Summer Flounder Allocation Analysis

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U.S. Department of Commerce
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1.0 Abstract

This report examines the current summer flounder allocation and makes recommendations as to the optimal allocation between recreational and commercial users based on the equimarginal principle. Commercial estimates of the marginal value of a pound of summer flounder are generated using a dual revenue model of this multi species fishery. On the recreational side, several random utility site choice models are estimated for summer flounder harvest using data collected from the Marine Recreational Fisheries Statistical Survey (MRFSS), including a model weighted to account for choice based sampling in the MRFSS survey. Proxy estimates are generated for the for-hire recreational industry because no cost and earnings data exists for this sector. Consumer marginal values are estimated from an almost ideal demand system using dockside prices. The modeling results indicate that the total value to society would increase if the allocation shifted further in the direction of the recreational sector. Unfortunately, uncertainty in the recreational estimates and limitations in the recreational demand modeling make it impossible to define the optimal allocation point.

2.0 Introduction

The summer flounder stock has been under a rebuilding plan since 1993 and stocks are increasing. At the same time the stocks are increasing recreational and commercial catch limits have been regularly exceeded. This has lead to increasingly restrictive management for both sectors while each sector advocates for the relaxation of restrictions in the face of improving stocks. Compounding this problem, the recreational sector believes the current allocation to be unfair and has advocated increasing their quota share.

Recreational effort has been on the rise in all recreational fisheries including the summer flounder fishery. Total catch and harvest have increased due to increased effort and increased catch per unit effort (CPUE). Increasing CPUE suggests that the stock is indeed improving. While not addressed in this report anglers are attracted to improved catch rates, which at least partially explains the increasing effort. However, increasing effort and increasing CPUE means that it is easier to exceed harvest targets, and summer flounder harvest targets have been exceeded during two of the last five years, with overages in both years exceeding 25%.

This two edged sword of increasing harvests on one side and a rebuilding plan with strict harvest limits on the other side, is a recipe for further ratcheting down of regulations on summer flounder anglers. Increased restrictions have lead for calls by the recreational community to revisit the commercial recreational split which currently stands at 60% commercial and 40% recreational

While the resource is not in serious trouble, the Atlantic States Marine Fisheries Commission and the Mid-Atlantic Fishery Management Council are concerned about the allocation of the resource among competing user groups including commercial fishermen and recreational anglers. Based on the reported or estimated landings and catch of summer flounder, it is clear that summer flounder is an important species for the two user groups. A major question, therefore, is whether or not there is an allocation between the two groups, which might enhance overall net benefits to society. This report details the calculation of marginal benefits across the private recreational anglers, consumers, and commercial fishermen. This report begins with a review of catch and effort trends in the fishery followed by commercial valuation, consumer valuation, and recreational valuation chapters.

2.1 Background and Trends

Summer flounder, *Paralichthys dentatus***,** is an important commercial and recreational species. Summer flounder is also known as fluke, and may occasionally be misidentified as a southern flounder (*Paralichthys lethostigma)*. Both species are left-eyed flounder, which means its eyes are on the upper surface of the head when the fish is facing left. Summer flounder are distributed from the coastal waters of the southern gulf of Maine to Florida, with large concentrations in the Mid-Atlantic region of the northwest Atlantic. They grow up to 32 inches in length and may weigh up to approximately 15 pounds. Their approximate maximum age is 10 years.

The most recent stock assessment for summer flounder indicates that although summer flounder are not overfished, the biomass has not recovered to desired levels (Terceiro, 2006)[1]. The assessment also indicated, however, that overfishing was occurring in 2005, and that the current level of fishing mortality (0.407) was above the target and threshold fishing mortality rates of 0.280. The abundance of most age classes did increase over the past ten years, but the 2005 year class was estimated to the be the smallest since 1988—approximately 15.0 million fish (Terceiro, 2006).

Of the total volume (weight in pounds) caught and landed or retained between 1981 and 2006, the recreational sector accounted for 39.0 % of the total summer flounder caught and retained. In four of the years (1997, 1998, 2000, and 2001) between 1981 and 2006, recreational harvest accounted for more than 50 % of the total weight of all summer flounder caught and retained by commercial fishermen and recreational anglers. Over the entire 1981 through 2006 period, the recreational sector has accounted for 39.0 % of the total landings, while the commercial sector has accounted for 61.0 % of the total landings of summer flounder.

2.1.1 Commercial Trends

Summer flounder is an important commercial species from Cape Hatteras to Cape Cod. The summer flounder stock migrates from inshore waters to offshore waters, and they are concentrated in coastal bays and estuaries from late spring through autumn when they move to the outer continental shelf for the winter. Spawning occurs offshore and larvae are pushed into estuaries by prevailing water currents. This seasonality is an important part of the commercial fishery.

The otter trawl is the predominate gear type in the summer flounder fishery and Figure 2.1 displays summer flounder landings by gear type. There are two major trawl fisheries; a winter offshore fishery and a summer inshore fishery. The percentage of landings coming from the otter trawl fishery has ranged from almost 93% to a low of 64% in 2007 with other gear use increasing dramatically since 2003. There are a number of other gears used in the fishery including; pots, dredges, pound nets, gill nets, hoop nets, fyke nets, hand lines, long lines, beam trawls, and others. Only dredge (5.9%), line (3.5%), and pound net (1.6%) gear types exceeded one percent of landings in 2007. For gears other than otter trawl, their catch of summer flounder is better characterized as bycatch whereas the otter trawl gear, while a multi-species fishery, catches a higher proportion of summer flounder.

Harvests for summer flounder peaked in 1983 at 57.5 million pounds and has declined since (Figure 2.2). Recognizing a declining harvest trend after 1983, summer flounder's first management plan was put in place. 1991 saw the definition of overfishing and it was found that the summer flounder stock had been undergoing overfishing since 1982. A rebuilding schedule was developed in 1993 requiring limited entry, reporting requirements and input regulations mainly focusing on mesh size. Recreational harvest limits were also established in 1993 along with size limits. Currently, recreational and

[1]Since the first submission of this work as a grant ending report, an updated stock assessment has been completed (Terceiro, 2009). The author's chose to not update this section of the report with the updated stock assessment as the data underlying all the analysis in this report is tied to the same year (2006) as the previous stock assessment. Because all analysis results are conditional on the stock in 2006, it was decided to leave the stock information from the 2006 assessment.

commercial total allowable catches (TACs) are assigned to the states for management and the states can transfer quota to each other.

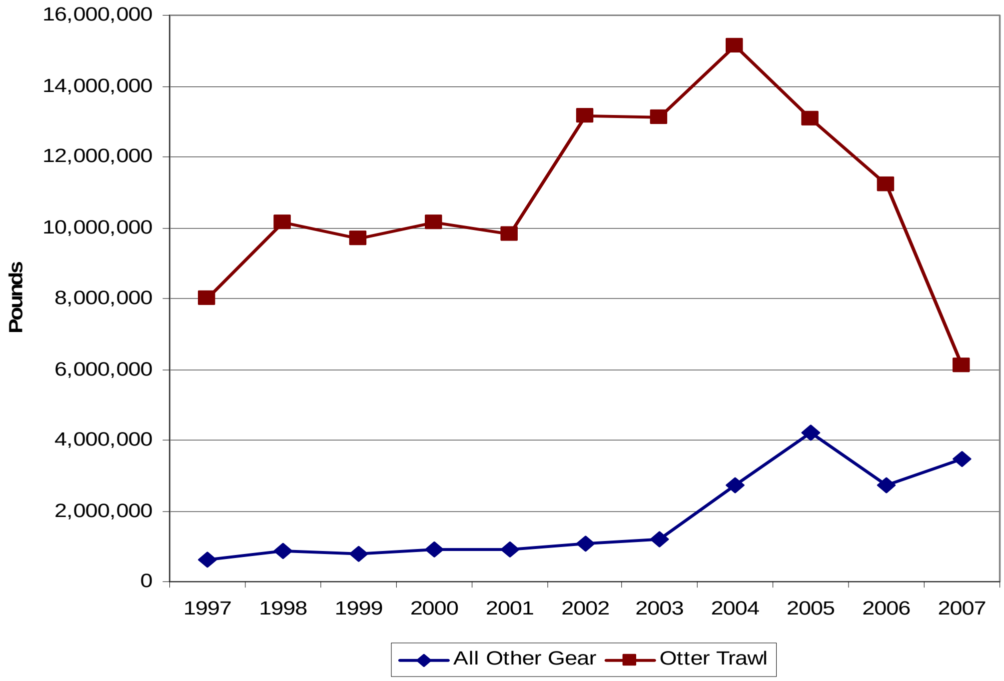

Figure 2.1. Landings by Gear Type, 1997-2007

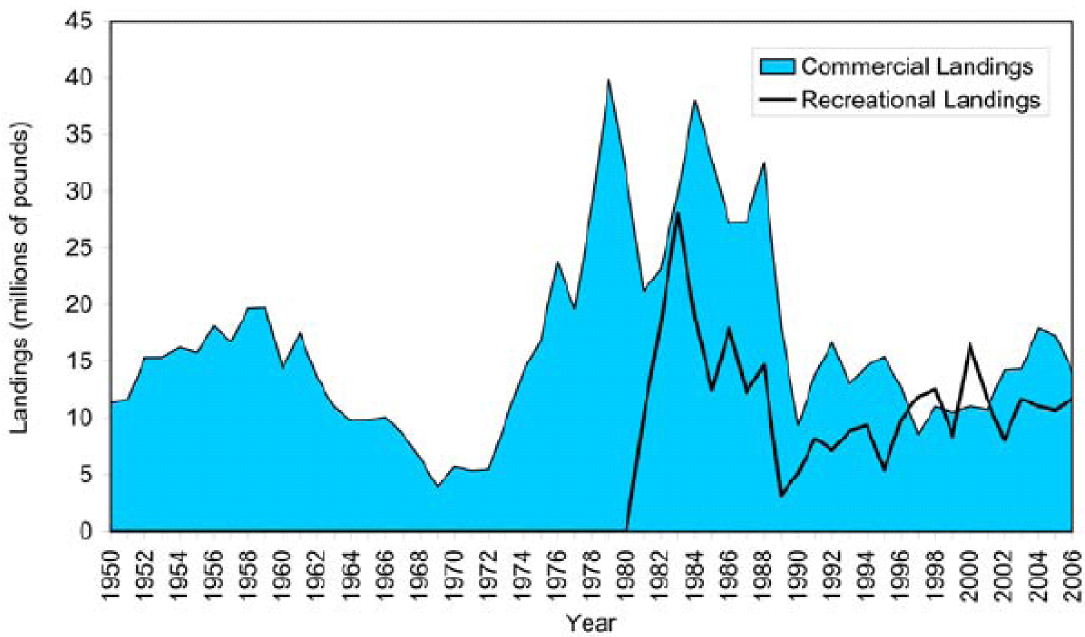

Figure 2.2. Summer Flounder Commercial and Recreational Landings (Terceiro, 2006)

Currently the summer flounder fishery is not a directed fishery but a bycatch fishery. This is mainly driven by low TACs during the rebuilding phase. As the stock rebuilds, abundance increases causing commercial fishermen to catch summer flounder in areas where they haven't been in years. As a result, commercial fishermen feel they are being kept out of this fishery unnecessarily. This is same stock recovery trap felt by the recreational anglers. Bycatch of summer flounder is high for otter trawl caught fish and, as abundance increases, more and more summer flounder are caught in the indiscriminate otter trawl gear. Due to the low TACs, less fish are being landed but mortality is still high.

As of the most recent stock assessment, summer flounder is not overfished and not experiencing overfishing, but the stock is not rebuilt yet. The current rebuilding schedule has the stock rebuilt by 2013 (Terceiro 2006). 2007 represents the first year the stock was not overfished since 1982. Figure 2.3 shows the spawning stock biomass threshold and target. The stock has been below the threshold since 1982. In 2001, the stock climbed above the threshold, but is still well below the target. Current spawning stock biomass target is 132 million pounds and the stock is at 72% of that level. Recent stock assessments used a new model that allows a higher TAC. The 2009 TAC was up 2.68 million pounds from the 2008 TAC to 18.45 million pounds split 11.07 million pounds for the commercial sector and 7.38 million pounds for the recreational sector.

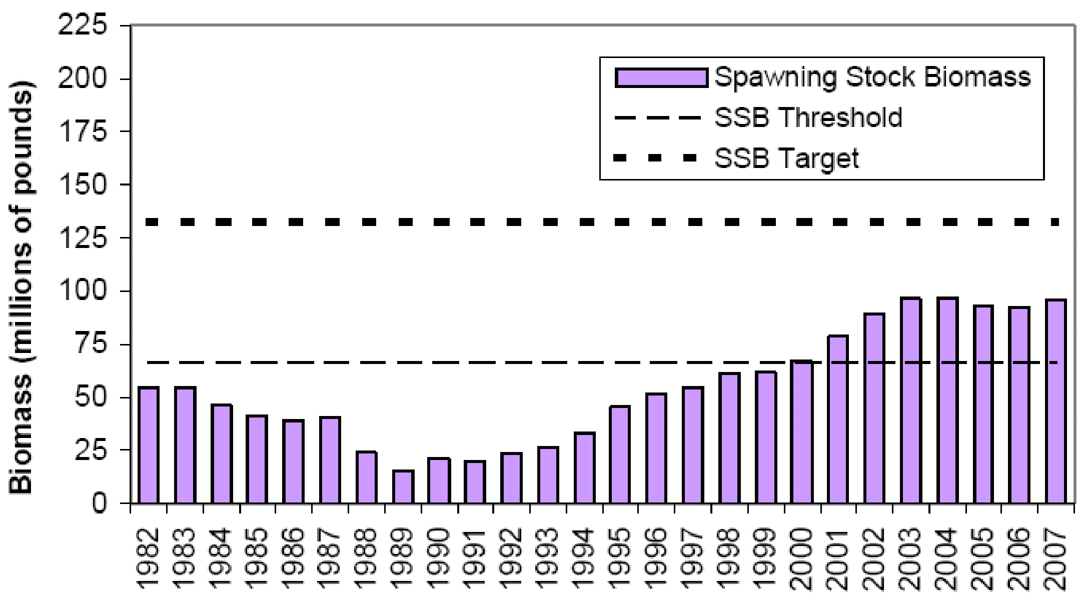

Figure 2.3. Summer Flounder Spawning Stock Biomass (Terceiro, 2006)

The remainder of the commercial analysis will focus on the otter trawl commercial gear type for a number of reasons. All other gear types harvest a very small portion of the catch. Also, all the other gear types are very different from the otter trawl and different from one another with regards to their cost structures. The other gear types are more aptly described as by-catch fisheries while summer flounder makes up a significant percentage of the otter trawl catch. Finally, and most importantly, cost data is far better for otter trawls. The National Marine Fisheries Service (NMFS) uses the observer program to collect trip cost information and many of the other gear types operate in state waters only. Boats operating in state waters are not required to carry observers, and, as such, no trip costs information is collected for those gear types.

2.1.2 Recreational Trends

Summer flounder is caught recreationally from North Carolina through New Hampshire, with the majority of the harvest coming from Virginia northward. During the last ten years, no summer flounder landings have been reported in Maine. Summer flounder fishing is very popular in the Northeast accounting for 22% of all recreational effort for all species. Figure 2.4 details total effort and two definitions of summer flounder directed effort. The American Fisheries Society (AFS) defines directed effort as any trip that caught and/or targeted summer flounder. This definition is used to estimate the line in Figure 2.4 entitled "Targeted and Caught." NMFS occasionally defines directed effort as only those trips where summer flounder was caught. This definition is also included in Figure 2.4. While summer flounder effort has increased 14% under the more conservative definition and 15% under the AFS definition, total effort is up 24%.

Summer flounder is considered an excellent food fish which increases it attractiveness as a target for recreational anglers. Figure 2.5 displays total catch trends from 2002 to 2006. The Marine Recreational Fisheries Statistical Survey (MRFSS) has three types of catch: harvest measured and weighed by an interviewer (type A); catch not seen by an interviewer but released dead or otherwise dead but not observed by an interviewer (type B1); and catch released alive and not observed by an interviewer (type B2). The summer flounder stock assessment assumes 10% recreational release mortality (Terceiro 2006). For the purpose of this report, total catch is defined as A + B1 + B2 catch while harvest is defined as A + B1. It is important to note that both types B1 and B2 represent self reported data.

In 2006, 22.2 million summer flounder were caught. Total catch during over the five years in Figure 2.5 has gone up 33% with a sharp rise in 2005 where catch was up 62% since 2002. The private boat mode dominates all fishing modes catching 18.8 million fish, or 85% of the harvest. Shore and for-hire fishing modes are distant followers with the for-hire mode overtaking the shore mode in 2006 with 2.4 million fish and 11% of the total.

Figure 2.6 details summer flounder harvest (A + B1) by mode. In 2006 4.2 million fish were harvested. Looking back at Figure 2.5, this means that 81% of all summer flounder caught are released because regulations forced the release or the fish were released for conservation reasons. It is no longer possible in the MRFS to separate released fish into fish released for regulatory reasons or fish released for conservation reasons. In 2004 the MRFSS eliminated the use of the disposition code in the intercept survey that indicates whether the fish released alive was large enough to keep. Trends in release vary considerably by mode. The shore mode has the smallest release percentage at 65% released followed by the private boat and for-hire modes with 80% and 95% release rates respectively. Again, the private boat mode dominates 2006 harvest with 3.7 million fish followed by the shore and for-hire modes with 381,053 and 129,701 fish respectively.

Looking at harvest weight per fish (Figure 2.7) and catch per unit effort (CPUE) (Figure 2.8) fishing quality is on the rise for every mode except the shore mode. Harvest weights are up, except for the shore mode: up 17% in the private boat mode, up 4% in the for-hire mode; and down 17% in the shore mode. This of course is partially driven by higher minimum size limits, but when coupled with increasing CPUE, it suggests quality is on the rise. There is an unexplained drop in weight per fish for the for-hire mode in 2004. CPUE is also up in all modes except the shore mode. CPUE is a direct measure of quality and is up 33% for the for-hire fleet, up 16% for the private boaters, but is completely flat for the shore mode since 2002. In 2005, the shore mode was up 32% over 2002, potentially indicating that other factors besides stock size and availability reduced CPUE in 2006.

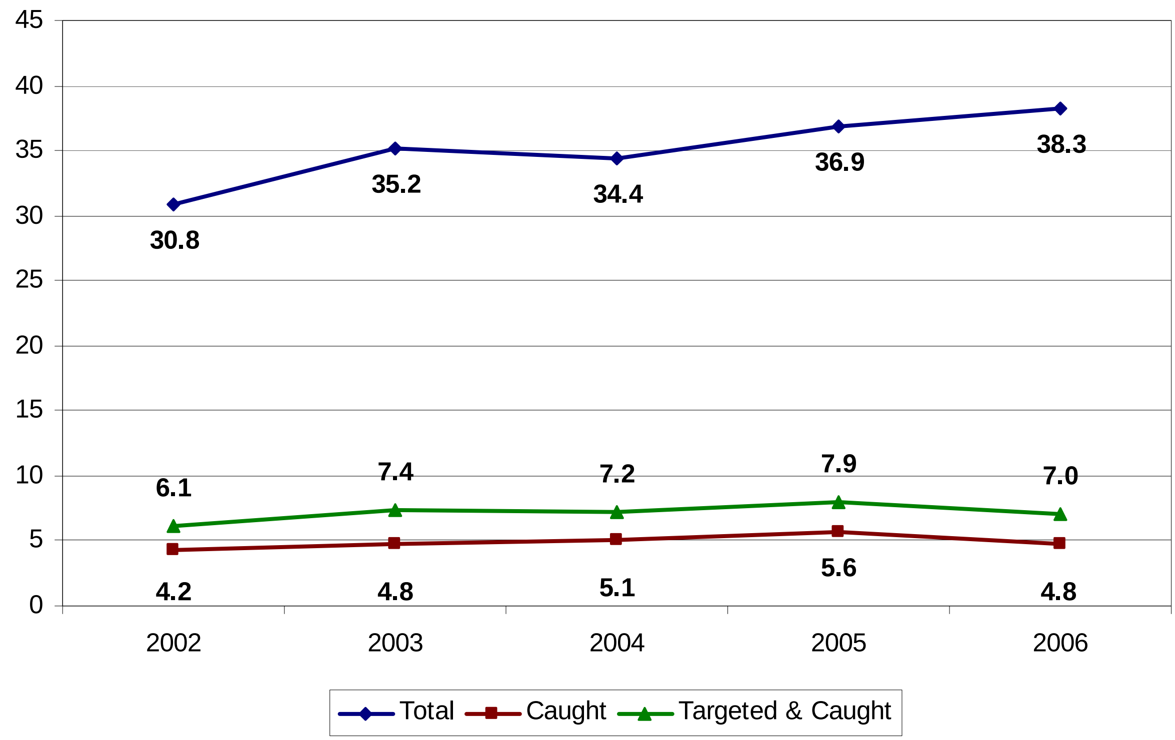

Figure 2.4. Total and Directed Effort for Summer Flounder in Millions of Trips, 2002-2006

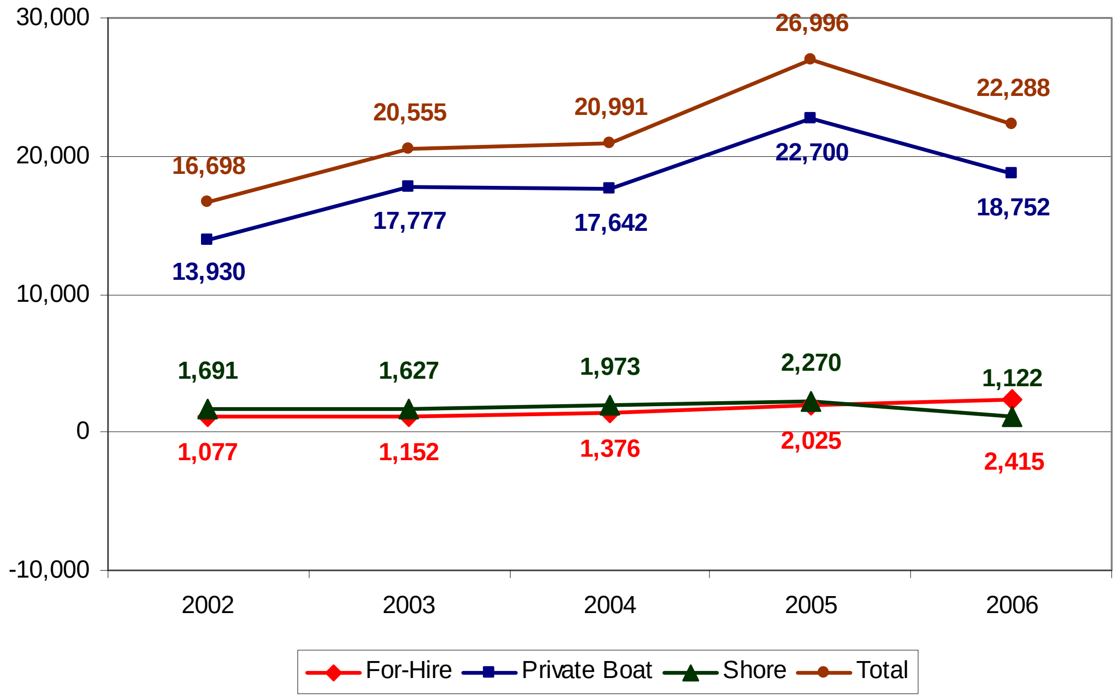

Figure 2.5. Total Summer Flounder Catch by Fishing Mode in Thousands of Fish, 2002 – 2006

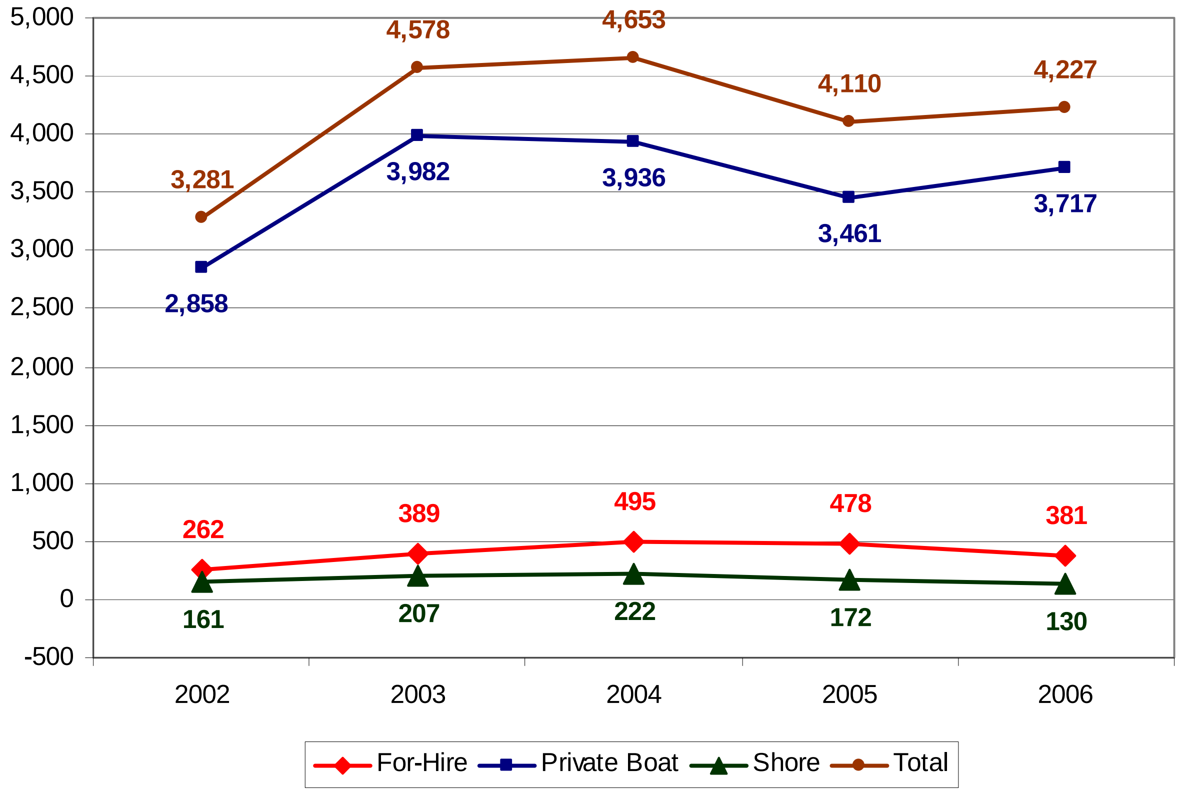

Figure 2.6. Summer Flounder Harvest (A+B1) by Mode in Thousands of Fish, 2002-2006

As the stock recovers, CPUE will increase. This in turn may attract additional effort which will catch fish more efficiently with increased CPUE. These factors decrease the likelihood of recovering the stock and increase the regulations needed to achieve harvest goals. As a result the recreational summer flounder fishery has become a highly regulated fishery and Table 2.1 details the progression of regulations since 1993. Also, as regulations have been tightened, they have become increasingly complex with each state having its own bag and size limits.

Looking at Table 2.1, size limits have consistently gone up with some states currently using a 20.5" minimum size limit. Using a length/weight calculator from NMFS a 20.5" summer flounder weighs 4.7 pounds, which is considerably higher than the average weight per fish in Figure 2.7 (NMFS 2008a). This brings up another interesting point; as minimum size limits go up it takes fewer fish to reach a harvest quota. Bag limits have also been falling and fishing seasons have also been reduced. To take into account the increases in effort, total allowable harvest was increased in 2002, dropped in 2003, increased in 2004 and 2005, and dropped again in 2006. Over the 16 years in Table 1 landings exceed the harvest limit during nine years. During the last five years, the harvest limit has been exceeded twice. In both overage years, the harvest limit was exceeded by 26%.

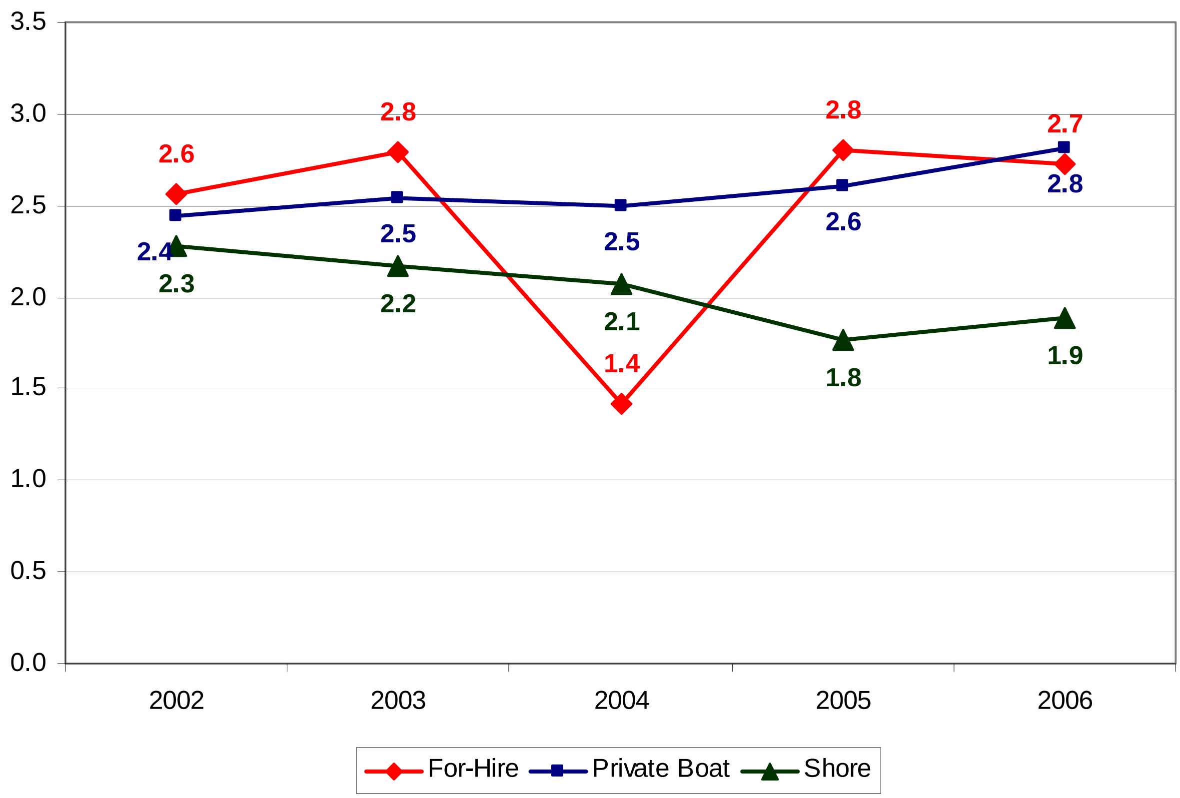

Figure 2.7. Summer Flounder Weight per Fish, 2002-2006

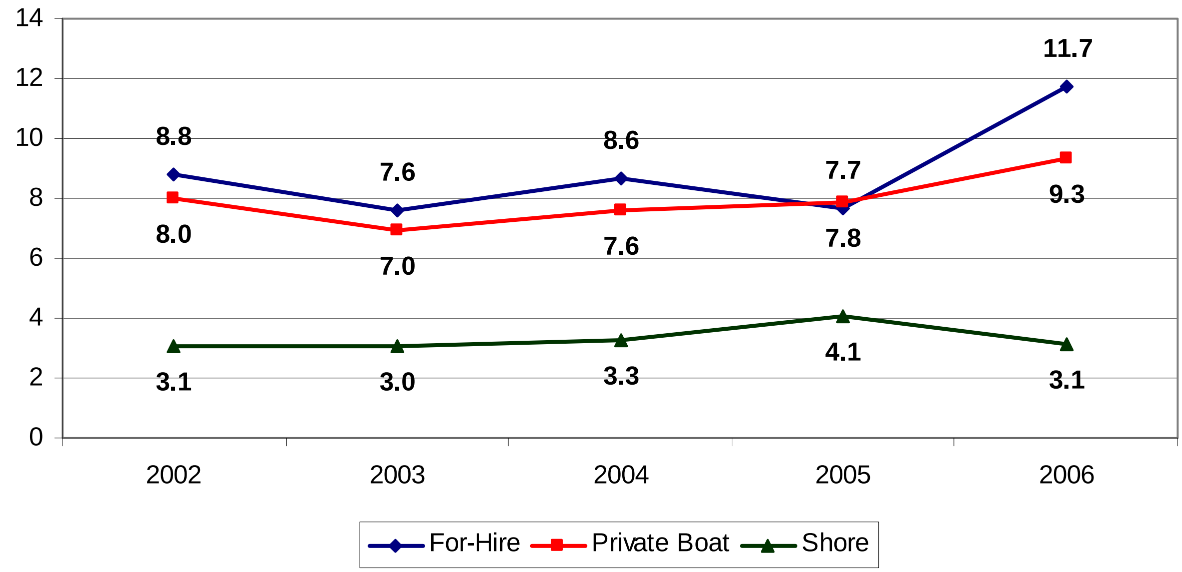

Figure 2.8. Trends in Summer Flounder Catch per Unit Effort (CPUE), 2002-2006

Table 2.1. Table 1Summer Flounder Regulations since 1993

Regulation	1993	1994	1995	1996	1997	1998	1999	2000
Harvest Limit (m lb)	8.38	10.67	7.76	7.41	7.41	7.41	7.41	7.41
Landings (m lb)	8.84	9.33	5.42	9.82	11.87	12.52	8.37	16.52
Possession Limit	6	8	6 to 8	10	8	8	8	8
Size Limit (TL in)	14	14	14	14	14.5	15	15	15.5
Open Season	5/15 - 30-Sep	4/15 - 15-Oct	1/1 - 31-Dec	1/1 - 31-Dec	1/1 - 31-Dec	1/1 - 31-Dec	5/29 - 11-Sep	5/10 - 2-Oct
Regulation	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Harvest Limit (m lb)	7.16	9.72	9.28	11.21	11.98	9.29		
Landings (m lb)	11.66	8.03	11.66	10.99	11.17	11.74[a]		
Possession Limit	3	4 to 8[b]	4 to 8[b]	3 to 8[b]	2 to 8[b]	2 to 8[b]	2 to 8[b]	1 to 8[b]
Size Limit (TL in)	15.5	15.5 - 18[b]	14 - 17.5[b]	14 - 17.5[b]	14 - 17.5[b]	14 - 18[b]	14 - 19.5[b]	14 - 20.5[b]
Open Season	4/15 - 15-Oct	Varies[b]	Varies[b]	Varies[b]	Varies[b]	Varies[b]	Varies[b]	Varies[b]

[a]Projected using 2005 landings proportions by wave and 2006 waves 1-5 data.

[b]State-specific conservation equivalency measures.

Summer flounder is an important food fish and an important target species for the party boat fleet. While the angling community sees the improvements in the stock through their increased catches, they see the regulations getting tighter and tighter. As the seasons get shorter, the for-hire industry's bottom line is directly impacted. As a result, the recreational community has criticized the MRFSS data collection program and called for harvest limits to be raised for the recreational sector. Many have suggested that the additional fish needed to increase the harvest limits come from the commercial sector through a reallocation.

2.2 Basis for Economic Allocation Analysis

Broadly defined, economists use two different metrics to examine the implications of policy decisions on society: economic value and economic impacts. The first, economic value, also known as economic benefit or welfare, monetizes the value society places on resources or activities. Economic value should be the metric used to decide between one course of action and another (Freeman 1993, Edwards 1990, and others). Economic value, however, is not the only criteria that should be examined when focusing on resource allocation questions. Equity, fairness, distributional concerns, and other social impacts are important (Edwards 1990), but will not be addressed in this report.

The second, economic impacts, examines the flow of expenditures on fishery resource activities and products as that spending moves through a community. While economic impact measures should not be used to choose a course of action, they can be used to examine what particular sectors in the economy are hurt or helped by a particular policy and to what degree. Economic impact analysis examines the distribution of value changes identified when comparing benefits, making both types of analysis complementary.

Edwards (1990) developed a guide for the allocation of fishery resources and this discussion follows his framework. Very few allocation studies have been conducted for saltwater recreational fishing. Kirkley, et al. (2000) conducted a study for striped bass allocation in Virginia examining total value in each sector. Carter, Agar, and Waters (2008) conducted an allocation analysis for the red grouper fishery in the Gulf of Mexico using the equimarginal principle.

For both the recreational and commercial sectors, total value is the sum of consumer and producer surplus. Producer surplus is measured by examining the supply curves for commercial producers of seafood, including harvesters, processors, wholesalers, and distributors, as well as the supply curves for for-hire recreational service providers. Essentially, producer surplus is the difference between the cost of producing the good and the dollar value generated by the sale of the good. Consumer surplus is measured by examining the demand for goods at the consumer level including the demand for fish at markets and restaurants and the demand for recreational fishing trips. Consumer surplus is the difference between the amount society would be willing to pay for the good in question and what consumers actually paid for the good in the marketplace.

For the recreational sector, total value or net benefits is the sum of the consumer surplus from recreational fishing participants and producer surplus from for-hire charter and head boat operators. For the commercial sector, total value is the sum of consumer surplus from the purchase of seafood products in markets and restaurants and the producer surplus from harvesters, processors, wholesalers, and distributors of those fishery products.

Value is not static across all allocations, and, as any consumer obtains more of a good, the marginal value of obtaining the next unit of that good falls. That is, there are diminishing returns to additional consumption of any good and this is a fundamental tenet of consumer demand, which has important implications for allocation decisions. A similar tenet exists for producers, but does not always hold depending on the character of the industry. As a result, it is important to examine the schedule of these marginal values in each sector. Societal benefits are maximized at the allocation where commercial sector marginal value is equal to the marginal value from the recreational sector. This is known in economics as the equimarginal principle. Using the equimarginal principle is widely recognized as the best way to maximize societal value in an allocation analysis Freeman 1993, Edwards 1990).

Estimating producer surplus and the marginal value of a pound of summer flounder harvest for the commercial fleet requires data on the costs and earnings of all the various businesses involved in the production and sale of seafood or recreational services. Very little of this type of information exists, making the calculation of producer surplus difficult at best and impossible at worst. Multi-species fisheries, like summer flounder otter trawl fishery complicate estimation. For this effort, data on trip costs from a sample of otter trawl trips will be used to estimate the trip costs for all otter trawl trips taken between 2005 and 2007.

Estimating consumer surplus entails estimating demand curves for both the angling experience and for consumer purchases of seafood. On the recreational side of the equation, estimating consumer surplus involves specialized surveys of anglers. NMFS periodically collects the data necessary to estimate site choice recreational demand models. NMFS has spent considerable time and effort developing site choice models[2] and, currently, site choice models are the agency's preferred recreational valuation technique.[3]

On the seafood consumer side, data on the prices and quantities of seafood purchased in markets and restaurants is needed. Unfortunately this type of data rarely exists. Instead there are techniques that utilize landings data to estimate consumer demand functions that can be used to calculate the marginal value of summer flounder consumption at the retail level. Those techniques will be used here.

In summary, the equimarginal principle is the preferred method to examine allocations. Often, it is difficult to develop a complete schedule of marginal values across all possible allocations. In this case, it is appropriate to examine total value, recognizing, however, that total value may not take diminishing marginal returns into account.

[2] A partial list of the research in recreational site choice models conducted or sponsored by NMFS or using Marine Recreational Fisheries Statistical Survey data include: Gautam and Steinback (1998); Gentner (2007); Gentner and Lowther (2002); Gillig, Woodward, Ozuna, T., and Griffin (2000); Haab, Hicks, Schnier, and Whitehead (2008); Haab, Whitehead, and McConnell (2000); Haab and Hicks (1999); Whitehead and Haab (1999); Hicks, Gautam, Steinback, and Thunberg (1999); and Hindsley, Landry, and Gentner (2008).

[3] See the Center for Independent Experts evaluation of NMFS' recreational economic program. Center for Independent Experts. (CIE 2006).

3.0 Commercial Valuation

This chapter estimates commercial harvesters' marginal value for summer flounder. Typically, cost and earnings information for commercial harvesters is sparse or non-existent. In this case, trip cost data was collected from a sample of otter trawl fishermen and those trip costs are used in a regression model to estimate trip costs for the entire fleet. Estimated trip costs are then used to model input compensated supplies for summer flounder and four other species groups harvested by otter trawl fishermen. From these input compensated supply equations, it is possible to estimate the current marginal value for a pound of summer flounder and simulate that marginal value across the entire range of potential allocations.

3.1 Estimation of Trip Costs and Data Manipulation

This study uses data from 2005, 2006, and 2007. Estimation of commercial harvester profits requires data on both harvester revenues and harvester costs. NMFS collects revenue information from a combination of self-reported logbook entries and seafood dealer data. To collect cost information, NMFS uses the observer program to collect very accurate trip cost data across a sample of otter trawl and other vessels. Because the observer program samples commercial trips, NMFS does not have trip costs for all reported trips.

To address the need for trip costs for all trips, NMFS contracted with the Woods Hole Oceanographic Institute to develop a regression based model to predict trip costs for boats not included in the observer sample. That work is detailed in Jin (2008). His model used trip cost data from the 2006 observer year. Jin's (2008) work estimated regression models for fixed costs, labor costs, and trip costs. While the trip cost data is considered to be very accurate as it is collected by the observer during the trip, the fixed cost data, collected using a separate survey, is felt to be problematic.

The 2006 data contained a large number of available data points. Generally, trip costs are influenced by gear typed, vessel characteristics, days at sea, fishing location, fishing time, the value of landings, and other characteristics. To develop a regression relationship using the observer, logbook, and dealer data, Jin created the following independent variables; monthly dummies, vessel age, engine age, total horsepower, total landed value, total landings in pounds, principle port dummies, vessel ownership dummies, vessel construction type, fuel type, trip duration in hours, fishing time in hours, squares and square roots of vessel length, horsepower, and age, and area fished dummies. The dependent variable, trip costs, was the sum of ice, food, fuel, damaged gear, supplies, water, oil, and bait costs. All dollar values were converted to 2007 dollars using the producer price index.

While Jin estimated a number of models, the focus here is on the otter trawl gear type. Jin's otter trawl modeling was performed in two phases. The first phase used a stepwise linear regression to select the relevant variables. This was performed in SAS using the Proc REG procedure, and that procedure adds independent variables to the model one at a time. The decision rule for inclusion is maximizing r-square while retaining only those variables with a significance level of 0.15 or better. This process yielded the following variables; total trip duration, steam time, gross tons, gross tons squared, April monthly dummy, and North Carolina and Rhode Island principle port dummies.

Heteroscedasticity (HSK) was found in these initial selection regressions. To address the HSK, Jin used SAS Proc MODEL to estimate the final regressions. This procedure utilizes a generalized method of moments (GMM) estimator using instrumental variables to control for HSK. With this procedure, if HSK is present, the ordinary least squares parameters are unbiased and efficient, but the covariance matrix used is White's. Jin's original coefficients are found in Table 3.1.

Because this effort had access to two additional years of data (2005 and 2007), it was decided to follow Jin's procedure to estimate another otter trawl cost model. Following the exact same data creation and modeling steps as Jin, an updated otter trawl cost model was developed. Table 3.2 contains the means and descriptive statistics for the variables created and used in the stepwise regression.

Across all three years, total trip duration was almost 66 hours on average; they steamed for almost eight hours and fished for 58 hours. On average, the captains are very experience with nearly 22 years of commercial fishing experience. On average, the boats are; 70.5% steel, 64.4 feet in length, displaces 90.6 gross tons, and is 30 years old. For power, almost 93.9% have one diesel engine and that engine has on average has 484 horsepower. The most frequent month for trips is July, followed by May and January. The lowest activity month is October, although November and December aren't far ahead. Massachusetts (29.5%) is the most popular principle port followed by Rhode Island (22.5%) and New Jersey (17.3%). Principle port is different from landing port that will be used later in the analysis. Principle port is considered the boat's home port whereas the port of landing is where the boat sold its catch for that trip.

Table 3.1. Otter Trawl Cost Model Parameters (Jin 2008)

Variable	Estimate	Approximate Standard Error	Approximate Pr >|t|
Intercept	-105.925	102.8	
Trip Duration	43.65556	2.8352	0.3031
Steam Time	69.44759	22.0714	<.0001
Gross Tons Sqrd	0.193516	0.0279	0.0017
Age*Gross Tons	-0.54886	0.0963	<.0001
April Dummy	896.9853	406.1	<.0001
North Carolina	-1207.29	418.2	0.0274
Rhode Island	-578.67	233.8	0.004
Adjusted r-square	0.8039		

Table 3.3 contains the results of the GMM estimation and, by inference, the stepwise selection model. With the additional years of data, the r-square increases to 0.8695. Some of the same variables were significant, however there were some changes. Trip duration and steam time where both positive, although only total trip duration was significant. Steel vessel construction decreases cost as does length, to a point, as length squared is positive. Additional horsepower also increases cost. Two monthly dummies were selected in to the model and both January and March reduce costs although March is only significant at the 0.15 level. Both state dummies were significant with boats having an NC principle port having higher lower costs and boats from MA having higher

costs. Both White's test and the Breusch-Pagan test indicate that the HSK was remedied using the GMM estimator.

Figure 3.1 plots the actual costs versus the predicted costs and the model predicts quite well. With the exception of a few extremely high actual cost values, the predictions are very close to the actual values. Also, since the data was sorted by year, notice the upward shift in costs in 2007 around observation 600. Table 3.4 compares the predictive accuracy of both sets of parameters. The trip cost average across the data used was $3,681.64 and the model estimated here (Table 3.3) predicts costs, on average, only $10.06 higher while Jin's parameters (Table 3.1) predicts cost, on average, $87.53 higher. Interestingly, the confidence interval on the predicted cost from the model in Table 3.3 is tighter than the actual cost confidence interval, so while it predicts slightly higher, it predicts less volatility. Both models predict negative trip costs; 26.4% for the parameters in Table 3.1 and 17.0% for the parameters in Table 3.3. When the parameters in Table 3.3 are applied to all otter trawl trips from 2005, 2006, and 2007, only 6.46% of the trip costs were negative. Those observations were subsequently dropped from the analysis.

Table 3.2. Means and Descriptive Statistics for the Dependent Variables

Variable	Mean	StdErr	95% Lower Confidence Limit	95% Upper Confidence Limit
ATRIPDUR	65.94	2.62	60.81	71.08
CAPTYRS	21.72	0.39	20.96	22.48
STEAMTIM	7.76	0.29	7.20	8.32
TIMELOST	1.62	0.23	1.16	2.08
XTRIPDUR	87.50	3.14	81.34	93.66
age_eng1	19.56	0.51	18.57	20.56
LEN	64.36	0.49	63.40	65.31
VHP	483.60	8.64	466.64	500.56
GTONS	90.58	1.75	87.15	94.01
tonage	2,636.46	51.21	2,535.95	2,736.98
age	30.32	0.36	29.61	31.03
ENG2EXIST	6.05%	0.87%	4.35%	7.75%
M1	12.27%	1.16%	9.99%	14.54%
M2	8.39%	0.98%	6.46%	10.31%
M3	5.63%	0.82%	4.03%	7.23%
M4	7.26%	0.92%	5.46%	9.06%
M5	14.64%	1.25%	12.19%	17.10%
M6	9.39%	1.03%	7.36%	11.41%
M7	18.27%	1.37%	15.59%	20.96%
M8	8.39%	0.98%	6.46%	10.31%
M9	8.26%	0.97%	6.35%	10.17%
M10	2.38%	0.54%	1.32%	3.44%
M11	2.50%	0.55%	1.42%	3.59%
M12	2.63%	0.57%	1.52%	3.74%
CORP	73.29%	1.62%	70.10%	76.47%
soleown	64.58%	1.69%	61.26%	67.90%
partner	17.15%	1.33%	14.53%	19.77%
firmown	8.14%	0.97%	6.24%	10.03%
CT	4.63%	0.74%	3.17%	6.09%
ME	1.50%	0.43%	0.66%	2.35%
MD	2.13%	0.51%	1.12%	3.13%
MA	29.54%	1.61%	26.37%	32.71%
NJ	17.27%	1.34%	14.64%	19.90%
NY	15.77%	1.29%	13.24%	18.30%
NC	4.51%	0.73%	3.06%	5.95%
RI	22.53%	1.48%	19.63%	25.43%
VA	1.38%	0.41%	0.57%	2.19%
fiberg	12.14%	1.16%	9.87%	14.41%
steel	70.46%	1.61%	67.29%	73.63%
diesel	99.62%	0.22%	99.20%	100.05%
GOM	0.25%	0.18%	-0.10%	0.60%
GB	2.50%	0.55%	1.42%	3.59%
SNE	9.64%	1.04%	7.59%	11.69%
spec124	2.38%	0.54%	1.32%	3.44%
spec818	3.00%	0.60%	1.82%	4.19%
spec5240	12.02%	1.15%	9.76%	14.27%
spec8009	0.50%	0.25%	0.01%	0.99%

Table 3.3. Nonlinear GMM Parameter Estimates

Variable	Estimate	Approximate Std Err	t Value	Approximate Pr > |t|
Intercept	-177729	93629.2	-1.9	0.058
ATRIPDUR	52.37899	2.7307	19.18	<.0001
STEEL	-99.6791	88.9099	-1.12	0.2626
STEAMTIM	18.01961	21.579	0.84	0.4039
LEN	-6636.37	3360.5	-1.97	0.0486
LEN2	20.03945	9.7026	2.07	0.0392
LENSQRT	64825.78	33619.9	1.93	0.0542
VHP	2.944961	1.0896	2.7	0.007
VHP2	-0.00029	0.000486	-0.6	0.5516
M1	-375.077	179.1	-2.09	0.0365
M3	-499.643	344.5	-1.45	0.1474
NC	-1817.2	411.1	-4.42	<.0001
MA	498.7661	206.3	2.42	0.0158
R-Square	0.8695			

Original plans included estimating profit models at the annual level, but that proved problematic because of missing information on vessel characteristics or trip characteristics necessary for modeling cost for 373 boats across the three year period. Initially, all trips for all vessels that landed summer flounder in each year were included. That data set included 71,746 trips distributed as follows: 25,138 trips across 427 vessels in 2005; 24,511 trips across 414 vessels in 2006; and 22,097 trips across 398 vessels in 2007. After estimating trip cost information those numbers fell to 55,066 trips with valid cost data. Most of the loss in observations was due to fishing time that exceeded total time away from port or missing vessel characteristics (combined 16.8%) and negative predicted trip costs (6.5%). For an annual model, this poses problems as the trip time and missing vessel characteristics made it impossible to aggregate all trips across all vessels. To estimate an annual model with only those vessels with good trip cost data for all trips, over 78% of the trips would have to be thrown out affecting 250 vessels in 2005, 76 vessels in 2006, and 47 vessels in 2007.

As a result, the remainder of this analysis will focus on the trip level. Across the three years, there were 36,413 trips that landed summer flounder and 33,773 of those trips allowed estimation of trip costs. The loss of observations were due to the following reasons: 3,452 trips were missing vessel characteristics (9.5%), 918 had fishing time greater than total trip time (2.52%), and 2,534 trips had negative estimated trip costs (7.0%). Table 3.5 contains the descriptive statistics for this data set. The number of vessels ranged from 379 in 2007 to 419 in 2005. Average trips per vessel ranged from 29.1 in 2007 to 36.9 in 2005. Overall, this data set represents the vast majority of summer flounder harvested in the otter trawl gear type, ranging from 89% to 95% of the summer flounder harvested by otter trawls in each year. As a result, this data still represents the majority of summer flounder harvest across all gear types.

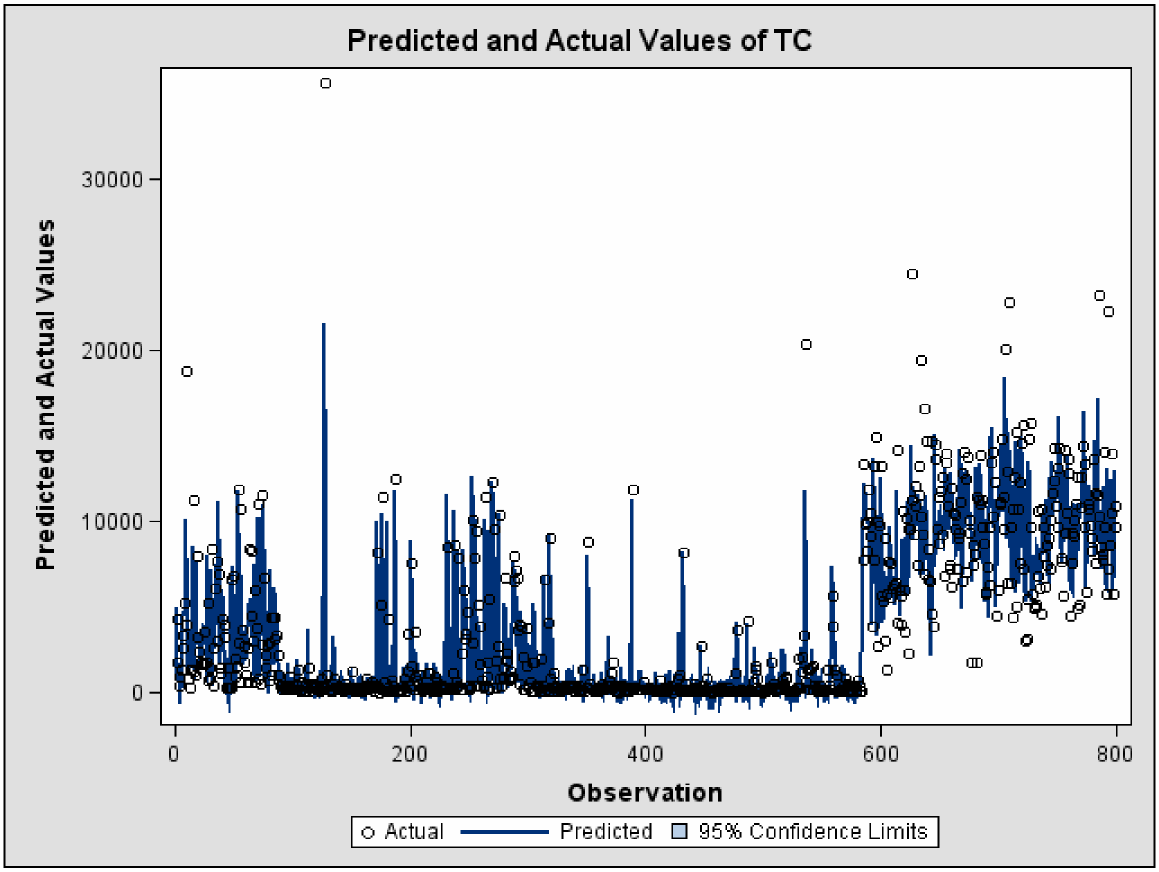

Figure 3.1. Actual Total Trip Cost Versus Predicted Trip Cost

Table 3.4. Actual Trip Costs and Predicted Trip Costs

Variable	N	Mean	StdErr	95% Lower Confidence Limit	95% Upper Confidence Limit
Trip Cost	799	$3,681.64	$172.14	$3,343.73	$4,019.54
Prediction from Model Reported in Table 3.3	795	$3,691.70	$161.13	$3,375.41	$4,007.99
Prediction Using Jin's Parameters (Table 3.1)	791	$3,769.17	$163.22	$3,448.78	$4,089.57

Table 3.5. Trip Data Set Characteristics, 2005 - 2007

Year	Number of Trips	Number of Vessels	Average Trips per Vessel	Percent of Total Otter Trawl Summer Flounder Harvest	
				Pounds	Value
2005	12,110	419	36.8	89.0%	88.2%
2006	11,924	403	35.2	93.9%	93.2%
2007	9,739	379	29.1	95.0%	94.1%

Table 3.6 details the average per trip total pounds landed, total landed value (revenue), estimated trip cost, and profit across this sample by year. Profit was calculated by subtracting estimated trip costs from total landed value. From the table, profits are quite low per trip but have been increasing. Total landed pounds have been decreasing but so have costs. Across the entire data set, 55.4% of all trips lose money (negative profits). When only those trips that make 25% or better of their revenue from summer flounder are examined, 63.9% of those trips lose money.

Table 3.6. Total Pounds, Value, Costs, and Profit per Trip 2005 - 2007 (2007 dollars)

Year	Variable	Number of Trips	Mean per Trip	95% Lower Confidence	95% Upper Confidence
2005	Estimated Trip Cost	12,110	$3,115.82	$3,054.02	$3,177.62
2005	Profit	12,110	$2,157.78	$2,013.18	$2,302.38
2005	Total Landed Pounds	12,110	5,198.65	5,019.91	5,377.39
2005	Total Landed Value	12,110	$5,019.20	$4,863.86	$5,174.53
2006	Estimated Trip Cost	11,924	$2,956.40	$2,897.18	$3,015.61
2006	Profit	11,924	$2,191.86	$2,071.34	$2,312.37
2006	Total Landed Pounds	11,924	4,835.54	4,674.66	4,996.43
2006	Total Landed Value	11,924	$5,024.62	$4,884.07	$5,165.17
2007	Estimated Trip Cost	9,739	$2,857.43	$2,793.06	$2,921.80
2007	Profit	9,739	$1,871.32	$1,750.72	$1,991.92
2007	Total Landed Pounds	9,739	4,284.50	4,119.68	4,449.31
2007	Total Landed Value	9,739	$4,706.60	$4,558.46	$4,854.73

Port of landing and principle port have both proven to be important descriptors of costs and therefore profits. In this data set, there are 83 individual landing ports with Point Judith, RI the single most important port in terms of summer flounder landings with 30.0% of all trips landing in Point Judith. A distance second is Belford, NJ with 10.5% of all trips landing there. Unfortunately, including 83 port dummies in the profit model is too many. As a result both state of landing and county of landing dummy variables were created. Figure 3.2 contains the distribution of trips by landing county. The city counties in the Virginia Beach area have been aggregated into one landing county creating 33 landing county dummies. There were a large number of landing counties with very few trips (less than 0.03% of the total trips) and those have been aggregated into a category called "All Other Counties." Again, the single biggest landing county is Washington County, RI (10,399 trips), followed by Suffolk County, NY (6,182 trips), and Monmouth County, NJ (3,553 trips).

Otter trawls catch a variety of species. In this data set there are over 21 including two miscellaneous categories with an unknown number of species in each. For the profit model, it is necessary to aggregate these species into fewer species groups. For this study, five species groups were developed: summer flounder; bait which includes menhaden, herring, butterfish, mackerel, and skate; other bottomfish which includes scup, black sea bass, monkfish, tilefish, small mesh species, and other flat fish; shellfish which includes shrimp, loligo squid, lobster, scallops, and illex squid; and other species which includes others species, highly migratory species, and bluefish.

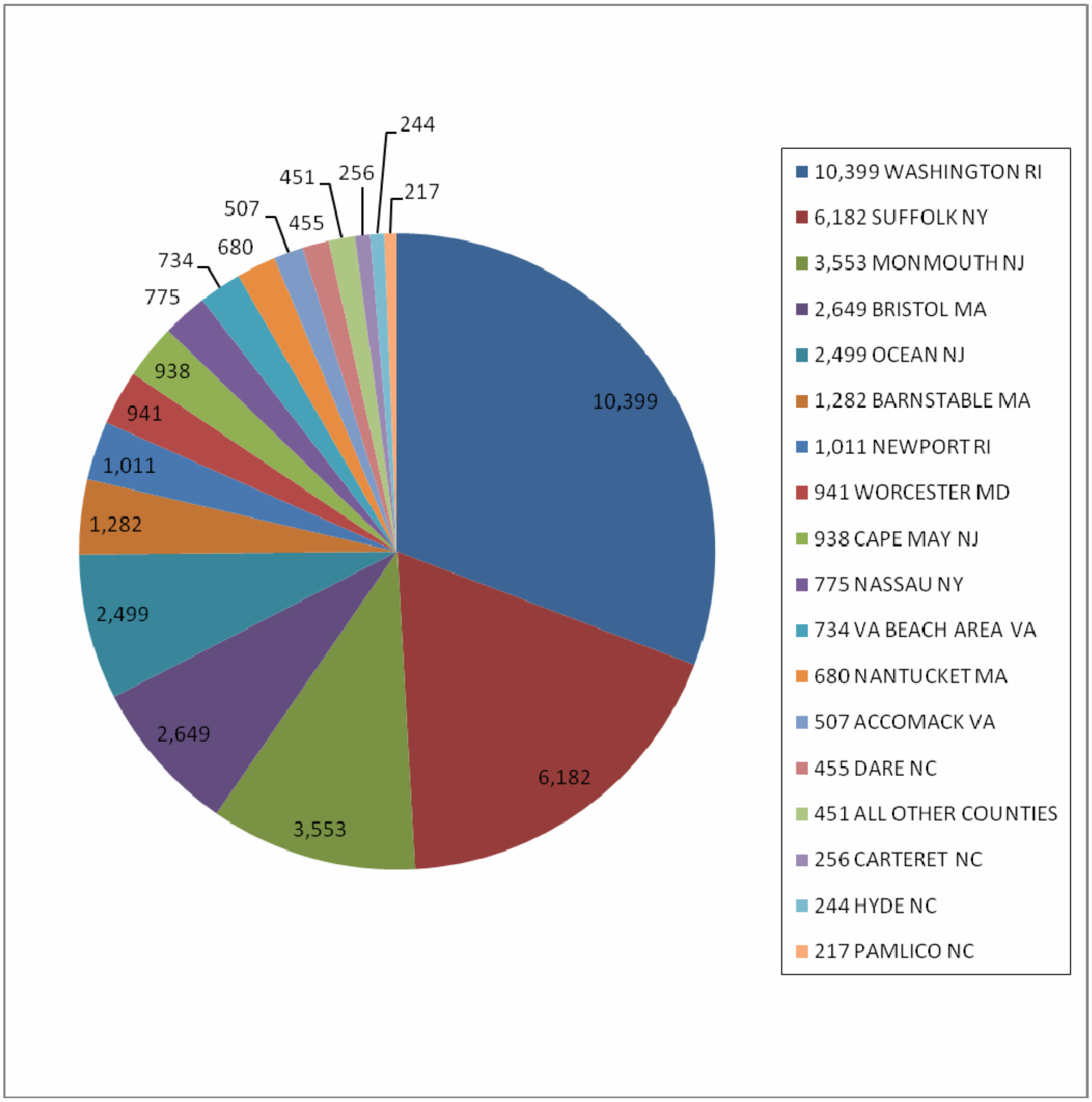

Figure 3.2. Number of Trips Landing in Each County, 2005-2007

Table 3.7 details the total landed pounds by each species group across the time series. Summer flounder, by definition, is landed in every trip as are shellfish and bait. On average, more shellfish are landed in this data set than summer flounder. Other bottomfish are not landed on every trip, but when landed, make up a significant portion of the catch.

Table 3.8 details the average price for each species group, per trip, for each year. In all years, summer flounder obtains the highest prices ranging from $2.40 to $2.95 per pound. Shellfish prices are the second highest ranging from $1.70 to $2.33 per pound. The lowest priced species group in all years is the bait category that ranges from $0.63 to $0.74 per pound.

Table 3.9 details the average landed value by species group and year. Across trips that land summer flounder, which includes all trips in this database, summer flounder is the highest value landed product. When other bottomfish are landed, they constitute a significant portion of revenue, but they are not landed on every trip. Both bait and other species make up very small portions of landed value.

Table 3.7. Pounds Landed per Trip by Species Group, 2005 - 2007

Year	Species Group	Number of Trips	Mean Pounds per Trip	95% Lower Confidence	95% Upper Confidence
2005	Bait	12,110	864	800	928
2006	Bait	11,924	836	768	904
2007	Bait	9,739	828	755	901
2005	Other Bottomfish	3,789	1,584	1,498	1,671
2006	Other Bottomfish	4,531	1,313	1,254	1,372
2007	Other Bottomfish	3,730	1,280	1,219	1,340
2005	Other Species	3,789	1,134	929	1,339
2006	Other Species	4,531	954	763	1,144
2007	Other Species	3,730	1,245	1,030	1,459
2005	Shellfish	12,110	1,303	1,192	1,415
2006	Shellfish	11,924	1,375	1,273	1,476
2007	Shellfish	9,739	883	789	976
2005	Summer Flounder	12,110	1,074	1,029	1,120
2006	Summer Flounder	11,924	933	888	977
2007	Summer Flounder	9,739	807	766	847

Table 3.8. Landed Price per Trip by Species Group, 2005 -2007 (2007 dollars)

Year	Species Group	Number of Trips	Mean Price per Trip	95% Lower Confidence	95% Upper Confidence
2005	Bait	4,295	$0.64	$0.63	$0.65
2005	Other Bottomfish	8,644	$1.73	$1.71	$1.75
2005	Other Species	3,789	$1.24	$1.20	$1.27
2005	Shellfish	5,602	$2.33	$2.27	$2.40
2005	Summer Flounder	12,110	$2.40	$2.38	$2.41
2006	Bait	4,865	$0.63	$0.62	$0.64
2006	Other Bottomfish	9,006	$1.74	$1.72	$1.76
2006	Other Species	4,531	$1.37	$1.34	$1.41
2006	Shellfish	6,480	$1.74	$1.69	$1.79
2006	Summer Flounder	11,924	$2.71	$2.70	$2.73
2007	Bait	4,512	$0.74	$0.69	$0.78
2007	Other Bottomfish	7,411	$1.74	$1.72	$1.76
2007	Other Species	3,730	$1.23	$1.20	$1.26
2007	Shellfish	4,566	$1.70	$1.65	$1.75
2007	Summer Flounder	9,739	$2.95	$2.93	$2.97

As is often done in multi-product fisheries models when one species is the focus, the use of a revenue cut off is explored here. All trips were removed from the data if the percent of summer flounder revenue was less than 25%. This drops the total number of observations 28.0% from 33,773 trips to 24,323 trips. Interestingly profit per trip is ten times lower for this subset, costs per pound go up $1.34 per pound, and summer flounder profit per pound drops $1.32 per pound.

Table 3.9. Landed Value per Trip by Species Group, 2005 - 2007 (2007 dollars)

Year	Species Group	Number of Trips	Mean Value per Trip	95% Lower Confidence	95% Upper Confidence
2005	Bait	12,110	$242.02	$223.51	$260.53
2005	Other Bottomfish	12,110	$2,017.71	$1,907.24	$2,128.19
2005	Other Species	3,789	$436.12	$378.42	$493.81
2005	Shellfish	12,110	$1,378.81	$1,277.19	$1,480.44
2005	Summer Flounder	12,110	$1,899.68	$1,834.20	$1,965.17
2006	Bait	11,924	$219.11	$199.88	$238.34
2006	Other Bottomfish	11,924	$1,787.24	$1,703.58	$1,870.89
2006	Other Species	4,531	$368.41	$326.69	$410.13
2006	Shellfish	11,924	$1,305.83	$1,217.02	$1,394.64
2006	Summer Flounder	11,924	$1,859.68	$1,784.25	$1,935.11
2007	Bait	9,739	$286.18	$260.30	$312.06
2007	Other Bottomfish	9,739	$1,598.21	$1,521.42	$1,675.01
2007	Other Species	3,730	$534.19	$466.24	$602.15
2007	Shellfish	9,739	$859.27	$775.19	$943.35
2007	Summer Flounder	9,739	$1,815.70	$1,738.14	$1,893.26

3.2 Model

There has been considerable work on multiproduct fisheries models in the literature. Generally, these models use similar specifications and assumptions. In this body of work commercial fishermen are profit maximizers that face a two stage problem (Kirkley and Squires 1991). In the first stage, the fishing trip, the vessel operator chooses the revenue maximizing output bundle subject to fixed inputs, weather, resource quotas, and relative product prices. It is important to note that, for the commercial fisherman, inputs are fixed once they leave the dock. Because of this characteristic, the input bundle can be specified as a single composite input. There have been some detractors of this assumption (McConnell and Price 2006) due to the share system used in fisheries to compensate labor. Under the share system, labor cost is an endogenous function of harvest. Often effort, expressed as days at sea or gross tonnage, is used as the quasi fixed input because trip cost information is typically lacking. In the second stage, firms adjust their levels of effort to minimize production costs by selecting the optimal vessel size or capital stock. This second stage takes place over a 3-14 month horizon (Squires and Kirkley 1991).

Typically, these dual revenue models are estimated using translog or generalized Leontief functional forms, with the generalized Leontief used most frequently (Kirkley and Strand 1988, Squires and Kirkley 1991, Vestergaard 1999, Carter et al 2008, and others). The generalized Leontief is usually selected because it places few restrictions on the underlying technology. The generalized Leontief also allows the analysis of input separability and non-jointness, but at the cost of imposing linear homogeneity in prices (Carter et al 2008). Also, the generalized Leontief allows the estimation of output levels directly instead of output shares like the translog making the result more intuitive and improving the ease of estimation of the derived demands.

The generalized Leontief requires a series of sometimes limiting assumption. First, profit must be non-decreasing in output prices and fixed factors. Profit must also be non-increasing in input prices, linearly homogeneous in prices and convex in prices. It also must be concave in fixed quantities, continuous, and twice differentiable (Carter et al 2008). Additionally, input and output separability are important testable assumptions regarding the underlying technology. Separability implies that there are no interactions between any one input and any one output. If this assumption holds, it allows the use of composite inputs and composite outputs in the function being estimated.

Jointness in inputs is another testable assumption. Jointness in inputs implies that it takes all inputs to produce all outputs. That is, harvesting processes are interrelated. If jointness is not found, it means that there is a separate production function for each output or groups of outputs. While this assumption does not often hold, it is suspected that is might for a gear like the otter trawl.

3.2.1 Literature Review

Kirkley and Strand (1988) were one of the first to apply a dual revenue function to look at the Georges Bank multiproduct trawl fishery. The main goal of their work was to test general assumptions about the typical multiproduct specification that requires separability and non-jointness in production. They estimated a revenue function using a generalized Leontief function using the product of days at sea and gross tons as their quasi-fixed input. Their analysis used NMFS data containing 175,000 trips taken on Georges Bank. They used eight species groups including; cod, haddock, yellowtail flounder, pollock, winter flounder, other flounder, miscellaneous, and a catch all group equal to the total landed pounds minus the sum of the seven above. They estimated firm level annual input compensated supply functions using an iterated Zellner approach. Zero outputs by species groups can pose problems for these models. In this case, they left the zero outputs as zero as less than 11% of the trips contained zero outputs for any one species group. Their analysis showed that the assumptions of separability and non-jointness do not hold, but also felt gross tons and days absent may not have had enough variation or enough systematic variation to use as their quasi fixed input.

Squires and Kirkley (1991) used a dual revenue function to examine quota management in the multiproduct sablefish fishery. They used a generalize Leontief revenue function using total revenue as the dependent variable and output prices, composite input, landing port dummy and quarterly dummies as the independent variables. Similar to this analysis, they chose to include only those trips that landed more than 1,000 pounds of sablefish. Instead of allowing zero outputs to remain zero, they replace zero outputs with a trivial value of 0.1. The found the input output separability was rejected but that jointness overall was a valid assumption.

Squires and Kirkley (1996) used a dual revenue function to estimate the virtual prices in a multi-species fishery for the purpose of analyzing an individual transferable quota. Under the same assumptions as the above work, they used gross tonnage as their single composite input and measure of effort. Again they used a generalized Leontief imposing symmetry, linear homogeneity in prices and assuming input separability. Also, zero outputs were replaced with a small value of 0.1. The focus of this paper was to estimate a firm's input compensated supply equations so that they could derive the virtual price for quota. As will be done below, they horizontally sum the firm inverse derived demands to obtain the market inverse demand. Since the overall quota equals a perfectly inelastic supply of quota they equate the market inverse demand to overall quota and solve for the equilibrium market price for quota. From a static model, this price is equivalent to the price from an open auction. Integrating under these curves estimates producer surplus.

Vestergaard (1999) examined a multiproduct fishery with joint input production. With joint technology, as is the case with the otter trawl fishery, there are spillover effects on other output when one output is controlled through regulation. An allocation change, which is essentially a change in a sector's TAC or quota, is a perfect example of an output control. In this analysis Vestergaard assumes a multiproduct firm faces a perfectly elastic demand for its outputs and input supply curves as assumed perfectly price elastic. The study estimates a profit function to measure the quasi-rent. Quasi-rent is the return to the fixed factors and is more useful than profit functions for obtaining producer's surplus. An important point posited by Vestergaard is that these types of models as short run only and conditional both on the existing biomass and the available biomass. Vestergaard's goal is to estimate producer surplus. To do this, he assumes production is joint in inputs with technology interdependence. He also posits that there may be one output for which zero production is possible, if and only if, no production takes place at all (Just et al 1982). He calls this the necessary output. Most multispecies fisheries fit this model well with joint production and little ability to adjust output composition, which is certainly the case with otter trawls (Kirkley and Strand 1988, Squires 1987, Squires and Kirkley 1991, 1996).

3.2.2 Theoretical Model Specification

Recently Carter et al (2008) performed a comprehensive analysis of both recreational consumer surplus and commercial producer surplus in the red grouper fishery in the South Atlantic and Gulf of Mexico. Their analysis follows the above literature closely and the structure of their model will be used here. Fulginiti and Perrin (1993) describe the linkage between quota constrained quasi-rent and the unconstrained quasi-rent using the concept of a virtual price. Under this structure, the virtual price is the output price that induces the firm to produce at a given quota level. Virtual price is defined as:

$$\frac{\partial \pi}{\partial p_{v_1}} = \overline{q_1} \qquad 3.1)$$

where $\overline{q}_1$ is the quota for output 1, p_{v1} is the virtual price for output 1, and π is profit in this multiproduct fishery. Furthermore:

$$p_{v_1} = \left(p_1 - \lambda_1\right) \qquad 3.2)$$

where p_1 is the output price and λ_1 is the rent per unit of quota or the marginal value of output 1. At the virtual price for quota 1, the quota quasi-rent function must equal the quota free quasi-rent function:

$$\pi\left(p_1, p_h, w; \overline{q_1}, K\right) = \pi\left(p_v, p_h, w; K\right) \qquad 3.3)$$

where p_h is the price vector for all other output prices in this multiproduct fishery, w is a vector of input prices, and K is the quasi fixed input. Quasi rent can be expanded and rewritten as follows for a two output single quasi fixed input case:

$$\pi\left(p_1, p_h, w; \overline{q_1}, K\right) = \sum_{i=2}^{n} p_i y_i\left(p_1 - \lambda_1, p_h, w; K\right) + \lambda_1 \overline{q_1} - \sum_{j=1}^{m} w_j x_j\left(p_1 - \lambda_1, p_h, w; K\right) \quad 3.4)$$

where x_j is the single quasi fixed input, w_j is the single input price, y_i is a vector of the two output quantities. Using Hotellings lemma:

$$\frac{\partial \pi}{\partial p_i} = y_i\left(p_1 - \lambda_i, p_h, w; K\right) \forall i \geq 2 \quad 3.5)$$

$$\frac{\partial \pi}{\partial w_j} = -x_j\left(p_1 - \lambda_i, p_h, w; K\right) \quad 3.6)$$

Where 5) is the output supply and 6) is the input demand. Inverse derived demand for quota found by differentiating 4) above with respect to quota 1:

$$\frac{\partial \pi}{\partial \overline{q_1}} = \lambda_1\left(p, w; \overline{q_1}, K\right) \quad 3.7)$$

Market output price (landed price) less the virtual price is the marginal quota rent. This expression for the inverse demand captures the optimal adjustment in inputs used and captures optimal adjustments in other outputs (Carter et al 2008). As such, it is the marginal value of the next unit of quota in fishery 1. While it is possible to calculate producer surplus by integrating below the market price and above the output supply, producer surplus can be derived using the input demands as the area under the implicit derive derived demand for quota measures quasi rent (Carter et al 2008).

$$PS = \int_0^{\overline{q_1}} \lambda_1\left(p, w; \overline{q_1}, K\right) dy_1 = \pi\left(p, w; \overline{q_1}, K\right) \quad 3.8)$$

The total derived demand for the commercial sector is simply the horizontal sum of the individual firm and trip level demands. Therefore, commercial quota rental price for the last unit of quota is found by setting the total demand equal to the perfectly inelastic supply curve for quota, also known as the TAC. Quasi rent is estimated by integrating under different levels of the TAC at each level of allocation change being considered.

3.2.3 Empirical Model

The general specification of a non-homothetic generalized Leontief quasi-rent function is:

$$\pi(p; K) = \sum_{i=1}^{n} \alpha_i p_i K^2 + \sum_{j \neq i} \beta_{ij} \left(p_i p_j\right)^{1/2} K \quad 3.9)$$

where p_i is output price of species i, and K is the quasi-fixed input. Symmetry is imposed by restricting $\beta_{ij} = \beta_{ji}$ for each i not equal j. Using Hotellings lemma, the input-compensated unconstrained supplies are

$$\frac{\partial \pi}{\partial p_i} = y_i = \alpha_i K^2 + \beta_{ii} K + \sum_{j \neq i} \beta_{ij} \left(\frac{p_j}{p_i} \right)^{1/2} K \qquad 3.10)$$

The specification used for estimation is:

$$\pi(p;K) = \sum \alpha_i p_i K^2 + \sum_i \sum_j \beta_{ij} \left(p_i p_j \right)^{1/2} K + \sum_i \sum_k \delta_{ik} d_k p_i K + \sum_i \sum_l \varepsilon_{il} e_l p_i K + \sum_i \sum_m \phi_{im} f_m p_i K \qquad 3.11)$$

where p_i is the landed price for species i, K is the total estimate trip costs, d is a set of monthly dummies from January to December, e is a set of dummies for the three years in the data, and f is a set of landing county dummies. This study is fairly unique in that the data contains total estimated trip costs. These costs are quasi fixed since once a trip has started, the inputs available, both capital and labor, are fixed. Applying Hotellings lemma the input compensated supplies are:

$$\frac{\partial \pi(p;K)}{\partial p_i} = q_i = \alpha_i K^2 + \beta_{ii} K + \sum \beta_{ij} \left(\frac{p_j}{p_i} \right)^{1/2} K + \rho K \qquad 3.12)$$

where

$$\rho = \sum_k \delta_{ik} d_k + \sum_l \varepsilon_{il} e_l + \sum_m \phi_{im} f_m$$

Demand for quota is derived for the unconstrained output supply equations using the virtual prices. Virtual prices relate unconstrained output supply and factor demand functions by substituting the virtual price expression into 12).

$$\lambda_1 = p_1 - \left(\frac{K \sum_{j \neq 1} \beta_{1j} p_j^{1/2}}{\overline{q_1} - \alpha_1 K^2 - \beta_{11} K - \rho K} \right)^2 \qquad 3.13)$$

λ, the input compensated marginal quota rent rises the closer the quota comes to binding. The above expression is the inverse derived demand function for additional summer flounder quota (Squires and Kirkley, 1996).

Simulating the quota market involves horizontally summing the individual firm level trip demand functions. The market equilibrium lease price for quota is found by setting market derived demand equal to the TAC. The expression for the equilibrium quota market is:

$$\overline{Q_1} = \sum_k \left[\alpha_1 \left(K^k\right)^2 + \beta_{11} K^k + \sum_{j \neq 1} \beta_{1j} \left(\frac{p_j^k}{\left(p_1^k - \lambda_1^k\right)} \right)^{1/2} K + \rho K^k \right] \qquad 3.14)$$

where $\overline{Q_1}$ is the overall quota for summer flounder and k is the number of trips in the year.

3.3 Results

Model estimation was handled in SAS using Proc Model (SAS 2003). Each input scaled output supply function, summer flounder, baitfish, shellfish, bottomfish, and other, was estimated individually and tested for heteroscedasticity using White's test (White 1980). Table 3.10 contains the results of those tests. In each case the null hypothesis of homoscedasticity is rejected in favor of a heteroscedastic error structure. Heteroscedasticity stemming from the square of the quasi fixed input was anticipated (Squires and Kirkley 1991, Carter et al 2008), and it was found with this specification. To remedy the heteroscedasticity, the following systems regression was weighted by the quasi fixed input.

Table 3.10. Results of White's Test for Heteroscedasticity for Individual Equations.

Equation	Statistic	Degrees of Freedom	Pr > ChiSq	Variables
Summer Flounder	8,399	492	<.0001	Cross of all variables
Bait	2,686	492	<.0001	Cross of all variables
Shellfish	9,374	492	<.0001	Cross of all variables
Bottomfish	3,839	492	<.0001	Cross of all variables
Other	2,619	492	<.0001	Cross of all variables

The full system of input scaled output supply functions were estimated using FIML estimators (SAS 2003). Symmetry was maintained for the regression result reported here. Initially, the Atlantic cyclonic index by month was tried, but for the northern Atlantic, there was not enough variation in the index to provide additional explanatory power.

For this regression, the functional form is assumed exact rather than an approximation (Squires and Kirkley 1996). As such, the errors are then assumed to arise from optimization rather than the approximation. Zero outputs in any species group in the regression create a limited dependent variable problem that introduces bias and non-normality of the regression residuals. As a result, zero outputs were replaced with the value of 0.1. See Squires and Kirkley (1991) and Carter et al (2008) for a more complete discussion of the impact of this replacement and other potential solutions that weren't possible due to computational feasibility or assumptions that would impact the analysis negatively.

Parameter estimates and regression diagnostics are detailed in Appendix 1. The summer flounder equation (parameters a1-a42) had the highest R-squared at 0.7594, which was to be expected. Also as expected, trip costs, the quasi fixed input, was positive and significant and trip cost squared was negative, small, and significant. Additionally, the prices of the other four species groups were positive and significant. Landings during the late winter (January, February, and March) and fall (October and November) had positive effects in the regression and were significant with the exception of the parameter on November. The spring and summer months had negative and significant impacts on the regression, with the exception of September which was negative, but not significant. There are far too many ports modeled to discuss each individually. Many of the port variables were insignificant.

The second best R-squared, 0.2427, came from the bottomfish output supply equation (parameters d1-d42). Unexpectedly, trip cost and trip cost squared are both negative and significant. All prices for other species were positive and significant. The months of January through April have positive and significant impacts on quantity supplied while the remainder of the year has a negative impact.

The third highest R-square, 0.1591, came out of the shellfish model (parameters c1-2. As expected, trip cost is positive and trip cost squared is negative. Price of other fish is positive but insignificant. Summer flounder price and bait price are both positive and significant. The price of bottomfish however has a negative and significant effect on the output supply of shellfish. Seasonally, shellfish follows similar pattern as bottomfish.

The fourth highest R-square, 0.1566, comes out of the baitfish output supply (parameters b1-b42). Both trip cost and trip cost squared are negative and significant. Prices of other species are all positive and significant except for other fish price which is positive but insignificant. The lowest R-square, 0.0842, comes out of the other fish output supply (parameters e1-e42). Trip cost was negative and significant while trip cost squared was negative and insignificant. All other species groups prices were positive, but only bottomfish and summer flounder prices were significant.

The technology tests included nonjointness and symmetry and the results are displayed in Appendix 1. Overall non-jointness in inputs was rejected suggesting that all inputs are required to produce all outputs, and, by broader extension, that harvesting processes for each species are connected. Species specific non-jointness tests were also rejected for each species grouping. This suggests that the production of one group relative to the other groups is interrelated to the harvest and relative prices of the other species groups in this joint production function. Separability was also rejected indicating that neither inputs nor outputs can be represented by composite goods. That is, a specific output bundle is required to produce a specific input bundle.

Detailed cost data of the type used here for the otter trawl fleet was not available for the other gears that harvest summer flounder. In 2007, there were 33 other gears that harvested summer flounder with a percentage of total landings ranging from well less than 0.1% to 4.8% of the total summer flounder commercial harvest. Additionally, the otter trawl fleet is probably the closest gear type to a directed fishery for summer flounder, whereas the other gear types are bycatch fisheries.

In order to examine what the possible quota market would look like for the entire quota, the following simulation assumes that the marginal quota values that are generated for the otter trawl fleet are equivalent to the marginal quota values for quota across other gear types that harvest summer flounder. In 2007, 64% of the quota was harvested by the otter trawl fleet. Also in 2007, summer flounder dockside prices were $1.49/pound less (36.3% lower) for the other gears than the prices obtained from otter trawls. Because of this price difference, the marginal quota values presented here represent an upper bound on the true estimate. For this not to hold, the cost structure across the other gear types would need to be significantly lower than the otter trawl cost structure. This is possible given that the otter trawl gear is probably one of the more costly gear types compared to the other gears.

Two methods were tried to simulate the entire 17.1 million pound TAC. The first involved randomly sampling additional observations from the otter trawl data set until predicted harvests equaled the total TAC (Carter et al 2008). The other involved scaling the simulated values upwards to the total TAC holding prices constant. The two methods produced virtually equivalent marginal quota value schedules.

Equation 3.14 was simulated between the total TAC of 17.1 million pounds (100% commercial allocation) and zero pounds. By running the simulation across a different range of values for λ, the input compensated quota rent, the annual supply function for each vessel can be traced and the horizontal sum of those individual supplies produces a marginal willingness to pay (WTP) for quota schedule across a range of allocations. The results of this simulation are displayed in Figure 3.3. Additionally, only well-behaved observations or those observations that did not violate monotonicity requirements were used in the simulation (Squires and Kirkley 1996, Carter et al 2008). At the current total commercial summer flounder harvest of 10.3 million pounds, summer flounder commercial fishermen are willing to pay $1.06 for an additional pound of summer flounder quota. At a zero percent commercial allocation, summer flounder fishermen would be willing to pay $2.45/pound to participate in the summer flounder fishery.

3.4 Conclusions

Commercial WTP for summer flounder quota is $1.06/pound. Figure 3.4 charts the total commercial benefit at different allocation levels. At the current allocation, the fishery is worth $10.9 million and maximum commercial benefit of $12.0 million occurs at a quota of approximately 13.5 million pounds. Estimation of value in this section does not include fixed costs or labor costs. Since the trip decision is a short run decision, this is typical for the literature. However, if these two cost categories were included in the modeling they could significantly alter the long-run profitability and demand for quota. Long-run decision making has not been included in this analysis.

Looking closely at Figure 3.3, one notices that across high allocation values, the inverse derived demand for quota is actually upward sloping for across a narrow range of values implying upward sloping quota demand function. That is, it appears that there are two values for the dependent variable (marginal quota value) for a single value of the independent variable (pounds of quota). There are many possible explanations for this apparent violation of economic theory. The generalized Leontief functional form is a flexible functional form. Flexible functional form models do not forecast well outside the mean and have the potential to be unreliable for projections as far outside the mean predicted landings.

Second, the otter trawl fleet has high fixed costs. This could possibly explain the upward sloping quota demand. High allocations of the TAC would drive summer flounder dockside prices downward. At low dockside prices and high fixed costs, operators may be willing to pay more for more quota over a certain range. Examining this issue further is beyond the scope of this analysis. As a result, caution is warranted when making recommendations based on the shape of this function too far outside of the current mean landings.

Finally, the results of the technology tests have implications for potential allocation changes that may be examined. Because overall nonjointness in and individual species group tests were rejected, changing allocations for summer flounder may have spillover effects on other species. While it seems intuitive in a multispecies fishery such as the otter trawl fishery, this result quantifies that if summer flounder allocations go up or down it may increase exploitation of other species.

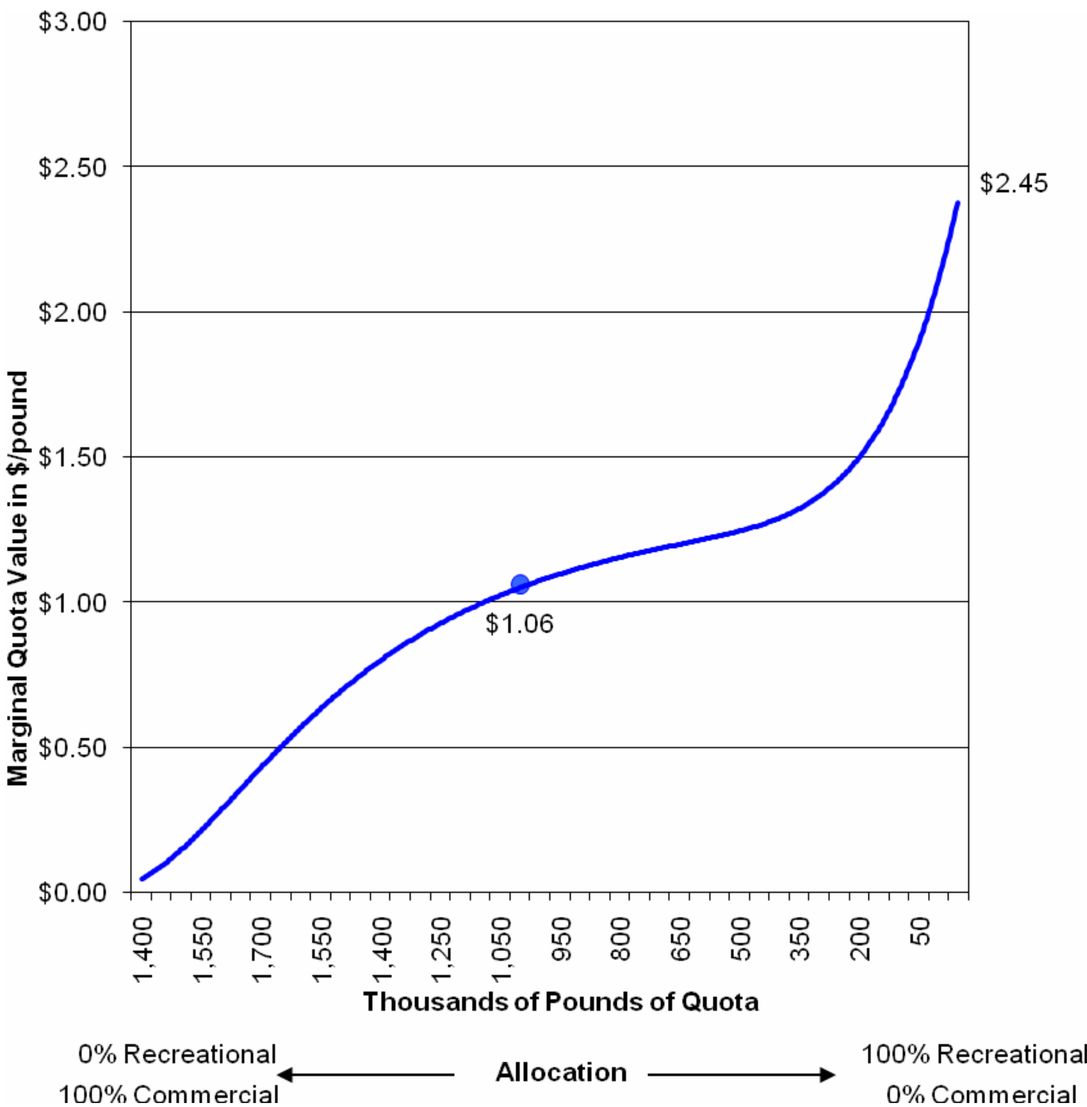

Figure 3.3. Simulated Marginal Quota Value for Summer Flounder Quota Pounds (2007 dollars)

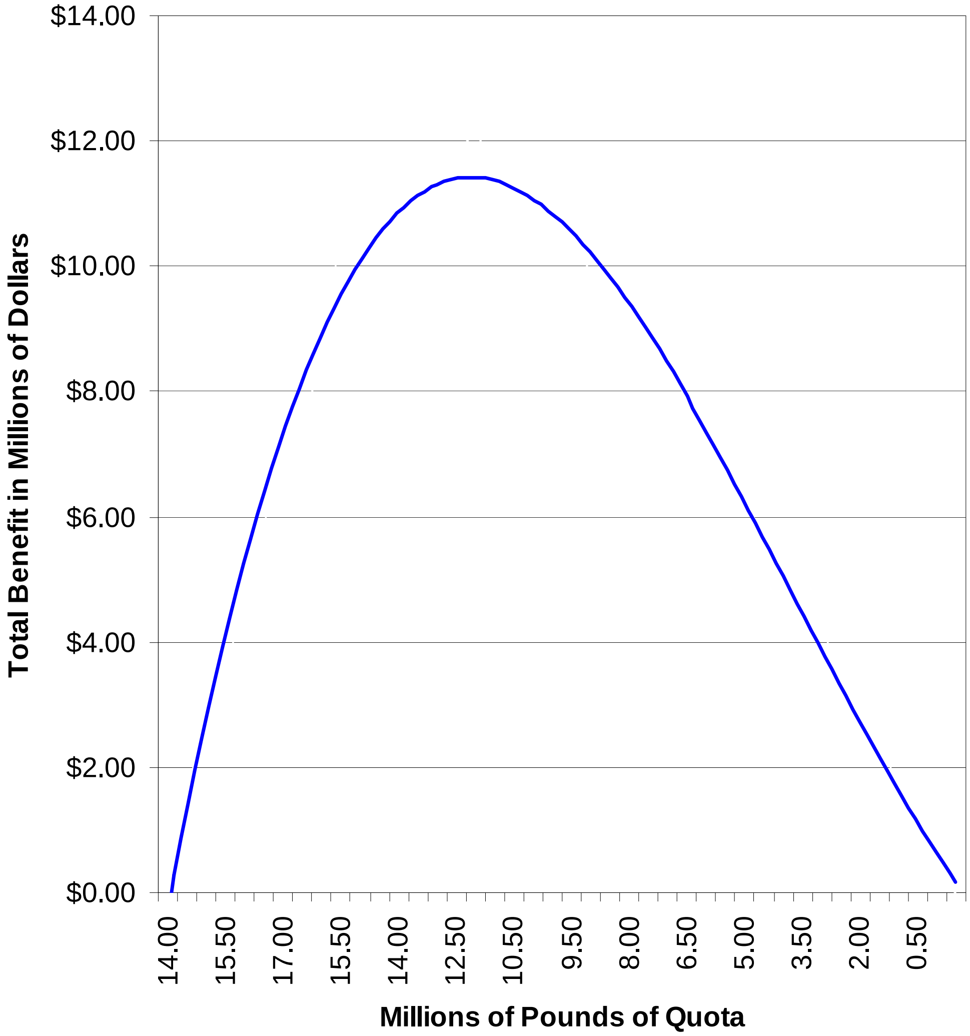

Figure 3.4. Summer Flounder Commercial Total Net Benefits (2007 dollars)

4.0 Consumer Valuation

Determining an allocation that maximizes benefits to the nation is extremely complicated. Estimates of net benefits from the fishery must include producer benefits, recreational angler benefits, for-hire industry benefits, and summer flounder consumer benefits. In this brief report, we provide a broad overview of a framework to estimated consumer benefits for the commercial sector using compensating variation as the benefits metric. We also provide a framework for estimating changes in prices associated with changes in landings. Using the models developed, this report provides estimates of changes in prices, nominal and real revenues, and compensating variation corresponding to a 10 % reduction in commercial landings of summer flounder; and estimates of compensating variation per pound landed for the period 1991 through 2006.

4.1 Methodology

The body of literature describing approaches for estimating both market and non-market values for various goods, services, and states of the environment is rich (see, for example, Freeman, 1989 and Bockstael and McConnell, 2007). Our primary focus here, however, is estimating how changes in commercial landings affect commercial prices, ex-vessel revenues, and compensating variation for consumers. Further attention is focused, then, on estimating market values for summer flounder.

4.1.1 The Synthetic Inverse Demand System

There is an extensive literature of estimating commercial demand functions. This includes literature on functional form specification as well as whether or not fish demand models should be price or quantity dependent. There is no precise answer, but the available literature suggests that the demand for many agricultural and fishery commodities should be expressed as price dependent equations (Barten and Bettendorf, 1989; Barten, 1993; Brown et al., 1995; and Park et al., 2004).

One approach gaining favor by empirical researchers is the synthetic inverse demand system (SIDS). This is a flexible functional form specification of an inverse demand, which facilitates testing various restrictions to determine if other alternative specifications of demand can be used. These alternative specifications include the inverse Rotterdam demand model (IROT), the inverse almost ideal demand system (IAIDS), the inverse Central Bureau of Statistics (ICBS) demand model, and the inverse National Bureau of Research (INBR) demand model.[4] All these models maintain desirable properties of demand theory and facilitate estimation of changes in prices, revenues, and consumer benefits associated with changes in the demand (landings) of agricultural and fishery commodities.

Within the SIDS framework, a system of demand equations can be estimated by seemingly unrelated regression or, if there are cross equation constraints, maximum likelihood estimation techniques. The basic specification used in the analysis contained in this paper follows Park et al. (2004):

$$w_{it}\,\Delta\ln v_{it} = \alpha_i + \sum_{j=1}^{n}\pi_{ij}\,\Delta\ln q_{jt} + \pi_i\,\Delta\ln Q_t - \theta_1 w_{it}\,\Delta\ln Q_t - \theta_2 w_{it}\,\Delta\ln\left(\frac{q_{it}}{Q_t}\right)_{it} + \varepsilon_{it}, \quad 4.1)$$

where $\ln Q_t = \sum_{j=1}^{N} w_{jt}\ln q_{it}$.

In this specification, q_i is the per capita quantity demanded for the i^{th} quantity; v_i is a normalized price for the i^{th} commodity (i.e., $v_i = p_i/m$, where p_i is the price of the i^{th} commodity, and m is the per capita level of total expenditures for all commodities under consideration); α_i, π_i, and π_{ij} are coefficients to be estimated; Δ is a change operator; ε_{it} is the error term, which is assumed to be normally distributed with a mean of zero and constant variance; and θ_1 and θ_2 are estimable parameters. θ_1 and θ_2 are further assessed, via parametric restrictions, to determine if one of the four basic inverse demand models best describe the demand for seafood. If $\theta_1 = \theta_2 = 0$, the model reduces to the inverse Rotterdam model; if $\theta_1 = \theta_2 = 1$, the model becomes the inverse almost ideal demand system (IADS) model; if $\theta_1 = 1$ and $\theta_2 = 0$, the model becomes the ICBS model; and if $\theta_1 = 0$ and $\theta_2 = 1$, the SIDS model becomes the INBR model.[5] The inverse demand system of equations requires several constraints consistent with demand theory: (1) symmetry in

[4] Park et al. (2004) provide a comprehensive discussion and illustration of the SIDS model.
[5] See Park et al. (2004) for a detailed discussion of the SIDS and related inverse demand models.

which $\pi_{ij} = \pi_{ji}$, (2) adding up in which $\Sigma_i \pi_{ij} = 0.0$, (3) homogeneity in which $\Sigma_j \pi_{ij} = 0.0$, and (4) $\Sigma_i \pi_i = 0.0$.

Excluding halibut, there are approximately 11 species of flounder landed in the United States: (1) arrowtooth flounder, (2) pacific sanddab, (3) southern flounder, (4) starry flounder, (5) summer flounder, (6) windowpane, (7) winter flounder, (8) witch flounder, (9) yellowtail flounder, (10) plaice, and (11) righteye flounder. Based on some simple analyses of correlations and preliminary regressions, it was decided to aggregate 10 of the species into two groups: (1) other flounder 1, which consists of arrowtooth, southern, starry, winter, and plaice flounder, and (2) other flounder 2 containing windowpanes, witch flounder, and yellowtail flounder. We also include imports of all flatfish and flounder as another group to consider in the demand analysis. Therefore, we have four equations in our system of demand: (1) summer flounder, (2) other flounder 1, (3) other flounder 2, and (4) imports.

No retail data exists for seafood at the species level. As a result these species groups were constructed using a review of the literature, simple correlation analysis from landings data, and through discussions with retailers. No models were run examining different aggregations among the flatfish species other than the aggregation detailed above. Also, data on all other protein expenditures, while important in explaining seafood protein expenditures were not included due to data and modeling limitations. It is very time consuming to set up each species group and most modeling programs are limited in the number of simultaneous equations that can be supported. It has been the author's experience that adding additional sectors adds little to change the parameter estimates, after a certain point. Asche et al (2005), Parks et al (2004) and others find that focusing on a narrower range of species thought to be substitutes or complements a priori has little effect on overall estimates.

NMFS suggested that anecdotal information indicated that tilapia may be used as a summer flounder substitute. No attempt was made to examine this for a number of due to data limitations. During the period included in this analysis, there has been a structural change in the tilapia industry and, early in the time series, tilapia is not well identified in the data.

Although most researchers estimate the system of demand equations using iterative Zellner (1962), Greene (2003) demonstrated that maximum likelihood should be used to estimate the system of equations when cross equation constraints are imposed. We, therefore, apply the maximum likelihood routine available in LIMDEP to estimate the system of seemingly unrelated demand equations.

The cross equation constraints used include:

$$\sum_i \left(\pi_{ij} - \theta_2 \ w_i \delta_{ij} + \theta_2 w_i w_j\right) = \sum_i \pi_{ij} = 0 \ \textit{adding up}$$
$$\sum_i \left(\pi_i - \theta_1 \ w_i\right) = 1 \ \textit{adding up}$$
$$\sum_j \left(\pi_{ij} - \theta_2 \ w_i \delta_{ij} + \theta_2 w_i w_j\right) = \sum_j \pi_{ij} = 0 \ \hom ogeneity \qquad 4.2)$$
$$\pi_{ij} = \pi_{ji} \ \textit{symmetry}$$

The SIDS model is quite convenient because it easily facilitates calculation of various compensated and uncompensated price flexibilities or elasticities and measures of welfare, which include compensated and equivalent variation and consumer surplus. Calculations of the elasticities are as follows:[6]

$$\textit{scale elasticity} = f_i = \frac{\pi_i}{w_i} - \theta_1,$$

$$\textit{compensated cross} - \textit{quantity elasticity} = f_{ij}^* = \frac{\pi_{ij}}{w_i} + \theta_2 w_j, \qquad 4.3)$$

$$\textit{compensatedown} - \textit{quanitity elasticity} = \frac{\pi_{ii}}{w_i} - \theta_2 w_i,$$

$$\textit{uncompensated quantity elasticity} = f_{ij}^* + w_j f_i.$$

In the analysis contained in this report, we consider only compensating variation. Typically, there is little difference between compensating variation, equivalent variation, and consumer surplus. Moreover, Freeman (1979) suggests that the Marshallian consumer surplus measure is without economic foundation, and thus, recommends using compensating variation as the preferred measure of welfare or benefits. Compensating variation is simply the level of compensating payment or offsetting change in income, which is necessary to make an individual indifferent between an original situation and new situation. It may also be interpreted as the maximum amount an individual would be willing to pay for the opportunity to consume the same quantity of goods at a new price, as consumed under the original price.

Park et al. (2004) provide three convenient formulas for calculating all three welfare measures. While we present all three formulas, we stress that we estimate only compensating variation. The three are as follows:

[6] The elasticities and respective calculations are further derived in Park et al. (2004). The scale flexibility or elasticity is often equated to the income elasticity in demand. As shown by Park and Thurman (1999), however, they are not equivalent. Scale flexibility is defined to be the proportional change in a normalized price, v_i in our model, resulting from a scalar expansion of all commodities in the consumption bundle (i.e., all q_i in our analysis). The scale flexibility is restricted to a radial expansion from the origin to the indifference curve or utility function.

$$equivalent\ variation = (-\Delta q)\left\{v^1 - 0.5\ x\left[(compensated\ \ flexibility)\frac{v^0}{q^0}\right]\Delta q\right\}$$

$$compensating\ variation = (-\Delta q)\left\{v^0 - 0.5\ x\left[(compensated\ \ flexibility)\frac{v^0}{q^0}\right]\Delta q\right\} \quad 4.4)$$

$$consumer\ surplus = (-\Delta q)\left\{v^0 - 0.5\ x\left[(uncompensated\ \ flexibility)\frac{v^0}{q^0}\right]\Delta q\right\}$$

For welfare gains, the estimates of compensating and equivalent variation are negative, and for welfare losses, the estimates are positive.

A remaining concern is estimating changes in demand price and corresponding revenues. Park et al. (2004) provide a convenient equation for estimating the demand price corresponding to a change in demand:

$$v^1 = v^0 + \Delta v = v^0[1\text{-(flexibility)x}(\Delta q/q)], \qquad 4.5)$$

where p is the normalized price (price divided by total expenditures); v^1 and v^0 represent normalized prices at time 1 and time 0; flexibility is the compensated quantity elasticity; and $\Delta q = q^1 - q^0$. In this particular situation, we define q to equal the reported quantity landed divided by the U.S. population.

4.1.2 Statistical Estimates of the SIDS Model

The previously discussed SIDS model was estimated by the method of maximum likelihood. As shown by Greene (2002), maximum likelihood is preferred over iterative seemingly unrelated regression when cross equation restrictions are imposed, and estimation requires dropping one equation from the estimation to avoid singularity. There are four equations: (1) an inverse demand for summer flounder, (2) the inverse demand for other flounder, group 1, (3) the inverse demand for other flounder, group 2, and (4) the inverse demand for imports. One equation must be omitted to avoid singularity. For the purpose of estimation, we omit imports from the system of equations. Parameter estimates for imports are directly obtained via restrictions imposed on the system of equations (e.g., homogeneity and adding up constraints).

Data on annual landings and ex-vessel values were obtained from NOAA Fisheries, electronic databases. Landings data came from the commercial landings data files, and data on imports were derived from NOAA's international fisheries statistics. These data were used to construct prices and expenditures, with the latter equaling the sum of the price times the quantity of each of the species under consideration in the grouping. All landings and expenditure data were converted to per capita statistics by dividing by the resident civilian population. Data covered the period 1989 through 2006. Data for 1989 and 1990, however, were omitted because it was necessary to take first differences of all variables.

The system of equations contained 26 parameters. The statistical results were mostly significant, and all equations had relatively good fit (Table 4.1). Adjusted R-squared values ranged from a low of 0.63 for other flounder (group 1) to 0.82 for other flounder (group 2). The adjusted R-squared for summer flounder equaled 0.69. Based on the Durbin-Watson statistics, autocorrelation did not appear to pose a problem. Spurious correlation was also not a problem because all equations were specified as first differences. We accept the original restrictions on the SIDS model regarding symmetry, homogeneity, and adding up. The Wald chi-squared statistic testing all restrictions is 9.65 with 10 degrees of freedom.

Table 4.1. Parameter Estimates of the SIDS Model for Flounder[a]

Group	Constant	Summer Flounder	Other Flounder GRP 1	Other Flounder GRP 2	Imports	A Divisia Quantity Index-Q	θ_1	θ_2
Summer Flounder	0.0003	-0.033*	0.002	-0.005*	0.037*	0.057*	1.41*	0.21*
Other Flounder 1	-0.0017	0.002	-0.104*	0.014*	0.088*	-0.054*	1.41*	0.21*
Other Flounder 2	-0.0015	-0.005*	0.014*	-0.050*	0.041*	0.034*	1.41*	0.21*
Imported Flounder	0.0029	0.037*	0.088*	0.041*	-0.166*	-0.037	1.41*	0.21*

[a]All variables, except constant are expressed in terms of change in natural log values. All landings data (each species or composite output) are expressed in terms of per capita consumption.
* indicates significant at 5 % level of significance.

The best model estimated was the SIDS model with unrestricted θ values, and these results are typical of many SIDS modes where the unrestricted values perform the best (Parks et al 2004). The IROT model restrictions ($\theta_1 = \theta_2 = 0$) yields a Wald of 1651.79; the ICBS model restrictions ($\theta_1 = 1$ and $\theta_2 = 0$) yields a Wald of 1380.54; the IAIDS model restrictions ($\theta_1 = \theta_2 = 1$) yield a Wald of 1346.23; and the INBR model restrictions ($\theta_1 = 0$ and $\theta_2 = 1$) yield a Wald of 1483.07. This suggests that none of the restrictions are appropriate. While the mixing parameters, θ_1 and θ_2, are close to the ICBS values of 1 and 0, they are not statistically the same. Furthermore, likelihood ratio test results for these same restrictions are shown in Table 4.2 (Brown et al 1995). These tests also indicate that the unrestricted model provides the best fit.

Table 4.2. Log Likelihood Ratio Test Results for Inverse Demand Structure

Log Likelihood Ratio	Model	Chi-squared	DF	Critical Value	
179.77	SIDS			5%	0.50%
172.32	IROT	14.90	2	5.99	7.88
172.93	ICBS	13.68	2	5.99	7.88
172.94	IAIDS	13.66	2	5.99	7.88
172.40	INBR	14.74	2	5.99	7.88

4.2 Prices, Revenues, and Compensating Variation

In this assessment, we initially present estimates of the scale elasticities and all compensated own and cross price elasticities (Table 4.3). We next consider a 10 % change in landings of summer flounder, and assess changes in ex-vessel prices, nominal and real revenues (revenue adjusted for inflation using the producer price index for finfish), and compensating variation. We also present estimates of the compensating variation on a per pound basis, and the compensating variation corresponding to a one unit increase in the demand for summer flounder (i.e., the marginal value of a one unit change in demand).

Table 4.3. Mean Compensated Own and Cross Price and Scale Elasticities

Group	Summer Flounder	Other Flounder-1	Other Flounder-2	Imports	Scale Elasticities
Summer Flounder	-0.225	0.004	-0.084	0.305	-0.71
Other Flounder-1	0.003	-0.770	0.114	0.653	-1.91
OtherFlounder-2	-0.093	0.170	-0.487	0.409	-0.94
Imports	0.033	0.097	0.041	-0.171	-1.46

Estimates of the scale elasticities were similar to those obtained in numerous other studies in which the values are near 1.0, which simply depict the percentage change in price as the quantity of each good in the system is changed by 1.0 % (Table 4.3). The scale elasticities for other flounder, group 1 and imports, however, were relatively high at 1.91 and 1.46 respectively. For example, if the quantity of all flounder species increased by 1%, the price of summer flounder would fall 0.71%, other flounder-1 would fall by 1.91%, other flounder-2 would fall by 0.94%, and import prices would fall by 1.46%. The compensated own and quantity elasticities were similar to those obtained in other studies on fisheries; the elasticities were all less than 1.0 % (Table 4.3). Note that positive cross-price elasticity indicates complementarity, while a negative cross price elasticity indicates substitutability. For summer flounder that means that other flounder-1 and imports are complements while other flounder-2 is a substitute. That is, as price for summer flounder decreases, the prices of other flounder1 and imports also fall and the price for other flounder-2 rises. Also observe that imports are complements to all three other species or aggregate outputs.

We next examine how prices, revenues, and compensating variation would change for a hypothetical 10 % reduction in landings of summer flounder. As is suggested by the quantity elasticities, prices are not very sensitive to changes in demand. In 2006, a 10 % reduction in demand induced only a 1.57 % increase in ex-vessel price, but ex-vessel revenues declined by 8.59 % (Table 4.4). Compensating variation or consumer benefits equaled \$2.9 million or roughly \$0.23 per pound in 2006. On average, compensating variation equaled \$3.2 million and \$0.27 per pound per year between 1991 and 2006.

Table 4.4. Changes in Ex-vessel Prices, Revenues, and Compensating Variation for a 10% Reduction in Demand for Summer Flounder[a]

Year	Observed Landings	10 % Reduction	Observed Price	Price for 10 % Reduction	Reported Revenue	Revenue For 10 % Reduction	Change in Revenue	Total CV	CV Per Pound
91	13,868,625	12,481,763	2.18	2.24	30,289,341	27,989,269	-2,300,072	2,842,752	0.23
92	16,635,703	14,972,133	2.11	2.14	35,022,834	32,068,152	-2,954,682	3,634,058	0.24
93	13,000,319	11,700,287	2.25	2.31	29,307,502	27,073,089	-2,234,413	2,931,849	0.25
94	14,572,895	13,115,606	2.44	2.48	35,589,417	32,523,143	-3,066,274	3,821,593	0.29
95	15,410,322	13,869,290	2.48	2.51	38,188,269	34,813,602	-3,374,666	3,951,534	0.28
96	12,656,451	11,390,806	2.33	2.37	29,438,656	26,988,626	-2,450,031	3,465,009	0.30
97	8,591,554	7,732,399	2.49	2.57	21,382,031	19,845,482	-1,536,549	2,441,433	0.32
98	10,984,327	9,885,894	2.29	2.34	25,103,058	23,159,392	-1,943,666	2,736,853	0.28
99	10,490,449	9,441,404	2.25	2.31	23,552,180	21,777,707	-1,774,473	2,523,956	0.27
00	11,019,193	9,917,274	2.14	2.21	23,569,837	21,870,650	-1,699,187	2,282,761	0.23
01	10,716,200	9,644,580	2.01	2.07	21,539,782	19,979,152	-1,560,630	2,413,921	0.25
02	14,227,332	12,804,599	1.84	1.88	26,129,954	24,096,394	-2,033,560	2,765,085	0.22
03	14,328,342	12,895,508	1.96	2.01	28,151,780	25,962,574	-2,189,206	2,729,797	0.21
04	17,883,808	16,095,427	1.85	1.88	33,029,025	30,264,644	-2,764,381	3,080,958	0.19
05	17,261,958	15,535,762	1.88	1.91	32,445,617	29,631,367	-2,814,250	3,182,719	0.20
06	13,960,339	12,564,305	2.05	2.08	28,647,306	26,186,987	-2,460,319	2,917,766	0.23
Mean Value Per Year								3,232,628	0.27

[a]All dollar values are in 2006 constant dollars.

A major concern for managers is the allocation of allowable harvests among competing user groups, which in this case consists of commercial fishermen and recreational anglers. A typical economic allocation rule is to allocate the resource until the marginal benefit of one user group equals the marginal benefit of the other user group. In this case, we consider the compensating variation for a one unit increase in the landings of summer flounder.

Not surprising, a one unit increase in summer flounder landings does not generate much additional revenues or consumer benefits. Table 4.5 contains the model results for a one unit increase in landings. Revenues increase by $1.73 in 2006, and consumer surplus, at the margin, equaled only $0.15 per pound; the corresponding ex-vessel price was $2.05 per pound. On average, revenue and compensating variation, respectively, increases by approximately $1.67 and $0.16 per year for a one pound increase in landings between 1991 and 2006.

Table 4.5. Prices, Revenues, and Compensating Variation for a One Unit Increase in Demand for Summer Flounder[a]

Year	Reported Landings	One Unit Increase in Landings	Reported Price	Price for One Unit Increase	Reported Revenue	Revenue for One Unit Increase in Landings	Change in Revenue	CV Per Pound
91	13,868,625	13,868,626	2.18	2.18	30,289,341	30,289,343	1.60	-0.01
92	16,635,703	16,635,704	2.11	2.11	35,022,834	35,022,836	1.74	-0.13
93	13,000,319	13,000,320	2.25	2.25	29,307,502	29,307,504	1.66	-0.17
94	14,572,895	14,572,896	2.44	2.44	35,589,417	35,589,419	2.07	-0.18
95	15,410,322	15,410,323	2.48	2.48	38,188,269	38,188,271	2.16	-0.16
96	12,656,451	12,656,452	2.33	2.33	29,438,656	29,438,658	1.89	-0.21
97	8,591,554	8,591,555	2.49	2.49	21,382,031	21,382,033	1.71	-0.32
98	10,984,327	10,984,328	2.29	2.29	25,103,058	25,103,060	1.71	-0.22
99	10,490,449	10,490,450	2.25	2.25	23,552,180	23,552,182	1.63	-0.22
00	11,019,193	11,019,194	2.14	2.14	23,569,837	23,569,838	1.48	-0.18
01	10,716,200	10,716,201	2.01	2.01	21,539,782	21,539,783	1.39	-0.20
02	14,227,332	14,227,333	1.84	1.84	26,129,954	26,129,955	1.38	-0.13
03	14,328,342	14,328,343	1.96	1.96	28,151,780	28,151,782	1.48	-0.13
04	17,883,808	17,883,809	1.85	1.85	33,029,025	33,029,027	1.51	-0.09
05	17,261,958	17,261,959	1.88	1.88	32,445,617	32,445,619	1.60	-0.11
06	13,960,339	13,960,340	2.05	2.05	28,647,306	28,647,308	1.73	-0.15

[a]All dollar values are in terms of 2006 constant dollar values. Note that compensating variation for a one unit increase is negative, which is a result of the calculation. For ease of interpretation, the compensating variation may be converted to positive values.

5.0 Recreational Valuation

This section details the calculation of unweighted and weighted recreational marginal value estimates using Marine Recreational Fisheries Statistical Survey (MRFSS) data. This chapter begins with a description of the unweighted methodology used to generate recreational value estimates and a discussion of the results of the modeling effort. Next, the weighted methodology and results are discussed. This report only contains marginal value estimates for the consumer side of recreational fishing. At this time there is insufficient data on for-hire industry's costs and earnings to calculate the marginal values of summer flounder harvest for the for-hire fleet.

5.1 Unweighted Methodology

Random utility models (RUM) rely on observed data on recreational site choices. The observed data for this study comes from the 2006 MRFSS intercept survey. In this section we will specify the RUM model and present the data manipulation process necessary to run a RUM for summer flounder using the Marine Recreational Fishery Statistics Survey (MRFSS) angler data.

This report relies on data from the National Marine Fisheries Service's MRFSS. The National Marine Fisheries Service (NMFS) is mandated by law to analyze the benefits, costs, and economic impacts of the recreational fisheries policies it promulgates. Since 1994, NMFS has used the Marine Recreational Fishing Statistics Survey (MRFSS) to gather the travel cost data necessary to estimate the value of access and the value of changes in catch rates.

The analysis presented here will utilize data collected by the MRFSS. The MRFSS consists of two independent and complementary surveys; a field intercept survey and a random digit dial (RDD) survey of coastal households. The intercept survey is a creel survey used to estimate mean catch-per-trip by species across several strata including, fishing wave (2-month period), fishing mode (shore, private or rental boat, or for-hire fishing vessel), and state. Data elements collected during the base part of the intercept survey include state, county, and zip code of residence, hours fished, primary area fished, target species, gear used, and days fished in the last two and 12 months. The creel portion of the survey collects length and weight of all fish species retained by the angler and the species and disposition of all catch not retained by the angler.

Because the MRFSS constitutes the best nationwide sample frame for marine recreational angling and offers considerable savings over implementing a new program, economic data collection is added-on to the MRFSS effort. During March through December of 2006, an intercept add-on survey was conducted to obtain data on angler trip expenditures. Upon completion of the base MRFSS survey in 2006, anglers were asked to complete a short add-on questionnaire. The intercept add-on survey was designed to collect the minimum data necessary to estimate RUM's of anglers' site choice decisions.

The intercept survey is designed to be a random sample of trips. As such the probability of being sampled is linked to the number of times an angler fishes with more avid anglers being intercepted more frequently. This is a type of choice-based sampling, also known as an endogenously stratified sample, and it impacts the estimation of metrics denominated by individual anglers. Thompson (1991) identified the impact this type of sampling has on recreational value estimates. Also, during a 2006 Center for Independent Experts (CIE) review of the NMFS economic data collection program, choice based sampling's impact on valuation estimates was identified as an area needing further examination (CIE 2006). Recent strides have been made to use weights from the RDD survey to eliminate this bias including work by this author (Hindsley et al 2008). Developing and using these weights to eliminate the choice based sampling bias require the estimation of the unweighted model first and the rest of this report will focus on the estimation of the unweighted model. The weighted model will be developed in a subsequent section.

5.1.1 Nested Logit

RUM's use all of the substitute recreational sites facing an angler to value attributes of the site chosen by an angler. In this case, we are interested in valuing summer flounder harvest rates. NMFS has sponsored a good deal of research into RUM's of recreational site choice to value site closures and angling quality (Hicks et. al, 1999, McConnell et al, 1994, Haab et al, 2000, Gentner 2007, to name a few). The majority of this work has involved specifying nested logit model of recreational site choice using expected catch rates as the measure of angling quality. This exercise follows previous NMFS RUM specifications as closely as possible given the data limitations described below. The specification of the nested logit model for recreational choices has been adapted from Haab and McConnell (2003).

Angler utility is specified as:

$$u_{jk} = v_{jk} + \varepsilon_{jk} \qquad 5.1)$$

where v_{jk} is an angler's indirect utility and ε_{jk} is a random error term for site j in mode k. For this exercise, it is assumed that the decision to fish for summer flounder is exogenous to the model. Subsequent to the choice to participate in summer flounder fishing, the angler is assumed to make a fishing mode choice and then a site choice conditioned on the mode choice. The upper level nesting structure includes the choice of fishing mode across shore fishing, for-hire fishing, and fishing from the private/rental boat mode. In this case, the global site list includes the same 63 aggregated sites as used in Hicks et al (1999), with some slight modifications discussed below.

An angler chooses a fishing site from the set of all alternative site and fishing mode combinations if the utility of visiting that site in that mode is greater than the utility of visiting any other site in any other mode in the global choice set.

$$u_{jk} \geq u_{j'k'} \forall j', k' \qquad 5.2)$$

Furthermore, summer flounder angler indirect utility is specified by:

$$v(y - c_{jk}, q_{jk}, s_k) = -\beta_y c_{jk} + q_{jk}\beta + s_k \gamma \qquad 5.3)$$

where y is income, c_{jk} is the cost of traveling to the site, q_{jk} is a vector of quality attributes that vary by site and mode choice, and s_k is a set of attributes that vary only by mode choice. Since income is an additive constant across all sites combinations in the choice set, it falls out of the nested logit probability. Following Hicks et al (1999), the vector q contains travel cost (travelc), the log of the number of MRFSS intercept sites aggregated into the sites used in this model (lnm), and the expected keep rate (ekarate). The keep rate was used to model mortality and not total catch. While the keep rate includes observed catch it also includes self reported mortality not seen by a MRFSS interviewer. It does not include any mortality of released fish unless the fish was dead before release. It is felt that this measure most closely approximates commercial mortality. The vector, s, contains two variables pr_boater and north_shore, which will be described below.

The nested logit probability is:

$$\Pr(j,k) = \frac{\exp\left(\dfrac{\alpha_k + v_{jk}}{\theta_k}\right)\left[\sum_{l=1}^{J_k} \exp\left(\dfrac{\alpha_k + v_{lk}}{\theta_k}\right)\right]^{\theta_k - 1}}{\sum_{m=1}^{K}\left[\sum_{l=1}^{J_m} \exp\left(\dfrac{\alpha_m + v_{lm}}{\theta_m}\right)\right]^{\theta_m}} \qquad 5.4)$$

where K is the total number of upper level nests, J_k is number of lower level sites for upper level k, m = (1,….,J), l = (1,….,K), α_k is the location parameter, and θ_k is the inclusive value parameter. This study is concerned with estimating the marginal net benefits of summer flounder harvest. The appropriate benefit metric in this case is compensating variation (CV) (Haab and McConnell, 2003). Within the nested logit model, indirect utility is specified as:

$$V(c,q,s,y) = \ln\left(\sum_{m=1}^{K} a_m \left[\sum_{l=1}^{J_m} \exp\left(\frac{v(y - c_{lm}, q_{lm}, s_m)}{\theta_m}\right)\right]^{\theta_m}\right) \tag{5.5}$$

CV is calculated by differencing the indirect utility before an allocation change to the indirect utility after an allocation change and is represented by:

$$V(c,q,s,y) = V(c^*, q^*, s^*, y - WTP) \tag{5.6}$$

where the star (*) denotes the changed indirect utility attributes. If V(*) >V(original) then CV is greater than zero. For quality changes that are the same for all sites, such as an allocation change, the CV calculation collapses to:

$$WTP = \frac{\Delta ekarate(\beta_{ekarate})}{\beta_{travelc}} \tag{5.7}$$

or the change in the expected keep rate times the parameter estimate for expected keep rate divided by the parameter estimate for travel cost. Please see Haab and McConnell (1999) for further details of this specification and the mechanics of the CV calculation.

5.1.2 Data Manipulation

Data for this effort comes from the MRFSS intercept survey. In 2006, NMFS conducted an expenditure survey that also collected the bare minimum number of additional variables for estimation of the site choice model. During 2006, 3,262 anglers caught summer flounder, finished the intercept add-on containing the necessary variables, and gave the interviewer a home zip code necessary for travel cost calculation. By wave, 1.7% of all anglers were intercepted in wave 2, 35.9% were intercepted in wave 3, 52.4% were intercepted in wave 4, 10% were intercepted in wave 5, and only 0.2% were intercepted in wave 6. No MRFSS sampling is conducted in wave 1. By fishing mode, 5.6% of all intercepts were in the shore mode, 41.2% were in the for-hire mode, and 53.2% were intercepted in the private rental mode.

Developing a data set for the nested logit model involves a series of steps. Initially, all sites were aggregated using the Hicks et al (1999) methodology. It was found during the estimation of keep rates that summer flounder has never been caught or targeted from Maine sites during the previous ten years, so all Maine sites were dropped leaving 55 sites in the model.

This model diverges from the model specified in both Hicks et al (1999) and Haab et al (2000) because less data was collected during the intercept add-on survey. A number of variables that have been collected in previous intercept add-on surveys, including boat ownership, income, and time off work without pay, were not collected during the intercept add-on in 2006 to make room for trip expenditure questions. As a result, travel cost does not contain calculations for time taken off work without pay as in Hicks et al (1999) and Haab et al (2000). Instead, two measures of travel cost are used here: travel cost only and travel cost plus the opportunity cost of time calculated using census income data. Travel cost is simply the round trip travel distance multiplied by the current federal government travel reimbursement rate of $0.585/mile. The opportunity cost of time was calculated by taking the travel time (calculated miles/40 mph average travel speed) and multiplying it by one-third the wage rate. Wage rates were calculated by taking median household income by zip code and dividing it by 2,000 work hours per year (U.S. Census Bureau, 2002).

CV estimates presented in this report that are based on travel cost alone represent a lower bound when compared to methodologies previously used by NMFS. On the other hand, CV estimates using U.S. Census income estimates to develop the opportunity cost of time likely represent an upper bound when compared to previous NMFS studies.

While boat ownership has shown to be an important explanatory variable when describing mode choice, that question was not asked on the intercept survey. Instead, a proxy for boat ownership was defined as taking the value of one if an angler purchased boat fuel during their intercepted trip and a value of zero otherwise. This variable was crossed with a dummy set to the value of one if an angler was intercepted in the private rental boat mode. This variable, pr_boater was used to explain mode choices in the upper level nest. The other variable describing the upper level nest mode choice, north_shore, took the value of one if an angler was intercepted in the shore mode in any state north of New York.

Following Hicks et al (1999) a keep rate matrix for all sites by mode was developed by taking the five year average keep at each site by mode. As described by Hicks et al (1999), these matrices contain many zero values that may indicate the site is not used as a summer flounder site or that may indicate that summer flounder has never been encountered by MRFSS interviewers at the site. Zeros were replaced using the nearest neighboring site in the same mode, if replacement was deemed appropriate based on examination of the harvest data and the site's location. Table 5.2 contains the descriptive statistics for all variables used in the modeling.

Table 5.2. Descriptive Statistics for all Variables

Variable Name	Description	Mean	Standard Error	Lower Confidence Limit	Upper Confidence Limit
Hrsf	Hours Fished	4.032	0.026	3.980	4.083
Pr	Dummy for Private/Rental Mode	0.532	0.009	0.515	0.549
Charter	Dummy for Charter Mode	0.412	0.009	0.395	0.429
Shore	Dummy for Shore Mode	0.056	0.004	0.048	0.064
ffdays12	12 Month Avidity – number of days	25.331	0.601	24.154	26.509
Travel	Calculated Travel Cost	$51.88	$1.04	$49.84	$53.91
travel_opp	Travel Cost Plus Opportunity Cost of Travel Time	$75.420	1.460	$72.44	$78.28
Boater	Proxy for Boat Ownership	0.286	0.008	0.271	0.302
North	Equals 1 If Site is North of NY	0.413	0.001	0.411	0.414
Lnm	Log of Number of Aggregated Sites	2.924	0.001	2.921	2.926
Karate	Harvest per Trip – numbers of fish	0.356	0.001	0.355	0.357
Ekarate	Expected Harvest per Trip – numbers of fish	0.448	0.002	0.444	0.452
pr_boater	Private/Rental Mode Crossed with Boater	0.095	0.000	0.094	0.096
north_shore	North Crossed with Shore	0.114	0.000	0.114	0.115
wave3	Intercepted in Wave 3	0.357	0.008	0.340	0.373
wave4	Intercepted in Wave 4	0.524	0.009	0.507	0.541
wave5	Intercepted in Wave 5	0.100	0.005	0.090	0.110

5.1.3 Expected Keep Rates

To conform to current theories on the calculation of welfare effects stemming from quality changes, expected keep rates, rather than actual keep rates, were used as the quality variable in the nested logit model. Typically, a poisson regression is used to estimate expected keep rates. However, if over-dispersion is found in the data the zero alter poission (ZAP) or the negative binomial models are more appropriate. Initial runs using a poisson indicated over-dispersion in the data so both ZAP models and negative binomial models were estimated. The negative binomial model performed far better than the ZAP and was used here for expected keep rates. The specification of the negative binomial is:

$$\Pr(x_i) = \frac{\Gamma\left(x_i + \frac{1}{\alpha}\right)}{\Gamma(x_i + 1)\Gamma\left(\frac{1}{\alpha}\right)} \left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha} + \lambda_i}\right)^{\frac{1}{\alpha}} \left(\frac{\lambda_i}{\frac{1}{\alpha} + \lambda_i}\right)^{x_i} \qquad 5.8)$$

Where $\lambda_i = \exp(z_i \beta)$, x_i equals harvest, in numbers of fish, of individual i on the intercepted trip, and z_i contains variables describing the site and the individual including a constant term, karate, ffdays12, hrsf, wave3, wave4, and wave5. In previous studies (Hicks et al 1999, and Haab et al 2000), years of fishing experience was used to describe angler experience. This variable was not collected in the 2006 add-on, so 12 month fishing avidity was used as a proxy for fishing experience.

Table 5.3 contains the parameter estimates from the negative binomial expected keep model. All variables were significant at the 90% level except hours fished. All parameter estimates are significantly different from zero with a chi-squared test statistic of 619.1. The value of alpha, the over-dispersion parameter is 2.05 and significant indicating that over-dispersion was indeed a problem in this data set. All parameters had a positive and significant impact on the expected keep rate except for hours fished, which had a small, negative, and insignificant impact on expected keep. As expected, wave 4 keep had the strongest influence of the temporal dummies and the private/rental mode had the largest impact of the mode dummies, but just barely. This result shows the keep rates are very similar between the charter and private/rental modes. The parameters from this model were used construct the expected keep rates for all potential choices in the model.

Table 5.3. Negative Binomial Expected Keep Rate Model Results

Variable	Parameter Estimate	Standard Error	T-ratio	P-value
constant	-4.5935	0.6226	-7.3774	0.0000
Karate	1.4892	0.1434	10.3869	0.0000
ffdays12	0.0061	0.0012	4.9769	0.0000
Hrsf	-0.0011	0.0010	-1.0406	0.2981
Pr	1.5823	0.3850	4.1095	0.0000
Charter	1.5819	0.3918	4.0376	0.0001
wave3	0.8419	0.5118	1.6450	0.1000
wave4	1.3314	0.5093	2.6140	0.0089
wave5	0.9249	0.5258	1.7591	0.0786
Alpha	2.0460	0.1658	12.3386	0.0000
Log Likelihood	-2,436.9190			

5.1.4 Unweighted Model Results

The nested logit model was estimated in SAS using proc MDC (SAS 2003). Proc MDC utilizes full information maximum likelihood estimation techniques. Table 5.4 contains the parameter estimates and model fit information. Overall model fit was good with a McFadden's R of 0.44 and a Cragg-Uhler value of 0.99. Nested logit models collapse to the conditional logit model if all inclusive value parameters are equal to one. A test of this restriction rejects the hypothesis that the conditional logit is more appropriate which also indicates that a conditional logit model using this data would violate independence of irrelevant alternatives property of the conditional logit model.

Additionally, the inclusive value parameter for the shore mode nest was 1.2 from the initial estimation of the model. Inclusive value parameters greater than one indicate potential problems with utility maximization (Haab and McConnell, 2003), therfore this parameter was restricted to 0.9 for the final estimation. A likelihood ratio test for this restriction fails to reject the restriction (Table 5.4). As expected, travel cost is negative and significant suggesting that closer sites are preferred to more distant sites. The aggregation parameter is positive and significant suggesting that aggregated sites that contain more individual MRFSS sites are preferred to aggregated sites containing fewer MRFSS intercept sites. Also as expected, the parameter on expected keep is positive and significant suggesting that sites with higher expected keep rates are preferred to sites with less expected keep.

Table 5.4. Parameter Estimates and Model Fit

Parameter	Opportunity Cost of Time Not Included			Opportunity Cost of Time Included		
	Estimate	Standard Error	P-Value	Estimate	Standard Error	P-Value
Lower Level Nest						
travelc	-0.0333	0.0006	<.0001	-0.0229	0.0004	<.0001
lnm	0.5305	0.0233	<.0001	0.5317	0.0233	<.0001
ekarate	0.2216	0.0347	<.0001	0.2211	0.0348	<.0001
Upper Level Nest						
north_shore	-3.0300	0.3645	<.0001	-3.1070	0.3618	<.0001
pr_boater	5.3111	0.3576	<.0001	5.3189	0.3577	<.0001
Inclusive Value Parameters						
Shore Mode	0.9000	*		0.9000	*	
Charter Mode	0.4202	0.1446		0.3923	0.1424	
Private/Rental Mode	0.2335	0.1443		0.2037	0.1421	
UnModel Fit						
Log Likelihood	-9569.50			-9304.29		
McFadden's R	0.4435			0.4414		
Cragg-Uhler	0.9892			0.9892		
IIA Test	132.8458		<.0001			

*Restricted parameter. Likelihood ratio statistic = 0.3943 p-value = 0.532. Fail to reject restriction

Table 5.5 contains the CV estimates for one summer flounder and one pound of summer flounder as calculated using the parameters in Table 5.4. Confidence intervals were estimated using the method of Krinsky and Robb (1986). The marginal value of a summer flounder pound was calculated by dividing the CV for one fish by the average weight per fish of 2.77 pounds from the MRFSS web queries (NMFS 2008). Using the Northeast Fisheries Science Center length/weight/age conversion web site, this translates into a 17.5" summer flounder (NMFS 2008a). When opportunity cost of time calculations are included, CV estimates are 46% higher. Aggregating the per fish CV value across the current catch of summer flounder in 2006 (11.7 million pounds) the total value of the recreational summer flounder fishery was between \$28.7 and \$42.0 million in 2007 dollars.

Estimating a schedule of recreational marginal CV is not possible for two reasons. First, the standard RUM model does not have a flexible functional form and does not allow for diminishing marginal returns from increasing catch rates. Currently, there are not functional forms that allow the testing of actual demand curvature properties necessary to get a decreasing demand as a function of catch. Estimating a RUM that included curvature terms was beyond the scope of this project. Second, the actual catch rate increase that might manifest from an increase in recreational quota is dependent on the amount of additional effort attracted to the fishery as a result of improved catch quality. Even with a downward sloping catch demand function, the WTP function could be horizontal or upward sloping over the relevant range depending on the effort response. If effort stayed exactly the same, the WTP function would maintain the typical downward slope. If effort increased to the point where no actual catch rate increase was realized, the WTP function would be horizontal at the current point estimate. If effort increased enough such that catch rates actually declined, the WTP function would be upward sloping. The only way to properly estimate this relationship is using a full bioeconomic model of the fishery, which was beyond the scope of this analysis. Because the intercept data is collected after an angler has decided to take a trip, changes in effort cannot be modeled. Using the standard RUM, it is therefore impossible to estimate a full bioeconomic model of this relationship. As a result, it is impossible to trace out a recreational quota demand function as done for the commercial sector above.

Table 5.5. Compensating Variation Estimates for the Current Keep Levels (Unweighted 2007 dollars)

Model	Compensating Variation	Mean	Standard Error	95% Lower Bound	95% Upper Bound
Opportunity Cost of Time Included	One Summer Flounder	$9.65	0.0477	$9.53	$9.72
	One Pound of Summer Flounder	$3.48	0.0172	$3.44	$3.51
Opportunity Cost of Time Not Included	One Summer Flounder	$6.59	0.0329	$6.52	$6.65
	One Pound of Summer Flounder	$2.38	0.0119	$2.35	$2.40

5.2 Weighted Model

On-site sampling introduces potential biases in RUM model parameters that impact welfare estimates for summer flounder harvest rates. The RUM model presented in the previous chapter used the Marine Recreational Fisheries Statistical Survey (MRFSS) on-site sample of summer flounder anglers. In this section, Gentner Consulting provides: 1) an explanation of the potential consequences of onsite sampling when estimating recreation site choice models, 2) a method for addressing these biases, 3) correction methods applied to biases associated with on-site sampling, and 4) a discussion on the limitations of this approach.

In the empirical application of recreation site choice models, intercept samples, such as the MRFSS, result in two separate types of non-random sample selection bias, endogenous stratification and size-biased sampling. Endogenous stratification can be characterized by conditions where the endogenous variable (site choice) becomes an integral facet of a stratified sample selection process. Samples with endogenous stratification may also be referred to as choice-based samples. A thorough literature exists related to endogenous stratification in discrete choice models (Manski and Lerman, 1977; Manski and McFadden, 1981; Cosslett, 1981a; Cosslett, 1981b; Hsieh, Manski, and McFadden, 1985; Imbens, 1992; McFadden 1999; and Bierlaire, Bolduc, and McFadden 2008). In general terms, the MRFSS intercepts saltwater anglers at their chosen site and, as a result, the process of choosing an angler for the sample is directly linked with the behavioral process driving that angler's choice. In this scenario, unknown parameters associated with the choice process become part of the sample selection process.

The second type of bias, size-biased sampling, results when the probability of sample selection is a function of the size of one of the sample characteristics (Patil and Rao 1978). In single site recreation demand models, endogenous stratification and size-biased sampling are one in the same since the endogenous variable, trip frequency, is directly tied to angler avidity. The economics literature has outlined methods for addressing this type of bias in single site recreation demand models (Shaw 1988; Englin and Shonkwiler 1996). In recreation site choice models, angler avidity is an exogenous variable. Consequently, avidity may bias estimation, but this bias remains exogenous to the choice process. In the context of recreation site choice modeling, the MRFSS sample selection process represents what Bierlaire, Bolduc, and McFadden (2008) call Exogenous and Endogenous Sampling since bias results from both endogenous (site/mode choice) as well as exogenous sources (avidity).

5.2.1 Weighted Methodology

As discussed earlier, an extensive literature exists which depicts methods for addressing endogenous stratification in RUMs. In most cases, the literature focuses on what are called "pure choice-based samples." Pure choice-based samples do not suffer from size-biased sampling. In pure choice-based samples, within site characteristics are randomly assigned. In the context of recreation site/mode choice, this means that the share of anglers making site/mode choices in the sample may not equal those made in the population, but those anglers making a given site/mode choice are selected at random. Since estimation routines using intercept samples suffer from both endogenous stratification and size-biased sampling, we apply a method previously proposed by Hindsley et al. (2008) to address non-random sample selection biases in the MRFSS. This method combines the pseudo-likelihood estimators used to address endogenous stratification with propensity score methods. The propensity score methods, which we describe in more detail later, allow analysts to address non-random selection of anglers within a given site/mode choice.

The two most common methods for addressing endogenous stratification are Conditional Maximum Likelihood (CML) and Weighted Exogenous Sample Maximum Likelihood Estimation (WESMLE). Bierlaire, Bolduc and McFadden (2008) generalize these two methods into one convenient form. This formula divides the qualification probability (i.e. the probability of selection into the sample) into two separate functions, such that

$$r_s(i_n, z, s, \beta) = Q(i_n, z, s)A(i_n, z, s, \beta) \qquad 5.9)$$

where $r_s()$ represents the qualification probability. Note that $Q()$ contains no unknown parameters. Bierlaire, Bolduc and McFadden then utilize the segmented qualification probability within a pseudo-likelihood estimator

$$\hat{L}\hat{L}_{ESS}(\beta) = \sum_{n=1}^{N} Q(i_n, z, s)^{-1} \ln \frac{A(i_n, z, s, \beta)P(i_n \mid z, s, \beta)}{\sum_{j \neq i} A(j, z, s, \beta)P(j \mid z, s, \beta)}. \qquad 5.10)$$

when $A(i_n, z, \beta) = 1$, the estimator depicts Manski and Lerman's (1977) WESMLE and when $Q(i_n, z)^{-1} = 1$ the estimator represents CML. When applied to multinomial logistic regression, both estimators are consistent, but not necessarily efficient. In both cases, estimation necessitates a robust sandwich estimator for the calculation of the variance-covariance matrix. Failure to utilize the robust sandwich estimation leads to downward bias in the standard errors.

In our application, we utilize WESMLE. The WESML estimator was first developed by Manski and Lerman (1977) for instances where the sample is a "pure" choice-based sample and the population proportions of choices are known *a priori*. In this application, Manski and Lerman use the known population proportions and the sample proportions to develop an inverse probability weight. Cosslett (1981a) later devised a weight which could be estimated when population probabilities are not known, *a priori*. Much like Manski and Lerman's method, Cosslett's method also dealt with pure choice-based sampling. Hindsley et al (2008) extend Cosslett's estimated weighting strategy by utilizing propensity score based weights. Hindsley et al (2008) validate the use of propensity score based weights based on Wooldridge's (2002) finding that Inverse Probability Weights (IPW) can be used with M-estimators to address non-random sample selection. IPWs account for the observed components of non-random selection. Propensity scores represent a convenient method for estimating these probabilities.

Propensity scores represent a scalar probability value depicting observed differences between two groups. More specifically, the propensity score represents the conditional probability of assignment to a particular treatment given a vector of covariates (Rosenbaum and Rubin 1983). In our application we estimate a value depicting observed differences between the onsite sample and the Coastal Household Telephone Survey (CHTS) as an auxiliary sample. This propensity score can then be used to "quasi-randomize" the onsite sample based on the observed characteristics of the auxiliary sample.

Ridgeway (2006) gives a concise depiction of this weighting methodology where the two samples are divided such that

$$f(i_n, z_n, s \mid t=1) = Q_n(i_n, z_n, s)\, f(i_n, z_n, s \mid t=0) \qquad 5.11)$$

Where $f(i_n, z_n, s \mid t=1)$ are angler choices and characteristics conditional on being in the random sample, $f(i_n, z_n, s \mid t=0)$ are angler choices and characteristics conditional on being in the intercept sample, and $Q_n(i_n, z_n, s)$ is a weight that allows the joint distributions of the two samples to be equal. By solving for $Q_n(i_n, z_n, s)$ and using Bays Law, the above can be rewritten as

$$Q_n(i_n, z_n, s) = K \frac{f(t=1 \mid i_n, z_n, s)}{1 - f(t=1 \mid i_n, z_n, s)}. \qquad 5.12)$$

During estimation, the constant K cancels out, allowing the weight to be depicted as

$$Q_n = \Pr(i_n, z_n, s) \Big/ 1 - \Pr(i_n, z_n, s), \qquad 5.13)$$

which represents the odds that that an angler sampled onsite would be a member of the random sample. This odds ratio can be conveniently represented using binary models such as logit and probit models. See Hindsley et al. (2008) for a more detailed depiction of this weight.

5.2.2 Random Utility Model

In this section, we represent saltwater recreational anglers' site/mode choices through the application of the Random Utility Maximization (RUM) model. Assuming that anglers are utility maximizers, our model dissects angler choice behavior so that the probability of a choice is:

$$\begin{aligned} P(n \text{ chooses site/mode combination i}) &= \mathrm{P}(U_{ni} > U_{nj} \forall j \neq i) \\ &= \mathrm{P}(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj} \forall j \neq i) \qquad 5.14) \\ &= \mathrm{P}(V_{ni} - V_{nj} > \varepsilon_{nj} - \varepsilon_{ni} \forall j \neq i) \end{aligned}$$

where U_{ni} represents utility, V_{ni} the systematic portion of utility, and ε_{ni} represents the unobserved portions of utility. We assume that the systematic portion of utility, V_{ni}, is linear in attributes such that

$$V_{ni} = \gamma_1 TC_1 + \beta_1 X_1 + ... + \beta_n X_n \qquad 5.15)$$

where TC represents travel costs and X represents other site or choice characteristics.

We estimate the RUM using the conditional logit model. The conditional logit model has a random component assumed to be independently and identically distributed Type I extreme value (McFadden 1974). Train (2003) identifies the limitations of the conditional logit as 1) an inability to represent random taste variation, 2) restrictive substitution patterns due to the IIA property, and 3) an inability to be used with panel data when unobserved factors are correlated over time for each decision maker. In this study, we feel these limitations are outweighed by difficulties associated with addressing endogenous stratification with other types of discrete choice models, such as the nested logit model used in the previous chapter. The nested structure was chosen in the previous chapter because failing to account for substitution between modes has potentially large impacts on marginal CV estimates for harvest (Haab et al 2008). At this time, it is not possible to estimate nested models that account for biased sampling. We estimate an unweighted model as well as a model Hindsley et al. (2008) refer to as balanced WESMLE.

5.2.3 Data Manipulation

As with the MRFSS intercept survey, our use of the Coastal Household Telephone Survey (CHTS) was constrained due to data limitations associated with the sampling process. Table 5.6 contains all the descriptive statistics for all the variables used in this analysis from the CHTS data set. Table 5.7 contains the descriptive statistics for all the variables used in this analysis from the MRFSS intercept data set. First, the CHTS no longer collects certain types of data, including fish type targeted and 12 month avidity, variables that proved important in Hindsley et al (2008). In addition, the CHTS only surveys individuals living in coastal counties. As a result, the CHTS represents a geographically truncated version of the true angler population. The CHTS dataset includes 6,546 anglers in its entirety. By wave, 5.4% of all anglers were intercepted in wave 2, 24.8.9% were intercepted in wave 3, 32.3% were intercepted in wave 4, 26.2% were intercepted in wave 5, and only 11 % were intercepted in wave 6. No MRFSS sampling is conducted in wave 1. By fishing mode, 34.6% of all intercepts were in the shore mode, 10.9% were in the for-hire mode, and 54.4% were intercepted in the private rental mode.

Table 5.6. Descriptive Statistics for CHTS Variables

Variable Name	Description	Mean	Standard Error	Lower Confidence Limit	Upper Confidence Limit
Pr	Dummy for Private/Rental Mode	0.544	0.006	0.531	0.555
Charter	Dummy for Charter Mode	0.110	0.004	0.102	0.117
Shore	Dummy for Shore Mode	0.347	0.006	0.335	0.358
ffdays2	2 Month Avidity	5.817	0.092	5.636	5.998
wave3	Intercepted in Wave 3	0.248	0.005	0.238	0.259
wave4	Intercepted in Wave 4	0.322	0.006	0.311	0.334
wave5	Intercepted in Wave 5	0.261	0.005	0.251	0.272

Table 5.7. Descriptive Statistics for all Variables in Intercept Dataset

Variable Name	Description	Mean	Standard Error	Lower Confidence Limit	Upper Confidence Limit
Hrsf	Hours Fished	4.032	0.026	3.980	4.083
Pr	Dummy for Private/Rental Mode	0.532	0.009	0.515	0.549
Charter	Dummy for Charter Mode	0.412	0.009	0.395	0.429
Shore	Dummy for Shore Mode	0.056	0.004	0.048	0.064
ffdays12	12 Month Avidity	25.331	0.601	24.154	26.509
ffdays2	2 Month Avidity	5.897	0.131	5.641	6.153
Travel	Calculated Travel Cost	$51.88	$1.04	$49.84	$53.91
travel_opp	Travel Cost Plus Opportunity Cost of Travel Time	$75.420	1.460	$72.44	$78.28
Boater	Proxy for Boat Ownership	0.286	0.008	0.271	0.302
North	Equals 1 If Site is North of NY	0.413	0.001	0.411	0.414
Lnm	Log of Number of Aggregated Sites	2.924	0.001	2.921	2.926
Karate	Harvest per Trip	0.356	0.001	0.355	0.357
Ekarate	Expected Harvest per Trip	0.448	0.002	0.444	0.452
pr_boater	Private/Rental Mode Crossed with Boater	0.095	0.000	0.094	0.096
north_shore	North Crossed with Shore	0.114	0.000	0.114	0.115
wave3	Intercepted in Wave 3	0.357	0.008	0.340	0.373
wave4	Intercepted in Wave 4	0.524	0.009	0.507	0.541
wave5	Intercepted in Wave 5	0.100	0.005	0.090	0.110

5.2.4 Expected Keep Rates

To conform to current theories on the calculation of welfare effects stemming from quality changes, expected keep rates, rather than actual keep rates, were used as the quality variable in the nested logit model. Typically, a poisson regression is used to estimate expected keep rates. However, if over-dispersion is found in the data the zero alter poission (ZAP) or the negative binomial models are more appropriate. In some cases, such as ours, the most appropriate model may be the zero inflated negative binomial (ZINB). Initial runs using a poisson indicated over-dispersion in the data so ZAP, negative binomial, and ZINB models were all estimated.[7] The negative binomial model performed far better than the ZAP. Next we performed Vuong test to compare the performance of the negative binomial with the ZINB. The Vuong test indicates the ZINB as the preferred model.[8] The specification of the negative binomial is:

$$\Pr(x_i) = \frac{\Gamma\left(x_i + \frac{1}{\alpha}\right)}{\Gamma(x_i + 1)\Gamma\left(\frac{1}{\alpha}\right)} \left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha} + \lambda_i}\right)^{\frac{1}{\alpha}} \left(\frac{\lambda_i}{\frac{1}{\alpha} + \lambda_i}\right)^{x_i} \qquad 5.16)$$

Where $\lambda_i = \exp(z_i \beta)$, x_i equals harvest of individual i on the intercepted trip, and z_i contains variables describing the site and the individual including a constant term, karate, ffdays2, hrsf, shore, pr, and wave3. In previous studies (Hicks et al 1999, and Haab et al 2000), years of fishing experience was used to describe angler experience. This variable was not collected in the 2006 add-on, so 12 month fishing avidity was used as a proxy for fishing experience.

In the ZINB, the negative binomial accounts for over-dispersion and the zero-inflated model augments the negative binomial by combining it with a point mass at zero. Cameron and Trivedi (1998,2005) overview these methods. In our application, the model utilizes a binary logit model to determine if the observed state is a zero or a count. In a generalization of this equation, the ZINB can be depicted as

$$f_{ZINB}(y) = \pi \cdot I_0(y) + (1 - \pi) \cdot f_{NB}(y) \qquad 5.17)$$

where y represents a count, π represents the probability of a zero count (estimated by a binary logit), $I_0(y)$ is an indicator representing a zero count, and $f_{NB}(y)$ represents the negative binomial model with count y. In our application, the binary logit model was estimated with the following regressors: constant, hrsf, pr, and wave3.

Table 5.8 contains the parameter estimates from the negative binomial expected keep model. In the negative binomial model, all variables were significant at the 95% level except shore, which was significant at the 90% level. All parameter estimates are significantly different from zero with a chi-squared test statistic of 347.96. As discussed earlier, the value of alpha, the over-dispersion parameter is 0.776 and significant indicating that over-dispersion was indeed a problem in this data set. The Vuong test statistic is 3.07 and significant indicating a need to account for an excessive number of zeros during estimation. All parameters had a positive and significant impact on the expected keep rate except for shore and wave3. Historic catch rate had the largest impact

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[7] The test for overdispersion uses a likelihood ratio test where the null hypothesis assumes $\alpha = 0$. We rejected the null at the .001 significance level ($\chi^2(1) = 101$).
[8] The calculated Vuong test statistic was z = 3.07 with a pvalue of .0011.

on expected catch. As expected, hours fished also positively influenced expectations. The parameters from this model were used construct the expected keep rates for all potential choices in the model.

Table 5.8. Zero Inflated Negative Binomial Expected Keep Rate Model Results

Variable	Parameter Estimate	Standard Error	T-ratio	P-value
constant	-2.3033	0.2426	-9.49	0
Karate	1.4546	0.0363	4.35	0
Hrsf	0.1579	0.0049	6.34	0
ffdays2	0.0311	0.1099	4.29	0
Pr	0.4720	0.3856	-4.32	0
Shore	-1.6656	0.1307	-1.94	0.053
wave3	-0.2534	0.2426	-9.49	0
Inflate				
Hrsf	-0.3162	0.0922	-3.43	0.001
Pr	1.5817	0.5018	3.15	0.002
wave3	0.3682	0.3050	1.21	0.227
constant	-0.4661	0.6583	-0.71	0.479
Alpha	0.7762	0.1844		
Log Likelihood	-2,364.55			

5.2.5 Propensity Score Results

In our application, the propensity score methods model observed differences in the selection process between the two different samples. This represents a "quasi-randomizing" process, because the propensity score can only be used to balance differences between the two groups based on observed differences. Variable selection and model selection are vital components for any attempt to reduce differences between the two samples.

We attempted several different methods for estimating the propensity score. The most commonly applied propensity score estimators use parametric models such as the linear logistic regression model. When specifying these parametric models, variable selection becomes vital. Millimet and Tchernis (2008) have a detailed discussion of variable selection in propensity score estimation.

Our first attempts utilized the linear logistic regression model with variable selection algorithms developed by Dehejia and Wahba (2002) and Hirano and Imbens (2001). In our application, neither of these algorithms performed well due to the high number of dummy variables associated with mode, zone, and mode/zone interactions. Unfortunately, the MRFSS no longer collects information on quantitative variables such as angler experience. Qualitative variables provide less information for balancing differences between the samples.

Once we determined that traditional parametric methods would not perform well, we decided to estimate the propensity score models using a flexible, nonparametric method called a generalized boosted model (GBM) (McCaffrey, Ridgeway, and Morral 2004). Unlike traditional parametric methods, GBM is not constrained by large numbers of covariates. In fact, GBM can estimate models with large numbers of covariates in a nonlinear fashion without being hampered by issues such as multi-collinearity. GBM combines numerous simple functions to estimate one large smooth function (Friedman, Hastie, and Tibshirani 2000).

In our application, the GBM algorithm uses an iterative process to find a specification that maximizes a Bernoulli log-likelihood function. The first iteration begins by setting the log odds to a constant value (the average number of observations in the CHTS sample divided by the average number in the intercept sample, represented by $\log\left(\bar{t} / 1-\bar{t}\right)$). The GBM algorithm then iteratively works to make small improvements to this baseline estimate. In each iteration, the algorithm works find an improvement that increases the expected log-likelihood such that

$$E(LL(\hat{f}(i_n, z_n, s) + \lambda h(i_n, z_n, s))) > E(LL(\hat{f}(i_n, z_n, s))) \quad 5.18)$$

Each iteration contributes a small adjustment, $\lambda h(i_n, z_n, s)$ which updates the current estimate of $\hat{f}_k(i_n, z_n, s)$ such that

$$\hat{f}_{k+1}(i_n, z_n, s) \leftarrow \hat{f}_k(i_n, z_n, s) + \lambda h_k(i_n, z_n, s) \quad 5.19)$$

where k represents the current iteration, and k + 1 represents the updated estimate. With GBM, each adjustment is represented by the difference between the treatment indicator and the probability of treatment. The algorithm uses Classification and Regression Trees (CART), as developed by Breiman, Friedman, Olshen and Stone (1984), to estimate this difference. According to Friedman (2001), this difference, which can be interpreted as a type of residual, contains information pertaining to those values of i_n, z_n and s which fit the model poorly. CART evaluates this relationship using a piecewise constant function. GBM then uses a line search to find the coefficient λ with the greatest increase in the log likelihood. According to Ridgeway (2006), a bias/variance tradeoff exists where, with additional iteration, any reduction in bias comes at the expense of increasing variance. For the GBM package, we utilize the smallest average effect size difference across covariates between the treatment and comparison groups as our stopping rule (GBM 2006). The standardized effect size is the difference between the treatment group mean values and the control group mean values divided by the treatment group standard deviation. For more information on boosting algorithms, see Friedman, Hastie, and Tibshirani (2000).

In our GBM model, we allow for interactions between the three different variables types (site, mode, avidity) and we set the shrinkage coefficient to 0.0005. The shrinkage coefficient acts to constrain the size of the improvement possible in any given iteration. As a shrinkage coefficient decreases in size, it improves the accuracy of estimation, but necessitates many more iterations. Using these settings, the optimal mean effect size occurred after 23204 iterations. Tables 5.11 (unweighted), 5.9 (unweighted), 5.13 (weighted), and 5.10 (weighted) depict the means, standard deviations, standard effect sizes, t-values, and pvalues for the variables used in the propensity score model.

Although we primarily use the standardized effect size to determine balance, we are also interested in decreasing t-statistics. According to Cohen (1988), a rule of thumb generally applies when using the standardized effect size, where 0.2 is a small value, 0.5 is a medium sized value, and 0.8 is a large value. Our application resulted in a mean effect size of 0.0399, a decrease of roughly 79 percent from the baseline. This indicates that, on average, the absolute standard effect size is small after weighting. Using the estimated propensity scores, the maximum absolute effect size for a variable is .27 as compared to 1.95 in for the unweighted comparison. In a comparison of t-values, we find that the t-value for the site dummy variables (zone2) decreases from 81.35, a highly statistically significant value, to 0.797, a value which is not statistically significant. We also find that the t-value for 2 month avidity changes from -0.495 to 0.407, both statistically insignificant values. Last, the mode dummy variables (mode2) decreases from 840.76 to 13.47. This last t-statistic represents a statistically significant difference, but there was large decrease in the value. We will discuss limitations of this method more in the discussion section.

Figure 5.6 shows the change in the absolute standard effect sizes for mode, zone, and 2 month avidity. The blue lines depict a decrease in the absolute effect size before and after weighting and a red line depicts an increase. We find decreases in the absolute effect size for the mode and zone variable and a small increase for the 2 month avidity variable.

Table 5.9. Means before Propensity Score Weighting

variable	CHTS Mean	CHTS St Dev	Intercept Mean	Intercept St Dev	Standard Eff. Size	t-value	p-value
ffdays2	5.818	7.467	5.897	7.463	-0.011	-0.495	0.621
mode2:1	0.347	0.476	0.056	0.231	0.611	840.673	0
mode2:2	0.11	0.313	0.412	0.492	-0.967	NA	NA
mode2:3	0.543	0.498	0.532	0.499	0.023	NA	NA

Table 5.10. Means after Propensity Score Weighting

variable	CHTS Mean	CHTS St Dev	Intercept Mean	Intercept St Dev	Standard Eff. Size	t-value	p-value
ffdays2	5.818	7.467	5.68	6.931	0.018	0.407	0.684
mode2:1	0.347	0.476	0.23	0.421	0.245	13.471	0
mode2:2	0.11	0.313	0.092	0.289	0.057	NA	NA
mode2:3	0.543	0.498	0.678	0.467	-0.27	NA	NA

GBM has the ability to measure the relative influence for a given variable in explaining the differences between the CHTS and the intercept sample. Freidman (2001) determined that a variable's relative influence in a given iteration is the empirical improvement which results from partitioning the data at a given point using that variable. The TWANG package (Ridgeway et al 2006) allows us to determine the relative influence for a given model by using the average of these values over all iterations. This procedure indicates that the site represents 73.14%, fishing mode represents 21.23%, and 2 month avidity represents 5.62% of the difference between the two samples.

Table 5.11. Individual Site Choice Frequencies and Standard Effect Sizes between the CHTS Sample and the Intercept Sample before Propensity Score Weighting

variable	CHTS Mean	CHTS St Dev	Intercept Mean	Intercept St Dev	Standard Eff. Size	t-value	p-value
zone2:1	0.007	0.085	0.001	0.03	0.075	81.346	0
zone2:2	0.007	0.084	0.009	0.092	-0.018	NA	NA
zone2:3	0.012	0.108	0.001	0.035	0.098	NA	NA
zone2:4	0.026	0.158	0.032	0.177	-0.044	NA	NA
zone2:5	0.013	0.114	0.032	0.177	-0.169	NA	NA
zone2:7	0.058	0.233	0.097	0.296	-0.167	NA	NA
zone2:17	0.03	0.17	0.001	0.03	0.17	NA	NA
zone2:18	0.034	0.182	0.003	0.058	0.17	NA	NA
zone2:19	0.033	0.179	0.012	0.109	0.119	NA	NA
zone2:22	0.105	0.306	0.002	0.046	0.335	NA	NA
zone2:24	0.043	0.202	0.023	0.149	0.099	NA	NA
zone2:25	0.014	0.117	0.01	0.102	0.03	NA	NA
zone2:26	0.013	0.113	0	0.017	0.111	NA	NA
zone2:27	0.026	0.158	0.001	0.025	0.158	NA	NA
zone2:30	0.022	0.146	0.005	0.072	0.114	NA	NA
zone2:32	0.023	0.15	0.001	0.025	0.15	NA	NA
zone2:33	0.022	0.148	0.091	0.287	-0.462	NA	NA
zone2:34	0.008	0.088	0.012	0.107	-0.044	NA	NA
zone2:35	0.005	0.069	0.004	0.063	0.011	NA	NA
zone2:36	0.042	0.201	0.044	0.206	-0.011	NA	NA
zone2:37	0.016	0.125	0.04	0.196	-0.193	NA	NA
zone2:38	0.013	0.115	0.007	0.082	0.057	NA	NA
zone2:39	0.017	0.129	0.025	0.156	-0.061	NA	NA
zone2:40	0.01	0.098	0.051	0.22	-0.42	NA	NA
zone2:42	0.005	0.072	0.023	0.15	-0.247	NA	NA
zone2:43	0.005	0.068	0.003	0.058	0.018	NA	NA
zone2:44	0.006	0.076	0.003	0.055	0.036	NA	NA
zone2:45	0.003	0.052	0	0.017	0.047	NA	NA
zone2:46	0.009	0.092	0.004	0.061	0.053	NA	NA
zone2:47	0.007	0.083	0.041	0.198	-0.413	NA	NA
zone2:48	0.026	0.158	0.032	0.176	-0.042	NA	NA
zone2:50	0.01	0.101	0.209	0.407	-1.956	NA	NA
zone2:51	0.014	0.119	0.001	0.03	0.113	NA	NA
zone2:52	0.013	0.112	0.001	0.03	0.105	NA	NA
zone2:53	0.022	0.146	0.005	0.07	0.116	NA	NA
zone2:55	0.036	0.187	0.101	0.301	-0.343	NA	NA
zone2:56	0.028	0.165	0.03	0.171	-0.014	NA	NA
zone2:57	0.026	0.161	0.014	0.117	0.079	NA	NA
zone2:58	0.036	0.187	0.004	0.061	0.175	NA	NA
zone2:59	0.023	0.15	0.012	0.107	0.076	NA	NA
zone2:60	0.009	0.095	0	0.017	0.093	NA	NA
zone2:61	0.01	0.099	0.001	0.025	0.094	NA	NA
zone2:62	0.1	0.3	0.001	0.025	0.331	NA	NA
zone2:63	0.014	0.117	0.012	0.11	0.014	NA	NA

Table 5.12. Weighted Individual Site Choice Frequencies and Standard Effect Sizes between the CHTS Sample and the Intercept Sample after Propensity Score Weighting

variable	CHTS Mean	CHTS St Dev	Intercept Mean	Intercept St Dev	Standard Eff. Size	t-value	p-value
zone2:1	0.007	0.085	0.006	0.079	0.012	0.797	0.681
zone2:2	0.007	0.084	0.007	0.081	0.005	NA	NA
zone2:3	0.012	0.108	0.007	0.082	0.047	NA	NA
zone2:4	0.026	0.158	0.027	0.162	-0.008	NA	NA
zone2:5	0.013	0.114	0.009	0.096	0.034	NA	NA
zone2:7	0.058	0.233	0.083	0.275	-0.107	NA	NA
zone2:17	0.03	0.17	0.032	0.177	-0.015	NA	NA
zone2:18	0.034	0.182	0.042	0.2	-0.042	NA	NA
zone2:19	0.033	0.179	0.032	0.177	0.006	NA	NA
zone2:22	0.105	0.306	0.105	0.306	0	NA	NA
zone2:24	0.043	0.202	0.056	0.229	-0.064	NA	NA
zone2:25	0.014	0.117	0.014	0.117	0.001	NA	NA
zone2:26	0.013	0.113	0.014	0.116	-0.007	NA	NA
zone2:27	0.026	0.158	0.02	0.14	0.035	NA	NA
zone2:30	0.022	0.146	0.02	0.14	0.012	NA	NA
zone2:32	0.023	0.15	0.018	0.134	0.033	NA	NA
zone2:33	0.022	0.148	0.022	0.148	0	NA	NA
zone2:34	0.008	0.088	0.008	0.091	-0.005	NA	NA
zone2:35	0.005	0.069	0.005	0.072	-0.006	NA	NA
zone2:36	0.042	0.201	0.052	0.221	-0.047	NA	NA
zone2:37	0.016	0.125	0.018	0.133	-0.017	NA	NA
zone2:38	0.013	0.115	0.013	0.111	0.007	NA	NA
zone2:39	0.017	0.129	0.024	0.153	-0.055	NA	NA
zone2:40	0.01	0.098	0.012	0.111	-0.027	NA	NA
zone2:42	0.005	0.072	0.005	0.073	-0.003	NA	NA
zone2:43	0.005	0.068	0.005	0.068	-0.002	NA	NA
zone2:44	0.006	0.076	0.004	0.06	0.03	NA	NA
zone2:45	0.003	0.052	0.002	0.05	0.006	NA	NA
zone2:46	0.009	0.092	0.008	0.087	0.011	NA	NA
zone2:47	0.007	0.083	0.009	0.096	-0.03	NA	NA
zone2:48	0.026	0.158	0.025	0.155	0.005	NA	NA
zone2:50	0.01	0.101	0.015	0.121	-0.043	NA	NA
zone2:51	0.014	0.119	0.016	0.124	-0.011	NA	NA
zone2:52	0.013	0.112	0.012	0.109	0.007	NA	NA
zone2:53	0.022	0.146	0.03	0.17	-0.054	NA	NA
zone2:55	0.036	0.187	0.041	0.198	-0.024	NA	NA
zone2:56	0.028	0.165	0.035	0.184	-0.044	NA	NA
zone2:57	0.026	0.161	0.025	0.156	0.01	NA	NA
zone2:58	0.036	0.187	0.041	0.197	-0.022	NA	NA
zone2:59	0.023	0.15	0.022	0.147	0.005	NA	NA
zone2:60	0.009	0.095	0.008	0.09	0.01	NA	NA
zone2:61	0.01	0.099	0.005	0.071	0.049	NA	NA
zone2:62	0.1	0.3	0.029	0.168	0.237	NA	NA
zone2:63	0.014	0.117	0.018	0.133	-0.036	NA	NA