to 0 relative to 1 which indicates that the alternatives outside the mode nests are not good substitutes for the alternatives within the mode nests. In other words, party/charter boat trips and not good substitutes for private/rental boat trips (and vice versa) in the snapper-grouper recreational fishery.

The trip cost coefficients in the conditional logit models are 40% lower in absolute value relative to the trip cost coefficients in the nested logit models. This indicates that the effect of trip costs is attenuated when the mode choice is modeled as the first stage of decision-making. This effect will reduce the welfare measures obtained from the nested logit model relative to the conditional logit model.[7]

In Table 3-8 we present the willingness-to-pay for one additional fish caught and kept per trip. These values differ across model. As expected, accounting for the additional substitution patterns in the nested logit model drives the nested logit welfare values significantly below the conditional logit welfare values. Red snapper and the grouper aggregate is a valuable catch. In the conditional logit model, red snapper willingness-to-pay is significantly greater than grouper willingness-to-pay which is significantly greater than snapper willingness-to-pay. Accounting for the nested substitution pattern reduces the value of catch by 65%, 66% and 68% for grouper, snapper and red snapper. In the nested logit model an additional grouper is worth $32 and an additional red snapper is worth $39. These estimates are not statistically different. An additional snapper is worth significantly less, only $9. The snapper-grouper model results suggest that pursuing single species demand models is worthwhile.

[7] We also investigate the potential for diminishing marginal returns to catch with alternative functional forms. In addition to the linear catch models we also attempted models that include the square root of catch rates and quadratic catch rates. The square root model represents a statistical improvement over the linear model with a larger likelihood ratio statistic. The quadratic model is statistically inferior.

Table 3-1. Conditional and Nested Logit Models: Dolphin and Big Game

	Conditional Logit		Nested Logit	
Variable	Coeff.	t-stat	Coeff.	t-stat
Travcost	-0.040	-26.85	-0.057	-22.68
Pr_big	4.91	11.21	5.83	10.18
Pr_small	0.66	12.28	0.62	7.64
Big Game	2.36	2.02	4.68	2.62
Ln(Sites)	-0.050	-1.13	-0.059	-1.19
Inclusive value			0.40	10.51
Choices	34		34	
Cases	823		823	
Log-Likelihood	-1811		-1748	
Likelihood Ratio	2182		2309	

Table 3-2. Willingness-to-Pay for One Additional Fish Caught and Kept: Dolphin and Big Game

	Conditional Logit		
	Pr_big (Dolphin > 20”)	Pr_small (Dolphin < 20”)	Big Game
Lower 95%	99.70	14.35	1.77
Mean	123.18	16.57	40.46
Upper 95%	146.96	18.72	115.30
	Nested Logit		
	Pr_big (Dolphin > 20”)	Pr_small (Dolphin < 20”)	Big Game
Lower 95%	81.34	8.20	17.66
Mean	102.63	10.98	81.39
Upper 95%	125.87	13.80	142.44

Table 3-3. Conditional and Nested Logit Models: Mackerel and Small Game

	Conditional Logit		Nested Logit	
Variable	Coeff.	t-stat	Coeff.	t-stat
Travcost	-0.04	-37.93	-0.04	-32.53
Small game	0.12	4.36	0.14	4.46
King mackerel	0.78	2.47	1.05	2.97
Spanish mackerel	-0.40	-4.57	-0.34	-3.67
Ln(Sites)	0.66	14.65	0.66	14.66
Inclusive value			0.89	17.27
Choices	104		104	
Cases	1562		1562	
Log-Likelihood	-4062		-4060	
Likelihood Ratio	6052		6055	

Table 3-4. Willingness-to-Pay for One Additional Fish Caught and Kept: Mackerel and Small Game

	Conditional Logit		
	Small Game	King Mackerel	Spanish Mackerel
Lower 95%	1.71	2.68	-14.20
Mean	3.08	19.12	-9.87
Upper 95%	4.44	34.52	-5.54
	Nested Logit		
	Small Game	King Mackerel	Spanish Mackerel
Lower 95%	1.83	9.21	-13.15
Mean	3.32	25.37	-8.29
Upper 95%	4.80	41.09	-3.62

Table 3-5. Conditional and Nested Logit Models: Red Drum and Seatrout

	Conditional Logit		Nested Logit	
Variable	Coeff.	t-stat	Coeff.	t-stat
Travcost	-0.04	-67.63	-0.04	-67.48
Red drum	0.45	6.94	0.45	6.16
Seatrout	0.28	13.66	0.32	12.85
Ln(Sites)	0.55	19.75	0.55	19.63
Inclusive value			0.57	6.10
Choices	110		110	
Cases	4353		4353	
Log-Likelihood	-12,468		-12,460	
Likelihood Ratio	15,986		16,002	

Table 3-6. Willingness-to-Pay for One Additional Fish Caught and Kept: Red Drum and Seatrout

	Conditional Logit	
	Red Drum	Spotted Seatrout
Lower 95%	8.95	6.74
Mean	12.60	7.90
Upper 95%	16.36	9.04
	Nested Logit	
	Red Drum	Spotted Seatrout
Lower 95%	8.51	7.38
Mean	12.43	8.84
Upper 95%	16.18	10.28

Table 3-7. Conditional and Nested Logit Models: Snapper-Grouper

	Conditional Logit		Nested Logit	
	Coeff.	t-stat	Coeff.	t-stat
Travcost	-0.04	-29.91	-0.10	-26.91
Snapper	0.89	10.21	0.83	8.71
Grouper	3.27	27.41	3.11	15.83
Red snapper	4.43	21.76	3.82	13.93
Ln(Sites)	0.98	17.02	0.72	11.76
Inclusive value			0.14	14.79
Choices	71		71	
Cases	1086		1086	
Log-Likelihood	-2377		-2028	
Likelihood Ratio	4568		5203	

Table 3-8. Willingness-to-Pay for One Additional Fish Caught and Kept: Snapper-Grouper

		Conditional Logit	
	Snapper	Grouper	Red Snapper
Lower 95%	19.91	84.82	112.94
Mean	24.68	90.67	123.14
Upper 95%	29.55	96.28	133.99
		Nested Logit	
	Snapper	Grouper	Red Snapper
Lower 95%	6.52	27.89	33.16
Mean	8.53	31.91	39.18
Upper 95%	10.60	35.95	45.25

4. Mixed Logit Models

The conditional logit model of chapter 3 imposes potentially restrictive assumptions on the substitution pattern between fishing sites in the form of the well-known Independence from Irrelevant Alternatives assumption (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.

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 straight forward. 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 one unit change in any of the site attributes is the same for all individuals sampled. The additional utility gained from a $1 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.

As it turns out, a relatively new addition to the applied economics toolbox addresses both concerns with the conditional logit. The mixed logit (also called the random parameter logit) allows for more flexibility in the substitution pattern between alternatives and allows for preference heterogeneity across individuals. In what follows, we apply some of the simpler forms of the mixed logit to the four species (group) choice models described in previous chapters.

We focus on the simpler forms of the models for one primary reason: They are the most common and readily available models in existing statistical software packages. Understanding the impacts of making generalizations in these simpler models will inform later research using more computationally difficult techniques. With that said, we should not mistake availability in existing packages with computational simplicity. Advances in computing power over the last decade have made computationally intense models estimable without specific programming skills. Nevertheless, the models described in this chapter require significant computing power and time—for example, the simplest of the RPL models reported below takes over 10 minutes to estimate using a high powered desktop computer, with some taking close to an hour. Comparing that to the 3-4 seconds of CPU time it takes the same computer to estimate the conditional logit models in chapter 3 gives an idea of the computational intensity of these readily available techniques.

The Basic Mixed Logit Model

We will use equations (3-1), (3-2) and (3-3) as the point of departure for the mixed logit. Recall that in the standard conditional logit model, the individual indirect utility function for site i is expressed as the sum of a deterministic indirect utility component and a random error term:

$$(4\text{-}1) \quad u_i = v_i(y - c_i, q_i) + \varepsilon_i$$

where u is the individual indirect utility function, v is the nonstochastic portion of the utility function, 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, $s = 1, \ldots, i, \ldots J$. The random utility model assumes that the individual chooses the site that gives the highest utility

$$(4\text{-}2) \quad \pi_i = \Pr(v_i + \varepsilon_i > v_s + \varepsilon_s \ \ \forall\, s \neq i)$$

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

$$(4\text{-}3) \quad \pi_i = \frac{e^{v_i}}{\sum_{s=1}^{J} e^{v_s}}$$

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:

$$(4\text{-}4) \quad v_i = x_{ih}\beta$$

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 (4-3) unless they are interacted with alternative specific dummy variables—a level of complication we have chosen to avoid for the purposes of this report.

For the conditional (and nested) logit models, the parameter vector β is assumed to be constant across individuals. However, as noted in the introduction to this chapter, assuming a constant parameter vector implies that we as researchers believe that all individuals receive the same change in utility as a result of a change in one of the independent variables. However, it is plausible that people are different with regard to their preferences for travel costs and catch rates. Imposing preference homogeneity may result in a misspecified utility function and inaccurate estimates of the value of changes in the independent variables. At the very least, it is an attractive option to be able to allow for preference heterogeneity in the estimation of the model and then statistically test for preference homogeneity.

To allow for preference heterogeneity, we will assume that individual angler preferences randomly vary according to a prespecified population distribution such that:

(4-5) $\beta_{ih} = \tilde{\beta} + \eta_{ih}$

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.

Substituting 4-5 and 4-4 into 4-3 gives a new conditional expression for the choice probability for a specific individual:

(4-6) $\pi_{ih} | \eta_{ik} = \dfrac{e^{\tilde{\beta}+\eta_{ih}}}{\sum_{s=1}^{J} e^{\tilde{\beta}+\eta_{jh}}}$

The choice probability in 4-6 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 density function is $f(\eta|\gamma)$, the probability in (4-6) must be integrated over all possible values of η_{ik} to eliminate the conditioning:

(4-7) $\pi_{ih} = \int\limits_{\eta_{ih}} \pi_{ih} | \eta_{ih} \partial f(\eta_{ih}|\gamma) = \int\limits_{\eta_{ih}} \dfrac{e^{\tilde{\beta}+\eta_{ih}}}{\sum_{s=1}^{J} e^{\tilde{\beta}+\eta_{jh}}} \partial f(\eta_{ih}|\gamma)$

Ideally, the integration problem in (4-7) 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 (4-7) do not exist for common distributions (normal, uniform, log normal) and as such, estimation of the parameters in (4-7) requires simulation of the integral.

Without going into excruciating detail, and referring the reader to Train (2003) for details, the most common way to simulate the probability in equation (4-7) is to repeatedly draw from the multivariate distribution of η_{ik}, calculating the integrand in (4-7) at each draw and then averaging over the draws to find an estimate of π_{ih} conditional on β and γ. 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.

Estimation Results

In this section, we describe the results of two models on each species group. The two new models are mixed logits with a normally distributed travel cost parameter and with a uniformly distributed travel cost parameter.

In the appendix to this chapter, we also report parameter estimates for 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, it is our judgment that these models are not suitable for analysis. The results are presented in the appendix for completeness. 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]

Table 4-1 provides the estimation results for the two mixed logit models plus the conditional logit on the Dolphin data. It is apparent that mixing is appropriate in comparison to the conditional logit estimates. 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. For the model with a normally distributed travel cost parameter, the mean of the travel cost parameter is -0.097 with a standard deviation of 0.137. The 2.5th and 97.5th percentiles are -0.209 and 0.0069. For the uniform model, the range of the distribution of the travel cost parameter is (-0.27, 0.004) with a mean of -0.133.

Table 4-2 reports the parameter estimates for the mixed logits for the mackerel and small game model. 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. In contrast to the conditional logit, king mackerel catch rates are statistically insignificant in the random parameter models. Again, the model with catch rates randomized provided puzzling results. Small game and king mackerel catch rates are insignificant, and the spanish mackerel mean parameter jumps by an order of magnitude. The king mackerel catch rate becomes statistically significant in the uniformly mixed model, but the spread of the distribution is implausibly large.

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

The red drum and seatrout model parameter estimates tell a different story (Table 4-3). The travel cost only random parameter models are statistically different from the conditional logit, but the full mixed model (Appendix) is statistically indistinguishable from the travel cost only model indicating that mixing of the catch rate parameters is unwarranted.

The red snapper returns to the pattern of the Mackerel and Dolphin groups with the travel cost only model providing plausible parameter estimates and statistically different results from the conditional logit (Table 4-4). The fully mixed model (Appendix) again provides implausible parameter estimates.

Willingness-to-Pay

Tables 4-4 through 4-8 provide estimates of willingness-to-pay for one additional fish for each group. Due to the uncertain nature of the results from the fully mixed model, we focus only on the results from the mixed logit model with only the travel cost parameter randomized.

We report the confidence intervals around mean willingness-to-pay for all conditional logit models. For the mixed logits, we report the willingness-to-pay for the mean TC parameter, as well as the willingness-to-pay for the individual who falls at the 5^{th} and 95^{th} percentile of the travel cost distribution. For these models, confidence intervals are reported only for the median of the distribution of WTP.

With the dolphin data, willingness-to-pay estimates from the mixed logit models are significantly lower than the conditional logit model. Confidence intervals for all species are significantly different as well. With the king mackerel data, willingness-to-pay estimates from the mixed logit models are not significantly different, in general, from the conditional logit models or across species. This is likely due to the relative imprecision of the parameter estimates. With the red drum data we find results similar to those in the previous section of this report – no differences in willingness-to-pay. With the red snapper data, we find significant differences between the conditional logit and mixed logit models for groupers and red snapper (uniform distribution) and between the mixed logit models for each species. The normal distribution leads to greater willingness-to-pay values relative to the uniform mixing distribution.

Table 4-1. Mixed Logit Models: Dolphin and Big Game

Variable		Mixed Logit Normal	Uniform
Travel Cost	B	-0.117*	-0.155*
		(0.007)	(0.011)
	s	0.075*	-0.165*
		(0.008)	(0.013)
Pr_big	B	4.311*	4.524*
		(0.504)	(0.505)
Pr_small	B	0.428*	0.385*
		(0.063)	(0.061)
Big game	B	-0.051	0.142
		(0.835)	(0.834)
Log(Sites)		-0.221*	-0.230*
		(0.057)	(0.058)

*Significant at 5%
**Standard errors on parameter estimates in parentheses

Table 4-2. Mixed Logit Models: Mackerel and Small Game

		Mixed Logit	
Variable		Normal	Uniform
Travel Cost	B	-0.079*	-0.106*
		(0.003)	(0.005)
	s	-0.039*	-0.105*
		(0.003)	(0.005)
Small game	B	0.072*	0.058*
		(0.029)	(0.029)
King mackerel	B	0.516	0.347
		(0.338)	(0.341)
	s		
Spanish mackerel	B	-0.469*	-0.509*
		(0.091)	(0.091)
Log(Sites)		0.629*	0.616*
		(0.049)	(0.051)

*Significant at 5%
**Standard errors on parameter estimates in parentheses

Table 4-3. Mixed Logit Models: Red Drum and Seatrout

Variable		Mixed Logit: Normal	Mixed Logit: Uniform
Travel Cost	B	-0.054*	-0.067*
		(0.001)	(0.001)
	s	0.026*	0.065*
		(0.001)	(0.002)
Red drum	B	0.647*	0.731*
		(0.096)	(0.098)
Sea trout	B	0.354*	0.382*
		(0.031)	(0.032)
Log(Sites)		0.479*	0.445*
		(0.030)	(0.031)

*Significant at 5%
**Standard errors on parameter estimates in parentheses

Table 4-4. Mixed Logit Models: Snapper-Grouper

Variable		Mixed Logit Normal	Uniform
Travel Cost	B	-0.040*	-0.081*
		(0.001)	(0.004)
	s	-0.010*	0.077*
		(0.002)	(0.007)
Snapper	B	0.881*	0.875*
		(0.133)	(0.145)
Grouper	B	3.017*	2.218*
		(0.141)	(0.183)
Red Snapper	B	4.594*	4.854*
		(0.199)	(0.199)
Log(Sites)		0.914*	0.924*
		(0.051)	(0.053)

*Significant at 5%
**Standard errors on parameter estimates in parentheses

Table 4-5. Willingness-to-Pay for one additional fish caught and kept: Dolphin and Big Game

	Mixed Logit (Travel Cost Parameter Randomly Distributed)					
	Normal			Uniform		
	5th Percentile	Mean	95th Percentile	5th Percentile	Mean	95th Percentile
Pr_big	$16.21	$36.86	$523.50	$12.28	$29.76	$471.04
		(27, 47)			(22, 38)	
Pr_small	$10.35	$3.66	$339.91	-$4.77	$2.52	$187.72
		(3, 5)			(2, 3)	
Big game	-$14.50	-$0.52	$329.50	-$7.62	$0.89	$217.31
		(-15, 14)			(-10, 12)	

(95% Krinsky-Robb Confidence Intervals)

Table 4-6. Willingness-to-Pay for one additional fish caught and kept: Mackerel and Small Game

	Mixed Logit (Travel Cost Parameter Randomly Distributed)					
	Normal			Uniform		
	5th Percentile	Mean	95th Percentile	5th Percentile	Mean	95th Percentile
Small game	\$0.46	\$0.92	\$36.66	\$0.29	\$0.55	\$5.03
		(0, 2)			(-0, 1)	
King mackerel	\$3.33	\$6.57	\$262.93	\$1.74	\$3.29	\$30.31
		(-2, 15)			(-3, 10)	
Spanish mackerel	-\$3.02	-\$5.96	-\$238.54	-\$2.55	-\$4.83	-\$44.47
		(-89, -4)			(-7, -3)	

(95% Krinsky-Robb Confidence Intervals)

Table 4-7. Willingness-to-Pay for one additional fish caught and kept: Red Drum and Seatrout

	Mixed Logit (Travel Cost Parameter Randomly Distributed)					
	Normal			Uniform		
	5^{th} Percentile	Mean	95^{th} Percentile	5^{th} Percentile	Mean	95^{th} Percentile
Red drum	\$11.67	\$11.95 (8, 16)	\$12.24	\$5.83	\$10.90 (8, 14)	\$84.13
Spotted Seatrout	\$6.39	\$6.54 (5, 8)	\$6.70	\$3.04	\$5.69 (5, 7)	\$43.92

(95% Krinsky-Robb Confidence Intervals)

Table 4-8. Willingness-to-Pay for one additional fish caught and kept: Snapper-Grouper

	Mixed Logit (Travel Cost Parameter Randomly Distributed)					
		Normal			Uniform	
	5th Percentile	Mean	95th Percentile	5th Percentile	Mean	95th Percentile
	5th	50th	95th	5th	50th	95th
Snapper	$14.61	$21.96 (15, 29)	$43.37	$5.79	$10.82 (7, 15)	$74.51
Grouper	$50.05	$74.95 (66, 85)	$148.58	$14.68	$27.36 (22, 33)	$188.94
Red Snapper	$76.20	$114.28 (103, 127)	$226.23	$32.13	$56.51 (50, 64)	$413.46

(95% Krinsky-Robb Confidence Intervals)

Appendix to Chapter 4

The parameter estimates for the models with all travel cost and catch rate variables mixed are reported herein. While the estimates for the travel cost parameter seem reasonable, the estimated distributions of the catch rate parameters are troubling.

For example, in column 2 of table A4-1, the big game catch parameter is distributed normally with a mean of -15.342 and a standard deviation of 23.197. The 2.5^{th} and 97.5^{th} percentiles are -60.79 and 30.11. 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 distribution. Because the TC is in the denominator of the WTP expression, the 95% confidence interval will explode. 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. This seems implausibly large. The uniformly distributed results are similarly implausible.

Although we will report parameter estimates for the models with random parameters for travel cost and catch rates here, it is our judgment that the results of these models should be viewed with caution. As such, in the document, we focus our attention on the welfare estimates from the models that randomize the travel cost parameters only.

Table A4-1. Fully Mixed Model: Dolphin and Big Game

		Normal B~N(B,s)	Uniform B~U(B-s,B+s)
Travel Cost	B	-0.114	-0.146
		(0.009)	(0.010)
	s	0.062	-0.149
		(0.005)	(0.012)
Pr_big	B	4.226	5.580
		(1.079)	(1.186)
	s	6.227	-12.507
		(1.493)	(2.330)
Pr_small	B	3.082	2.516
		(0.314)	(0.317)
	s	-2.418	-3.097
		(0.604)	(0.722)
Big game	B	-15.342	-13.444
		(4.754)	(5.405)
	s	-23.187	-32.828
		(3.684)	(7.577)
Log(Sites)		-0.025	-0.021
		(0.060)	(0.062)

Table A4-2. Fully Mixed Model: Mackerel and Small Game

		Normal B~N(B,s)	Uniform B~U(B-s,B+s)
Travel Cost	B	-0.085	-0.110
		(0.003)	(0.005)
	s	-0.042	-0.109
		(0.002)	(0.005)
Small game	B	0.045	0.030
		(0.034)	(0.034)
	s	0.031	0.013
		(0.352)	(1.270)
King mackerel	B	-1.012	-1.632
		(0.662)	(0.794)
	s	5.173	-10.261
		(1.530)	(2.680)
Spanish mackerel	B	-3.029	-3.362
		(0.419)	(0.699)
	s	-3.683	-6.301
		(0.408)	(1.093)
Log(Sites)		0.583	0.596
		(0.051)	(0.053)

Table A4-3. Fully Mixed Model: Red Drum and Seatrout

		Normal B~N(B,s)	Uniform B~U(B-s,B+s)
Travel Cost	B	-0.054	-0.067
		(0.001)	(0.001)
	s	0.026	0.065
		(0.012)	(0.002)
Red drum	B	0.646	0.731
		(0.098)	(0.100)
	s	0.037	0.025
		(0.790)	(3.029)
Sea trout	B	0.354	0.382
		(0.032)	(0.032)
	s	0.000	-0.002
		(0.367)	(1.201)
Log(Sites)		0.479	0.445
		(0.030)	(0.031)

Table A4-4. Fully Mixed Model: Snapper-Grouper

		Normal	Uniform
		B~N(B,s)	B~U(B-s,B+s)
Travel Cost	B	-0.047	-0.092
		(0.002)	(0.005)
	s	-0.017	0.089
		(0.003)	(0.008)
Snapper	B	0.869	0.883
		(0.136)	(0.150)
	s	0.001	0.000
		(4.152)	(6.719)
Grouper	B	2.844	2.189
		(0.167)	(0.183)
	s	-0.004	0.001
		(1.257)	(1.958)
Red Snapper	B	6.164	8.992
		(0.684)	(1.243)
	s	-2.962	-9.660
		(0.694)	(1.776)
Log(Sites)		0.916	0.929
		(0.053)	(0.055)

5. Finite Mixture Model

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

$$(5\text{-}1) \quad V(X_{ij}, \beta^t \mid i \in t) = X_{ij}\beta^t + \varepsilon_{ijt}$$

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

$$(5\text{-}2) \quad P(j \mid X_{ij}, \beta^t, i \in t) = \frac{e^{X_{ij}\beta^t}}{\sum_{k \in K} e^{X_{ik}\beta^t}}.$$

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:

$$(5\text{-}3) \quad P(i \in s \mid Z_i, \delta^s) = \frac{e^{Z_i\delta^s}}{\sum_{t \in T} e^{Z_i\delta^t}}$$

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 (5-2) and (5-3) can be constructed for every individual i, tier t to calculate the overall probability of an observed choice Y_i as

$$(5\text{-}4)\quad P_i(j) = \sum_{t \in T} P(i \in t \mid Z_i, \delta^t) \times P(j \mid X_{ij}, \beta^t, i \in t)$$

In effect, using the tier probabilities in (5-3) the estimator mixes the tier-specific site choice models to estimate an overall probability of visiting site j. [9]

Implementation Issues

Although the number of tiers depicted in equation (5-4) 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, denoted crAIC and BIC respectively (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. The test statistics used to facilitate model selection are illustrated in Table 5.1.

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

It is also important to note that our models do not guarantee that we have found a global maximum for the likelihood function because of the mixing property implied by the behavioral heterogeneity distributions. As the number of tiers increases this becomes even more problematic because it increases the number of mixing distributions. This phenomenon could be driving our results when the tiers exceed two for the dolphin and big game, mackerel and small game and snapper-grouper models and three for the red drum and seatrout model. Given the complexity of our empirical model and the number of observations within the data set using alternative solutions methods (e.g., simulated annealing, genetic algorithms, randomization, etc.) would be computationally cumbersome. These combined factors make us more confident in our decision to be more cautious with our selection of tiers.

Welfare Measurement

Welfare measures in a finite mixture model follow closely the formulation found in

[9] In our implementation of the finite mixture model, 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 income for tier j: as income increases the respondent is more likely to be of type j than type 1.

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

$$(5\text{-}5) \quad WTP(X,Y,\beta^t \mid i \in t) = \frac{\ln\left(\sum_{k \in K} e^{X_{ik}^t \beta^t}\right) - \ln\left(\sum_{k \in K} e^{y_{ik}^t \beta^t}\right)}{\beta_{tc}^t}$$

where X and Y 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 Y.

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

$$(5\text{-}6) \quad WTP(X,Y,\beta,\delta) = \sum_{t=1}^{T} \left(\frac{e^{Z_i \delta^t}}{\sum_{j \in T} e^{Z_i \delta^j}} \right) \left[\frac{\ln\left(\sum_{k \in K} e^{X_{ik}^t \beta^t}\right) - \ln\left(\sum_{k \in K} e^{y_{ik}^t \beta^t}\right)}{\beta_{tc}^t} \right]$$

which is found by weighting each tier-specific tier CV with the corresponding probability of being in that tier. In this report when computing confidence intervals for finite mixture models, we take draws from the multinomial parameter distribution which includes each vector of β's and δ's for each tier.

Results

We discuss our results for each of the four species models considered in this report. All of the models we estimate follow a similar structure. The site specific variables (the vector **X**) are comprised of travel cost and the natural logarithm of the number of sites within the aggregate site, and a vector of catch-quality variables relevant for each species-specific model. The socio-demographic variables defining the finite mixture probabilities (the vector **Z**) are comprised of years fished, boat ownership, and the number of days fished within the past two months.

<u>Dolphin and Big Game</u>

The dolphin and big game model results are reported in Tables 5-2 through 5-4. The travel cost parameters are negative and significant across both tiers. Angler site choice in both tiers is not correlated with counties with a high number of interview sites. Furthermore, those decision agents in tier 2 are more responsive to travel costs than tier 1. However, if you weight the travel cost coefficients by the mean probability of tier participation (see Table 5-3) the travel cost coefficient is -0.056, which is similar to that estimated in our conditional logit model. This parameter is also within the distributional range of our 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, big dolphin and big game are both negative and statistically significant. This illustrates that the finite mixture model is sorting anglers based on their preferred targeting strategies.

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.[10] Furthermore, the model places much more weight on an angler being within tier 1 (77%).

The marginal value of catch for each species (point estimate by tier is reported in Table 5-3) generate results consistent with our parameter estimates. Individuals 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. In fact the marginal value of the dolphin catch coefficients in tier 1 are significantly higher than in any other model presented in this entire report.[11]

Comparing these results to the other models estimated, only our estimates of the marginal value for small dolphin is consistent with the mixed logit estimates, whereas the other marginal values are consistently greater than our other estimates. This suggests that caution should be utilized when interpreting these results because the model may not be well suited for a relatively small number of cases (this is the model with the second smallest number of observations, n=823, in a single species setting).

In Table 5-4 we present the tier probability weighted willingness-to-pay values and 95% confidence intervals. The confidence intervals for big dolphin and big game willingness-to-pay values overlap while small dolphin willingness-to-pay is significantly lower.

Mackerel and Small Game

The mackerel and small game results are illustrated in Tables 5-5 through 5-7. In both tiers sites further away are avoided and anglers seek sites with higher catch rates with the exception of king mackerel that possesses a negative yet statistically insignificant coefficient for both tiers.

Comparing the parameter estimates to the conditional and mixed logit results illustrates that 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

[10] Fishing experience could also be serving as a proxy for age and/or income.
[11] Please note that restricting our model to only 1 tier exactly reproduces the results for the basic logit models presented elsewhere in this report.

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 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, it is evident that anglers with fewer years of fishing experience and an increase in 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. More experienced angler site choice is also positively correlated with counties with a larger number of available interview sites.

The results in Table 5-6 show that the marginal value of catch 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. However, given that each individual possesses a continuous probability of being in each tier the “true” representation of each angler is a mixture of the two tiers. Weighting the mean values by the mean tier participations (0.65 and 0.35 for tiers 1 and 2 respectively) generates a marginal value of 18.92, -25.61, and 13.06 for small game, Spanish mackerel and king mackerel respectively, which are consistent with the welfare estimates illustrated in Table 5-7.

Comparing the welfare estimates in Table 5-7 with the conditional and mixed logit estimates illustrate a number of different asymmetries. The willingness-to-pay for small game is greater in the finite mixture model than either the conditional logit or mixed logit models. It is roughly six times the conditional and mixed logit estimates. The welfare measures for king mackerel are negative whereas they are positive in the conditional and mixed logit models. Finally, the welfare measures for Spanish mackerel are positive when they are negative in the conditional and mixed logit models. Therefore, the finite mixture model results indicate that anglers prefer Spanish mackerel over king mackerel, whereas the conditional and mixed logit models indicate the opposite. This result does suggest that caution should be used when utilizing these results for policy recommendations.

Red Drum and Seatrout

The red drum and seatrout model is the only model for which we were able to reliably estimate the tier specific parameters and welfare estimates beyond two tiers (Table 5-8). This is most likely due to the large sample size for this model (n=4353) relative to the other models estimated. In all tiers, sites with higher costs are avoided on average by anglers.

The catch coefficients for the two species illustrate that all three tiers value red drum catch and that tiers 1 and 3 value sea trout 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 but prefer to fish in counties with a lower number of sites. Therefore, once again, the finite mixture results appear to be sorting anglers based on their species catch preferences.

Looking at the parameters that determine tier participation it is evident that anglers who have fished a lot 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. Tier 3 (41%) is ranked the highest with tier 1 (38%) ranking second and tier 2 (21%) ranking third.

Table 5-9 illustrates the tier-specific marginal value for each species. Tier 1, the more experienced anglers, possesses the highest marginal value for drum and sea trout. Tier 2 possesses a slightly lower marginal value for drum but have a negative value for sea trout. Finally tier 3, the more inexperienced segment, possesses positive marginal 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.

Table 5-10 illustrates the predicted population welfare estimates which are all larger than those observed in the conditional and mixed logit models, but closer than those observed for the dolphin and mackerel fisheries. The marginal valuations for drum are roughly 72% greater than in the conditional logit model and between 80% and 100% greater than those within the mixed logit models. However, the finite mixture estimates are within the range estimated under the uniform mixing distribution mixed logit model. Marginal value estimates for sea trout are roughly 48% greater than the conditional logit model estimates and between 79% and 105% greater than the mixed logit estimates, but again within the welfare distribution estimated under the uniform mixing distribution.

Snapper-Grouper

The results for the snapper-grouper model are illustrated in Tables 5-11 through 5-13. Both tiers 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. Whereas with the earlier results we were able to 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. Table 5-12 illustrates the tier-specific marginal valuations for the different species. These results illustrate that the tier 1 anglers possess much higher marginal value for all three species. This is consistent with our earlier tier-specific welfare estimates where the more experienced anglers have larger marginal valuation for the species than less experienced anglers. Therefore, the finite mixture model is yet again sorting anglers according to their species valuation preferences because those anglers in tier 1 possess a higher marginal value for all three species.

The tier-weighted species-specific welfare estimates indicate that the average marginal value for grouper is 97.59, 9.44 for snapper and 102.86 for red snapper. The estimated marginal values for grouper and red snapper are consistent with those observed in the conditional and mixed logit models, whereas the snapper estimates are over 50% lower than those observed in the conditional and mixed logit models. Although the tier-specific estimates for tier 1 are lower than the conditional and mixed logit estimates for snapper, the largest decrease in value is driven by the low estimates for tier 2, combined with the high probability mass it possesses (40%).

Discussion

Because the estimated parameters are driven by the data, it is often difficult to provide intuitive explanations for differences across tiers (e.g. why one group is more travel cost sensitive than another) except to say that unlike simpler (and perhaps less realistic) models that do not allow for differences across anglers (e.g. the conditional logit model), this allows for different utility functions across anglers and does so in a way that is traceable back to socioeconomic factors.

Using finite mixture models to allow for angler heterogeneity has been a useful exercise. To sum up our overall conclusions, we tend to find at least two tiers with one valuing catch more highly and more willing to incur higher travel costs to attain these higher quality sites. This group, on average across models, tends to be more experienced and fish less avidly than other anglers. In all of our models, the probability mass assigned to this group is always non-trivial. The identification of this segment of anglers- and to see how the size of this segment varies over particular species- may be of great interest to fisheries managers. The finite mixture model allows for this kind of identification and is the only such model presented in this report capable of doing so.

We did encounter issues with our implementation of the finite mixture models. In particular, we found that a large number of observations are required in order to identify meaningful models with more than 2 tiers (the red drum and seatrout model with 4353 observations was the only model with more than two tiers). Consequently, the use of finite mixture models for small numbers of observations may or may not be fruitful and may vary on a case-by-case basis. The dolphin and big game model seems to be missing the mark by a very wide margin, yet the snapper-grouper model with only a few more observations performs very well relative to the standard logit and mixed logit models.

Table 5-1. Bayesian (BIC) and corrected Akaike Information Criteria (AIC)

Models	Dolphin		Drum		Grouper		Mackerel	
Tiers	BIC	crAIC	BIC	crAIC	BIC	crAIC	BIC	crAIC
T=1	-1795	-3613	-24902	-24926	-4719	-4744	-8087	-8114
T=2	-1373	-2812	-23044	-23121	-3709	-3778	-7073	-7148
T=3	-1318	-2744	-22883	-23011	-3614	-3728	-6889	-7012
T=4	-1265	-2681	-22619	-22797	-3343	-3501	-6810	-6980

Table 5-2. Finite Mixture Model: Dolphin and Big Game

Tier	Variable	Coeff.	Std. err.	t-statistic	p-value
1	Travcost	-.0110	.0016	-6.6844	0
	Log(sites)	-.2251	.1073	-2.099	.0361
	Pr_big	5.938	.9593	6.190	0
	Pr_small	.2949	.0723	4.0782	0
	Big game	2.9821	1.0135	2.9423	.0034
2	Travcost	-.2022	.0176	-11.4726	0
	Log(sites)	-.0668	.0775	-.8610	.3895
	Pr_big	-0.6886	.8947	-.7696	.4417
	Pr_small	2.9917	.4834	6.1887	0
	Big game	-9.3887	2.3019	-4.0787	0
tier=2	Constant	.3609	.2457	-1.4687	.1423
	Ffdays2	24.5601	3.8818	6.3269	0
	Yearfish	-1.7799	.8121	-2.1918	.0287
	Boatown	1.0896	.2371	4.5966	0
	Log Likelihood: -1308.13				

Table 5-3. Tier-Specific Willingness-to-Pay for one additional fish caught and kept: Dolphin and Big Game

	Tier 1	Tier 2
Pr_big	539.82	-3.41
Pr_small	26.81	14.80
Big game	271.10	-46.43
Probability	0.7656	0.2344

Table 5-4. Willingness-to-Pay for one additional fish caught and kept: Dolphin and Big Game

	Pr_big	Pr_small	Big Game
Lower 95%	272.08	13.36	55.22
Mean	411.75	23.44	202.27
Upper 95%	605.84	34.57	339.50

Table 5-5. Finite Mixture Model: Mackerel and Small Game

Tiers	Variable	Coeff.	std. error	t-statistic	p-value
1	Travcost	-.0161	.0010	-16.4607	0
	Log(sites)	0.9700	0.0870	11.1440	0
	Small game	0.4735	0.0676	7.0039	0
	King mackerel	-0.6093	0.7494	-0.8131	0.4163
	Spanish mackerel	0.3960	0.1213	3.2657	0.0011
2	Travcost	-.1994	.0130	-15.3814	0
	Log(sites)	-0.0193	0.0892	-0.2163	0.8288
	Small game	-0.1779	.0559	-3.1798	.0015
	King mackerel	-0.4964	.5014	-.9900	.3223
	Spanish mackerel	-1.7410	.2450	-7.1065	0
Tier=2	Constant	.9496	.2052	4.6273	0
	Ffdays2	2.6898	.8075	3.3310	.0009
	Yearfish	-1.8621	.5208	-3.5752	.0004
	Boatown	-.1532	.1864	-.8215	.4115
	Log Likelihood: -3587.98				

Table 5-6. Tier-Specific Willingness-to-Pay for one additional fish caught and kept: Mackerel and Small Game

	Tier 1	Tier 2
Small game	29.41	-0.89
King mackerel	-37.84	-2.49
Spanish mackerel	24.60	-8.73
Probability	0.6539	0.3461

Table 5-7. Willingness-to-Pay for one additional fish caught and kept: Mackerel and Small Game

	Small game	King mackerel	Spanish mackerel
Lower 95%	13.24	-83.00	3.50
Mean	18.84	-22.68	13.38
Upper 95%	24.57	40.67	24.03

Table 5-8. Finite Mixture Model: Red Drum and Seatrout

Tier	Variable	Coeff.	Std. Error	t-statistic	p-value
1	Travcost	-.0143	.0006	-25.7355	0
	Log(sites)	.3834	.0532	7.2074	0
	Red drum	.4609	.1007	4.5785	0
	Seatrout	.3598	.0286	12.5611	0
2	Travcost	-.0773	.0060	-12.9921	0
	Log(sites)	1.5877	.1549	10.2467	0
	Red drum	2.3884	.2493	9.5784	0
	Seatrout	-.3194	.2858	-1.1177	.2638
3	Travcost	-.2142	.0140	-15.3267	0
	Log(sites)	-.4404	.1085	-4.0590	.0001
	Red drum	1.6619	.3530	4.7086	0
	Seatrout	1.5383	.1223	12.5796	0
Tier=2	Constant	-.5938	.2172	-2.7336	.0063
	Ffdays2	2.0561	.9991	2.0580	.0396
	Yearfish	-.9029	.5660	-1.5951	.1108
	Boat own	.0217	.1993	.1090	.9132
Tier=3	Constant	.0024	.1294	.0184	.9853
	Ffdays2	1.7822	.5984	2.9781	.0029
	Yearfish	-.5295	.3079	-1.7194	.0856
	Boatown	.0540	.1198	.4511	.6519
	Log Likelihood: -11525.53				

Table 5-9. Tier-Specific Willingness-to-Pay for one additional fish caught and kept: Red Drum and Seatrout

	Tier 1	Tier 2	Tier 3
Red drum	32.23	30.90	7.76
Sea trout	25.16	-4.13	7.18
Probability	0.3837	0.2068	0.4095

Table 5-10. Willingness-to-Pay for one additional fish caught and kept: Red Drum and Seatrout

	Red Drum	Seatrout
Lower 95%	16.45	9.51
Mean	21.75	11.70
Upper 95%	27.22	13.75

Table 5-11. Finite Mixture Model: Snapper-Grouper

Tier	Variable	Coeff.	Std. Error	t-statistic	p-value
1	Travcost	-0.0165	0.0011	-15.5681	0
	Log(sites)	1.6535	0.1106	14.9553	0
	Grouper	2.2465	0.1196	18.7784	0
	Snapper	0.2236	0.0507	4.4132	0
	Red snapper	2.7083	0.1850	14.6362	0
2	Travcost	-0.3421	.0302	-11.3290	0
	Log(sites)	-.2546	.1500	-1.6975	0.0899
	Grouper	13.9047	1.0657	13.0479	0
	Snapper	.9543	.1610	5.9283	0
	Red snapper	3.7111	.4903	7.5692	0
Tier=2	Constant	-.5392	0.1805	-2.9877	0.0029
	Ffdays2	2.0512	1.1476	1.7875	0.0741
	Boatown	1.3663	.1830	7.4645	0
	Experience	-0.2608	0.6028	-0.4326	0.6654
	Log Likelihood: -1903.3998				

Table 5-12. Tier-Specific Willingness-to-Pay for one additional fish caught and kept: Snapper-Grouper

	Tier 1	Tier 2
Grouper	136.15	40.65
Snapper	13.55	2.79
Red Snapper	164.14	10.85
Probability	0.5996	0.4004

Table 5-13. Willingness-to-Pay for one additional fish caught and kept: Snapper-Grouper

	Grouper	Snapper	Red Snapper
Lower 95%	88.14	5.82	87.43
Mean	97.59	9.44	102.86
Upper 95%	109.57	13.29	121.07

6. 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 economics literature because they facilitate the investigation of the preference heterogeneity within the subject pool. To date, these methods are rarely compared to the other, however they are both usually compared to the standard conditional logit model that provides their foundation.

Single-Species Modeling

We determine that the MRFSS data will support only a few species-specific recreation demand models. We find sufficient evidence to suggest that single species target models are an important consideration when modeling marine recreational fishing demand. The 95% 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.

Willingness-to-pay Comparisons

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 the high degree of preference heterogeneity in the MRFSS data that may call into question the validity of the willingness-to-pay estimates from the traditional conditional and nested logit models.

In order to summarize our results, the willingness-to-pay values for one additional fish from each of the four models are presented in Table 6-1. We present the midpoint estimate from the mixed logit and finite mixture models. One criterion for choosing appropriate welfare measures is convergent validity. 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.

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 (i.e., confidence intervals overlap). 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 with each other. However, the preference heterogeneity models 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 small and 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, ranging from $12 to $22, with overlapping confidence intervals. We conclude that each model is convergent valid and we have high confidence in the welfare measures generated from each. The seatrout results are similar with only the finite mixture model estimate having a non-overlapping confidence interval.

Red snapper willingness-to-pay values range from $39 to $123 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 catch 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.

Overall Model Performance

In Table 6-2 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.

(6-1) $$RMSE = \frac{\sqrt{\sum_{i=1}^{K}(S_i^p - S_i^a)^2}}{K}$$

where S_i^p is the predicted share averaged over the entire 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% lower than the others. Similar to the consistency of willingness-to-pay across red drum and seatrout models, 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%, 11% and 53% lower than that of the conditional logit models.

Discussion

In 2 of our 4 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 2 models our results provide evidence that leads to defensible conclusions. We determine that 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 some times 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.

Future Research

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. 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.

Since there are a large number of policy simulations that can be run with the estimated models we focus our attention on estimating the marginal value of catch and keep rates. Each of the logit models that we present are capable of supporting a range of other policy analyses, for example, spatial and targeting changes in response to a situation where catch of the single species (i.e., dolphin, red snapper) is limited to zero or if fishing areas are closed.[12]

Revealed preference models of recreation behavior rely on observable variation in real-world conditions in order to quantify value for environmental amenities. In a recreation demand context, spatial variation in site-specific amenities is exploited for uncovering these tradeoffs. Unfortunately, there is very little to no spatial variation in management measures for the species considered here. By design, managers typically apply blanket size, bag, and seasons across counties and states in order to avoid confusion among anglers and debates about fairness.

Beyond the need for spatial variation in recreational management instruments, there are two additional issues that must be carefully considered in order to successfully capture regulation in recreation demand models of recreational fishing. The first issue concerns what fishermen value. Do fishermen value management measures directly or only as it pertains to their expectation of the fish they might take home at the end of a days fishing? This important question has received too little attention. While there are examples of stated preference studies that incorporate regulation directly into the indirect utility function, a more realistic approach is perhaps something along the lines of McConnell, Strand and Blake-Hedges (1995). This approach relies on the ability to identify expected catch models for each species in question and is useful for an analysis of bag limit changes only.

The second issue is the relative value of harvest versus release fishing. One behavioral response to more stringent management is to simply continue fishing but release whatever is caught over the limit. To capture preferences over both caught/kept and caught/released fish, the econometric model requires the ability to estimate the relative value of each of these types of fishing, and along with it, it is necessary to have spatial variation in catch versus catch and release rates. This further stratifies the MRFSS data and is simply too nuanced to be captured for the models presented here.

This research also raises questions about older recreation demand analyses with the MRFSS that are currently being used for policy analysis by the NMFS (Hicks, Steinbeck, Gautam and Thunberg, 1999; Haab, Whitehead and McConnell, 2001). Given the uncertainty of our conclusions, these older estimates must be considered policy relevant still. However, these models are dated. When they were developed, limited computing power constrained estimation to 2 stage limited information maximum likelihood nested logit models. With improved computing power, full information maximum likelihood nested logit models are possible, even with the large number of alternatives in the previous models. We recommend that full information maximum likelihood nested logit

[12] These analyses can be conducted with modifications to the computer programs available at the project website at http://econ.appstate.edu/marfin.

models with choice structures more consistent with past analyses be estimated and compared to determine the accuracy of the 1999 and 2001 reports.

All willingness-to-pay estimates are conditional on decisions made when developing the data. Expanding the data to include other fishing sites is likely to reduce willingness-to-pay. Only targeted species are included in each model. Expanding the data to include trips that do not target species or trips that catch the species included here by anglers not targeting those species is likely to reduce willingness-to-pay. Future research should examine the sensitivity of our results to these data management decisions.

Finally, our analysis is somewhat constrained by our choice of the 2000 MRFSS southeast add-on data. We chose the 2000 data over the 1997 add-on data due to its increased sample size and increased ability to support single-species models. However, even with the 2000 add-on we find that only four single-species models are supported. Future research should consider using the MRFSS data without the additional features of the add-on surveys to consider single-species models. MRFSS data without add-ons can support recreation demand analysis if simplifying assumptions are made about the opportunity cost of time and single-day trips. Zip code level income can be used instead of elicited income and reasonable single-day round-trip mileage cutoffs can be used instead of elicitations of single-day trips. These models can be compared to add-on data models to determine the tradeoff between the bias of simplifying assumptions and the efficiency of increased sample size.

Preference heterogeneity models may be more successfully implemented with the 1997 MRFSS add-on data that includes information on the number of mode and site-specific trips made by each angler in a two month wave (Haab, Whitehead and McConnell, 1997). Future research should use these data in preference heterogeneity models in comparison to the more traditional conditional logit and nested logit models. In this case the single-species target constraint must be dropped in order to have sufficiently large samples for analysis.

There are a large number of other issues that could be considered. We focused our analysis on the most basic specifications of utility functions. Extensions to the utility function that could be pursued are inclusion of alternative specific constants. Extensions that could be pursued that directly address preference heterogeneity besides the mixed logit and finite mixture models include interacting socioeconomic variables with alternative specific constants and choice attributes. We also adopt naïve choice sets based on convenience. It might be more appropriate to develop choice sets based on feasibile distance travelled or other criteria. Other results may be sensitive to any of these issues.

Table 6-1. Willingness-to-pay for One Additional Fish Caught and Kept

	Conditional Logit	Nested Logit	Mixed Logit[a]	Finite Mixture Model[b]
Dolphin (> 20”)	$123 (100, 147)	$103 (81, 126)	$37 (27, 48)	$412 (272, 606)
Dolphin (< 20”)	$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 WTP
[c]Predicted catch longer than 20”
Note: 95% confidence interval in parentheses.

Table 6-2. 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

References

Bockstael, Nancy, Kenneth McConnell, and Ivar Strand, “A Random Utility Model for Sportfishing: Some Preliminary Results for Florida,” *Marine Resource Economics* 6:245-260, 1989.

Gentner, Brad, Michael Price and Scott Steinback, Marine Angler Expenditures in the Southeast Region, 1999, NOAA Technical Memorandum NMFS-F/SPO-48, August 2001.

Green, Gretchen, Charles B. Moss, and Thomas H. Spreen, “Demand for Recreational Fishing Trips in Tampa Bay Florida: a Random Utility Approach,” *Marine Resource Economics* 12:293-305, 1997.

Haab, Timothy C. and Robert Hicks, “Choice Set Considerations in Models of Recreation Demand,” *Marine Resource Economics* 14:271-282, 1999.

Haab, Timothy C., John C. Whitehead, and Ted McConnell, “The Economic Value of Marine Recreational Fishing in the Southeastern United States. 1997 Southeast Economic Data Analysis,” NOAA Technical Memorandum NMFS-SEFSC-466, September 2001.

Hicks, Rob, Scott Steinbeck, Amy Gautam, and Eric Thunberg, “Volume II: The Economic Value of New England and Mid-Atlantic Sportfishing in 1994,” NOAA Technical Memorandum NMFS-F/SPO-38, August 1999.

Hicks, Robert L., Amy B. Gautam, David Van Voorhees, Maury Osborn, and Brad Gentner, “An Introduction to the NMFS Marine Recreational Fisheries Statistical Survey with an Emphasis on Economic Valuation,” *Marine Resource Economics* 14:375-385, 1999.

MacLachlan, Geoffrey and David Peel. 2000. *Finite Mixture Models*. John Wiley & Sons, Inc. New York.

McConnell, Kenneth and Ivar Strand, Volume II: The Economic Value of Mid and South Atlantic Sportfishing, National Marine Fisheries Service, 1994.

McConnell, Kenneth, Ivar Strand and L. Blake-Hedges, "Random Utility Models of Recreational Fishing: Catching Fish Using a Poisson Process," *Marine Resource Economics* 10:247-61, 1995.

McConnell, Kenneth E., and Ivar E. Strand, “Overnight Trip Choice for Marine Anglers,” Report on NMFS Contract Number 40ANF804203, 1999.

Parsons, George R., and Michael S. Needelman, “Site Aggregation in a Random Utility Model of Recreation,” *Land Economics* 68(4):418-433, 1992.

Schuhmann, Pete, “Deriving Species-Specific Benefits Measures for Expected Catch Improvements in a Random Utility Framework,” *Marine Resource Economics* 13:1-21, 1998.

Train, Kenneth E., *Discrete Choice Methods with Simulation*, Cambridge University Press, 2003.

Whitehead, John C. and Timothy C. Haab, “Southeast Marine Recreational Fishery Statistics Survey: Distance and Catch Based Choice Sets,” *Marine Resource Economics* 14:283-298, 1999.