Commercial and Recreational Allocation for Summer Flounder: an update to the 2017 Report

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Executive Summary

In this report, we update the allocation analysis reported in 2017 (Hicks and Schnier, 2017). The motivation for this update is the new method of data collection undertaken as part of the Marine Recreational Information Program for the recreational sector modeled in this work. Using this new data and more timely data from the commercial sector, this work develops economic models for assessing the economic efficiency from allocation decisions made between the recreational and commercial fishing sectors for summer flounder along the Atlantic Coast of the United States. In this work, we rely on the same existing datasets as before to analyze economic welfare changes for commercial and recreational stakeholders having direct engagement fishing for summer flounder. Our work shows that

- The existing 60/40 commercial/recreational allocation is not suboptimal from an economic efficiency perspective
- Using the new recreational data, the value of the fishery to the recreational sector has increased relative to our prior work
- Our work shows that modest changes to a 60/40 allocation *in either direction* would most likely not lower the economic benefits received from the fishery
- Due to data limitations, our ability to precisely estimate the recreational sector's value for additional quota hampers our ability to provide more concrete guidance about optimal allocations.

In the work, we note numerous caveats and will not list them again here. But any discussion or use of the results in this report must bear in mind the limitations of the models, the data, and the policy analysis. Even given these caveats, this work provides a useful metric for assessing the economic efficiency of various allocations across the commercial and recreational sectors for directly engaged stakeholders.

Document Roadmap

Chapter 1 provides a broader introduction to this report. In Chapter 2 we outline how this report is different from and similar to our previous report (Hicks and Schnier, 2017) hereafter referred to as the '2017 Report'. We develop economic models for the recreational (Chapter 3) and commercial (Chapter 4) sectors. In Chapter 5 we combine the recreational and commercial models for performing the allocation analysis, describe important caveats, and provide recommendations.

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Chapter 1

Introduction

In this report, we update the allocation analysis reported in 2017 (Hicks and Schnier, 2017). The 2017 analysis by the same authors as this report recommended continuing with the then current allocation of 60% commercial and 40% recreational. This and the 2017 report use the NOAA Marine Recreational Information Program (MRIPS hereafter) marine recreational data for estimating policy effects due to allocation changes. The MRIPS data has two components: 1) an in-person survey that intercepts angling trips while saltwater fishing (known as the intercept survey), and 2) a population-wide survey used to expand trip-level data to population estimates of catch, effort, and participation. For data used in the 2017 report, this second component used a survey methodology from a coastal county random digit dial approach (known as the Coastal Household Telephone Survey (CHTS)) [hereafter we will term this the "Old Method"]. Since the 2017 report, MRIPS has changed this second component to a mail-based survey known as the Fishing Effort Survey (FES) [hereafter we term this the "New Method"]. The reasons for the change to the FES are described in FES Transition Team (2015) and primarily relate to obtaining more reliable and precise estimates due to issues with phone survey methods. Compared to the "Old Method", the "New Method" has led to increased estimates of effort, participation, and catch in most cases (Andrews, Brick and Mathiowetz, 2015). Consequently, this report aims to mirror analysis undertaken in recent stock assessments (Northeast Fisheries Science Center, 2019) to model the recreational sector using recreational data from the "New Method" along with updated commercial sector models.[1]

[1] To make this report as comparable as possible to our prior work, the reader will notice similarities in organization and content wherever possible.

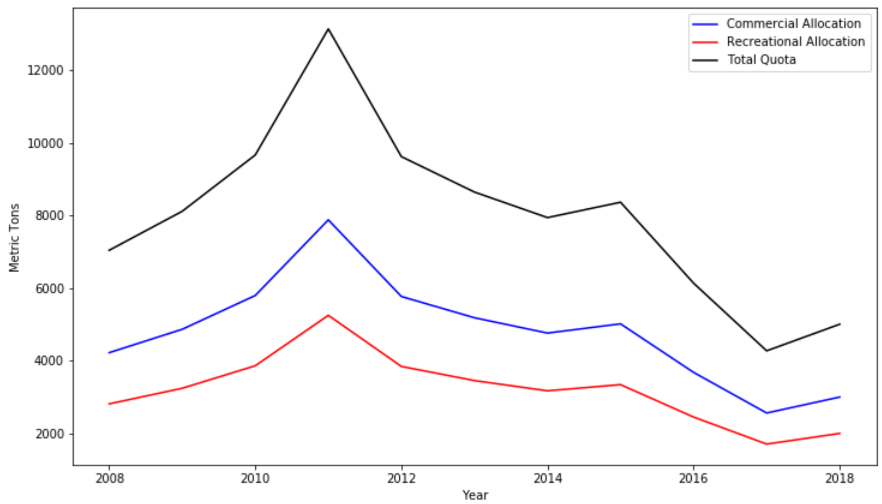
1.1 The Summer Flounder Fishery

Summer flounder, also know as fluke, is an important commercial and recreational species, and are found in pelagic and demersal waters from the Gulf of Mexico through North Carolina, with larger concentrations in the mid-Atlantic and northwest Atlantic region. They spawn during the Fall and Winter along the continental shelf and they exhibit a strong seasonal inshore-offshore movement. They inhabit shallow coastal waters in the warmer months and then remain offshore during the colder months (MAFMC 2016). This strong seasonality is an important aspect of the commercial fleet, which consists of a winter offshore and a summer inshore fishery. The recreational fishery also responds to this seasonality with most directed summer flounder trips occurring during the warm summer months. The nature of the harvesting also requires management coordination because fishermen operate within both state (less than 3 miles offshore) and federal (3-200 miles offshore) waters.

The commercial and recreational landings for summer flounder were exceptionally high in the late 1970s through the 1980s, peaking at 26,100 metric tons in 1983. During the late 1980s and early 1990s the landings substantially decreased as the stock was overfished and a limited access fishery program was implemented. The first Fishery Management Plan (FMP) for summer flounder was conducted in 1988, shortly after the stock had been declared overfished Terceiro (2012). The management of the stock is conducted jointly by the Mid-Atlantic Fishery Management Council (MAFMC) and the Atlantic States Marine Fisheries Commission (ASMFC). Official policies are established by the National Marine Fisheries Service (NMFS). In 2012 the stock was declared rebuilt. The most recently published stock assessment for summer flounder was conducted in 2013. At that time it was concluded that the summer flounder stock was not overfished and that fishing mortality had decreased since 1997 (57th SAW 2013). However, in 2016 the summer flounder quota was reduced by 29% because of the observed overfishing in 2014 and the below-average recruitment rates observed in the year classes from 2010-2013 (MAFMC 2015). As of 2017, the fishery has been determined to be "neither overfished nor did it experience overfishing" Northeast Fisheries Science Center (2019). Additionally, it should be emphasized the this latest stock assessment used the MRIP "New Method" for the stock assessment for the recreational compondent of the model.

Under Amendment 2 (ratified in 1992) of the summer flounder FMP, the total allowable catch for summer flounder is divided between the commercial and recreational sectors. Currently, 60% of the total allowable catch is allocated to the commercial sector and 40% is allocated to the recreational sector. All allocations were based on historical catch rates observed between 1980-89. In addition, the commercial landings were further subdivided among the states that landed summer flounder based on their historical landings between 1980-1989 (Terceiro (2012)). Sector allocations from 2003-2014 are illustrated in Figure 1.1 using data obtained from the Council (Staff, 2019).

Figure 1.1: Historical Recreational and Commercial Summer Flounder Allocations



1.2 Allocation Analysis

To formulate a recommendation regarding the allocation of summer flounder across the commercial and recreational fishing sectors we will employ the equimarginal principal. This method solely focuses on the economic impacts of the allocation, however distributional issues and social impacts may also be an important concern for policymakers (Edwards 1990). Given that one's value for summer flounder will depend on the current allocation of summer flounder to their respective sector, we account for this by calculating one's marginal value for a pound of summer flounder conditional on their current sector allocation. By equating marginal values between the commercial and recreational sectors we will be able to determine the sector allocations that maximize the total welfare.

Estimating the marginal value per a pound of summer flounder in the recreational sector utilizes a random utility model of site choice and follows an established literature discussed in Chapter 3. We develop a full model of recreational fishing along the Atlantic Coast and the model allows for mode, target, and species choice.

In order to estimate the marginal value per a pound of summer flounder in the recreation sector we use data from the NOAA Fisheries Office of Science and Technology's Marine Recreational Information Program. This data allows us to use better weighting methodology to improve our valuation models considerably (compared to the Marine Recreational Fisheries Statistics Survey Data). By linking policy changes to changes in expected catch in our model, we are able to develop measures of changes in the economic value of recreational fishing due to policy changes. Our measures are comparable to previous summer flounder studies (Gentner et al. (2010)) and Massey, Newbold and Gentner (2006)) and from our model we are able to develop marginal value estimates for a wide range of allocation possibilities.

Estimating the marginal value per a pound of summer flounder in the commercial sector has been traditionally approached from the consumer demand perspective (Carter et al. 2008; Gentner et al. 2010). However a limitation of this method is that it approaches it from a profit function perspective where harvest rates are a selection variable in a firm's profit maximization problem, whereas the modeling used to estimate recreational demand comes from a random utility model specification. The approach we elect to utilize in our modeling efforts utilizes the same random utility model foundation used in the recreational demand literature and combines it with fishery simulations to estimate the marginal values per a pound of summer flounder.

To estimate marginal value per a pound of summer flounder in the commercial fleet we will use observer data from 2000 through 2018 as well as trip level cost data from 2000 through 2014. The observer data contains detailed landings data for a sub-sample of the fleet operating off the east coast of the United States from Maine down to North Carolina. This includes the vessel's trip-level landings of summer flounder as well as all other species caught. The trip-level cost data contains detailed information on the costs vessels incurred during their fishing trips. These costs include fuel, food, bait, ice and other supply costs associated with the trip. Combining the information garnered from these two data sets we are able to construct expected profits from fishing in a particular location at a particular point in time and construct a fishery simulation to estimate marginal values.

1.3 Document Roadmap

To highlight differences between this and the 2017 report, we next describe similarities and differences between the two with respect to methodology, data used for models, and underlying policy environment. The reader will note we don't present a fishery description/summary as we did in our 2017 report. For readers interested in a detailed fishery description, we recommend Northeast Fisheries Science Center (2019) and at the Atlantic States Fisheries Management Council (*Atlantic States Marine Fisheries Commission Website for Summer Flounder*, 2020).

To perform the allocation analysis, we develop parallel models in the recreation (Chapter 3) and commercial (Chapter 4) sectors that are conceptually identical to our approach in 2017 report. In the recreational chapter, we discuss conceptual issues relating to defining the recreational choice problems, implement these, and present estimation results for a behavioral model of summer recreational flounder fishing. We describe how we use the model results to develop and marginal value schedule for quota allocation changes and discuss caveats. In the commercial chapter, we use a similar methodology to Chapter 3 for model parameterization, but then use this methodology to simulate fleet behavior when quota allocation changes. This allows us to measure changes in seasonal profits under various quota allocation levels, from which we derive the marginal value schedule for the commerical fishery.

Finally, we perform the allocation analysis, describe important caveats, and provide recommendations in Chapter 5

Chapter 2

Differences from 2017 Report

This update to the 2017 allocation report was undertaken primarily because of the transition to the "New Methodology" for the MRIPS data we use for the recreational model. To the extent possible, we endeavor to keep the methodological approach here consistent with our earlier report.[1] In this chapter, we provide an overview outlining differences from the 2017 report whether due from methodological changes, data used for the analysis, or due to the underlying policy environments.

2.1 Commercial Model Differences

There are number of differences between the prior commercial analysis and the one submitted within this report. To start we are using observer data from 2000 through 2018 versus from 2000 through 2014. This has expanded the number of trips in our analysis. Using this data we base our modeling on three different assumptions regarding the targeting of summer flounder, which differs from our prior analysis.

In our first model we look at all fishing trips that recorded landing any amount of summer flounder within this time period. In our second model we look at all trips that had at least ten percent of the total revenues derived on the trip coming from summer

[1]For readers interested in summary data on the Summer Flounder fishery, we recommend excellent discussions in Northeast Fisheries Science Center (2019) and at the Atlantic States Fisheries Management Council (*Atlantic States Marine Fisheries Commission Website for Summer Flounder*, 2020). Additionally, in the 2017 Report, we presented Commercial and Recreational Summaries for motivating the modeling choices. While there are quantitative differences in the summary data for both the recreational and commercial summer flounder fisheries when comparing this report to our earlier one, these are primarily due to 1) the different time period being studied, and 2) different data collection methodologies. However, we found that qualitatively these differences do not alter the modeling choices, and therefore for the sake of brevity, we do not have a fishery summary chapter in this report.

flounder and in our third model we expand this to thirty-three percent. Therefore, we estimate three different site choice models for each of these data assumptions. The purpose of this was to develop a more refined focus of what it means to be targeting summer flounder and focus on those vessels more narrowly. In our prior report we used one site choice model for all of the simulations, and in this report we provide the regression output for all three models used.

The three regression modeling assumptions also provide the basis for the simulation model used to extract the marginal value per a pound of summer flounder within the commercial fleet. The simulation models are the same as used in our prior analysis that incorporated state-specific constraints as well as seasonal harvesting patterns, the preferred model from our prior analysis. The preferred model, and the one we base our recommendations on, is the second model which focuses on trips that had at least ten percent of their revenues derived from summer flounder. These results are used in our final analysis.

2.2 Recreational Model Differences

As discussed in the Chapter 1, the primary motivation of revisiting the 2017 report is to examine how the more reliable and precise weights and the corresponding effort, participation, and catch estimates from the MRIPS using the "New Method" might change the policy guidance from our allocation analysis.

Table 2.1 outlines the most important differences between the 2017 and this report for the recreational model. By far and away the biggest difference is the use of the data and weights from the "New Method" methodology rather than the "Old Method" from the MRIPS program. Apart from these differences, we note that other differences include the time period of study and policy changes in the recreational sector for this time period, and the observed allocation (ie. observed landings). Similarities between this and the 2017 report include an exactly identical methodology for the policy models including the model of recreational angler behavior, the choice structure for this model, the statistical methods used, and the allocation model approach.

To understand how the transition to the MRIP "New Method" might play out in our analysis, a few features of the "New Method" for MRIP data collection are important to note. First, using a calibration method, historical data prior to 2015 are provided calibrated sample weights attached to each intercept record. This allows researchers

Methods	Item	2017 Report	This Report
Data	Data Source*	MRIPS	MRIPS
	Time Period Choice Model	2014	2018
	Time Period for Attribute Data	2010 - 2014	2014 - 2018
	Data Collection	“Old Method”	“New Method”
Statistical Weighting	Catch*	Yes	Yes
	Choice Model*	Yes	Yes
	Policy Welfare Measure*	Yes	Yes
Economic Models	Model of Behavior*	RUM	RUM
	Choice Structure*	Modified MS	Modified MS
	Opportunity Cost of Time*	Included	Included
Policy Environment	Allocated Landings*	60/40	60/40
	Observed Landings	60/40	45/55
	Bag and Size Limits	2010-2014	2014-2018

Table 2.1: Recreational Model Differences between 2017 and Current Report (* denotes identical approach)

using the data for stock assessments or policy models to use historical data collected under the "Old Method" regime alongside data collected by MRIPS using the “New Method”. Second, the data from the “New Method” require no changes to models or stock assessment methods that uses trip-level data as inputs, as these new weights (whether calculated directly from the FES or calibrated) allow trip-level data to be used in the exact same way. An important feature of the “New Method” is that once we apply the new weights, the conceptual basis for all of the recreational models (the economic model of behavior, calculation of welfare measures due to allocation changes, and the allocation analysis) remain unchanged. Therefore, using data from the "New Method", we only need to recalculate all estimates using the same approach as before.[2]

While the conceptual underpinnings of the recreational model presented in Chapter 3 remain unchanged using MRIPS data from the "New Method", we are likely to observe empirical differences in estimates between this and the 2017 report. These differences are down to differences in weights attached to each intercept record that we use for estimating population averages from trip-level data for the following calculations:

[2]We were able to use the 2017 code nearly without any changes to produce estimates in this report.

1. Catch estimates (average catch per trip) for both caught and released fish at the county, wave, and species (or species-group) level

2. Estimation of the statistical model for parameter estimates

3. Using parameter estimates to calculate per-trip welfare measures for policy changes

4. Use MRIP effort estimates to expand per-trip welfare measure to annual sector-wide welfare measure

Figure 2.1 shows that estimates of weight and catch have nearly doubled due to the "New Methods" particularly in more recent years when using the new weights. For the policy models this means that county level averages of caught and released fish- an important input in the policy models- is in all likelihood higher in this report. Consequently, we are likely to observe some empirical differences but we don't believe that item (1) from the list above will systematically drive large differences in estimates from the recreational model, since Haab and McConnell (2002) show that in the economic models used here, only relative differences between fishing alternative attributes (e.g. catch and release averages) matter when estimating model parameters. So if on average all catch and release averages increase by roughly the same proportion, the relative differences will be constant. So in a similar way, we expect differences driven by item (2) to be minor.

We expect items (3) and (4) to be the dominant factors driving differences in our allocation model driven by differences in catch, release, and effort derived from the MRIPS "New Method" data. To see how effort estimates have changed, Figure 2.2 shows striking differences in total effort derived from the two recreation methodologies (with FES being what we label the "New Method" and CHTS being the "Old Method").

As we allude to above, the recreational models used in this report are identical to those from 2017. These models are widely used in the recreational economics literature with well established properties for measuring societal values for policy changes being considered. Furthermore, changes to the MRIP data collection methodology to the "New Method" in no way would alter the modeling choices we would make for this analysis, and so we proceed by applying our 2017 model to the new data.

Consistent with the 2017 Report which used the period 2010-2014, we calculate the underlying environment for recreational fishing choices made in 2018 by characterizing the temporal and geographical state of the fishery using information from prior years

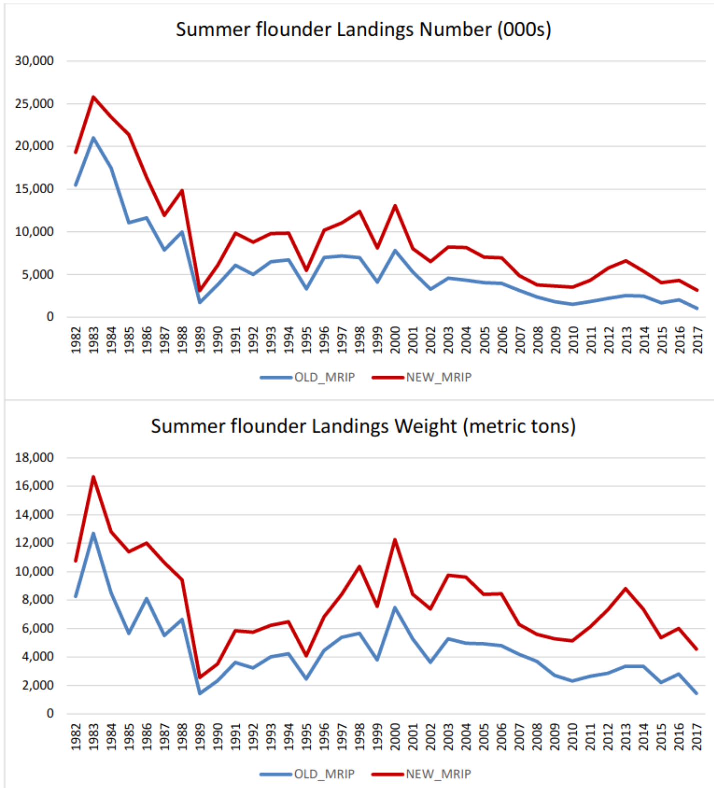


Figure 2.1: Differences in Total Landings and Weight between Old and New MRIP Methodologies (Northeast Fisheries Science Center, 2019)

(2014-2018). These calculations allow us to describe expected catch and expected release for each wave, county, and species/species group. Consequently, the model is conditioned by the bag limits, size limits, and seasonal restrictions inherent in the data for these periods. Table 2.2 shows these regulations for two years 2014 and 2018.

2.3 Sectoral Allocations and "New" versus "Old" Methods

We would also like to point out another important difference between this and the 2017 Report. In 2014, the recreational landings and the recreational allocation (with landings calculated using the "Old Method" which was in use at that time) were both approximately equal to the sector allocation consistent with the 60/40 split (with the recreational sector getting 40% of total landings). If we view 2014 using recreational landings esti-

Figure 4a. 2015 FES and CHTS shore fishing effort estimates by state, Mid Atlantic subregion

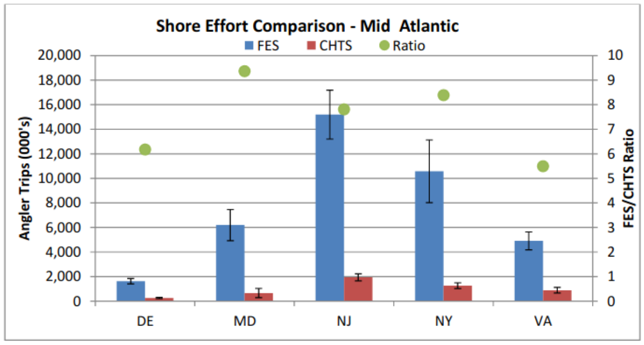


Figure 4b. 2015 FES and private boat fishing effort estimates by state, Mid Atlantic subregion

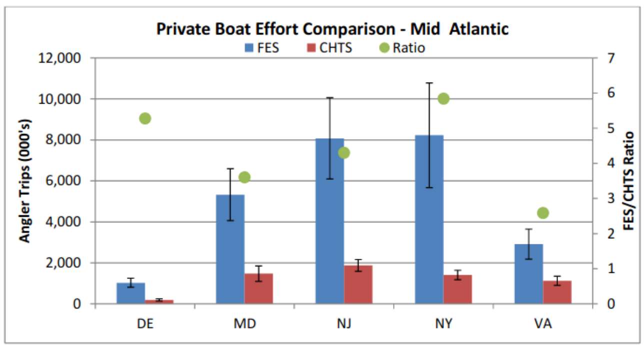


Figure 2.2: Differences in Effort between Old and New MRIP Methodologies (FES Transition Team, 2016)

mates using the "New Method", recreational landings account for approximately 55% of total landings and is inconsistent with the 60/40 split. Figure 2.3 contains two panels. In the top panel (Panel A), we have allocated quota as solid lines versus landings in dashed lines. Note that for the recreational sector we depict landings using both "New" and "Old" Methods. What is striking is that (1) commercial landings tracks extremely close to allocations with very minor divergences, (2) recreational landings using the "Old Method" also tracks fairly well with recreational sector allocations, but (3) we see very large divergences between allocated versus recreational landings from the "New Method". In Panel B of Figure 2.3, we see the how the fraction of total summer flounder landings (for the commercial sector) differ from the intended allocations from recreational landings calculated using the "New" and "Old" Methods. It is apparent that according

Table 2.2: Recreational Regulations by State in 2014 and 2018

State	Year	Size Limit	Bag Limit	Season Open	Season Closed
Connecticut	2014	18	5	May 17, 2014	Sep 21, 2014
Connecticut	2018	19	4	May 4, 2018	Sep 30, 2018
Delaware	2014	16	4	Jan 1, 2014	Dec 31, 2014
Delaware	2018	16.5	4	Jan 1, 2018	Dec 31, 2018
Maryland	2014	16	4	Jan 1, 2014	Dec 31, 2014
Maryland	2018	16.5	4	Jan 1, 2018	Dec 31, 2018
Massachusetts	2014	16	5	May 22, 2014	Sep 30, 2014
Massachusetts	2018	17	5	May 23, 2018	Oct 9, 2018
New Jersey	2014	18	5	May 23, 2014	Sep 27, 2014
New Jersey	2018	18	3	May 25, 2018	Sep 22, 2018
New York	2014	18	5	May 17, 2014	Sep 21, 2014
New York	2018	19	4	May 4, 2018	Sep 30, 2018
North Carolina	2014	15	6	Jan 1, 2014	Dec 31, 2014
North Carolina	2018	15	4	Jan 1, 2018	Dec 31, 2018
Rhode Island	2014	18	8	May 1, 2014	Dec 31, 2014
Rhode Island	2018	19	6	May 1, 2018	Dec 31, 2018
Virginia	2014	16	4	Jan 1, 2014	Dec 31, 2014
Virginia	2018	16.5	4	Jan 1, 2018	Dec 31, 2018

to recreational data from the “New Method” the fishery sector has been accounting for approximately 50 to 60% of total landings since 2014, with approximately 55% in 2018.

2.4 Summary of Differences

In conclusion, we are maintaining the models used in the 2017 report and applying them to the new data for both the recreational and commercial sectors for 2018 (while using data from the period 2014-2018 to help characterize the choice environment fishers face). Apart from the convenience of being able to compare the results in this report to our prior one and attribute differences to time (for both commercial and recreational sectors) and methodological differences in data collection (for the recreational sector), the models we apply here continue to be the best available and widely used models for analyzing marine policy changes such as allocation decisions.

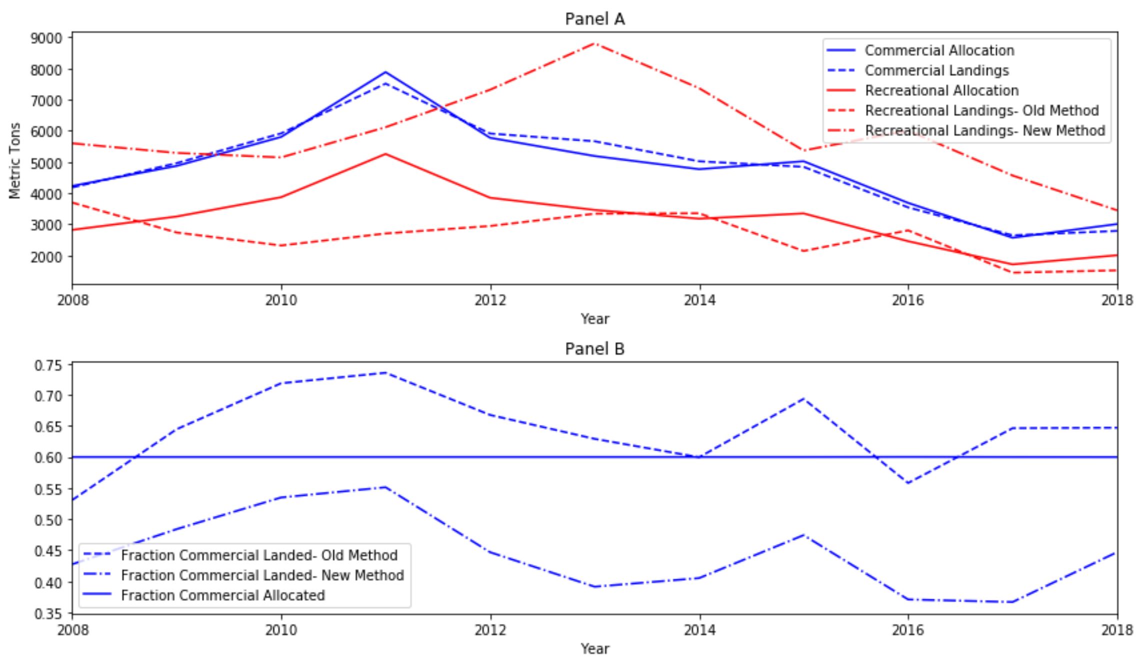


Figure 2.3: Allocations and Landings

Chapter 3

Recreational Model

Our work closely follows previous work in the valuation of marine recreational fishing using recreational fishing data from the National Marine Fisheries Service. Unlike many previous studies using the Marine Recreational Fishing Statistics Survey (Bockstael, McConnell and Strand (1989), McConnell and Strand (1994), McConnell, Strand and Blake-Hedges (1995), McConnell, Strand and Blake-Hedges (1995), Hicks et al. (1999), Haab, Whitehead and McConnell (2001), and Haab et al. (2008)), our work uses the new Marine Recreational Information Program (MRIP). This data continues to support recreational valuation models like those estimated using MRFSS data, but includes more refined survey methodology enabling for better estimation accounting for on-site sampling (see Lovell and Carter (2014), Hindsley, Landry and Gentner (2011), and Gentner et al. (2010)) and uses the Marine Recreational Information Program survey data from the "New Method". We also very closely follow Hicks and Schnier (2017).[1] Taken together, the recreational valuation model presented here

- Uses marine recreational data from the MRIP's "New Method"
- Accounts for on-site sampling and weights the statistical model appropriately
- Constructs a full choice structure of recreational fishing
    - Anglers not observed targeting summer flounder may still receive economic value from an allocation change
    - Anglers observed targeting summer flounder have many other species substitutes for targeting

[1]The reader will note this chapter very closely mirrors that from our 2017 report, since we use identical methods with the only difference being the new data associated with the "New Method".

- Estimates the WTP for summer flounder angling consistent with values observed in the literature (e.g. Massey, Newbold and Gentner (2006) and Gentner et al. (2010))

- Allows for the simulation of behavior and angler willingness to pay under different quota allocations.

3.1 The Choice Structure

It is important to note that our model considers choices *ex ante*, that is before any targeting or location decisions are made. This allows our model to capture angler choices over the full range of species they might catch. This feature of our model is important as summary data suggests that even those not directly targeting summer flounder may catch summer flounder and therefore, we develop a model that allows expected trip values to be influenced by a broad range of species.

Consistent with prior work in recreational fishing valuation (e.g. McConnell and Strand (1994), Gentner et al. (2010), and Hicks et al. (1999)) we model the choice of mode [shore, private/rental, party/charter], species group [small game, bottom fish, summer flounder][2], and fishing site (at the county level). Furthermore, we calculate site-specific quality measures (e.g. mean catch) per wave. Taken as a whole, the entire choice structure consists of **80 x 3 x 3 = 720** potential choice alternatives per observed trip in the data.

3.1.1 Species Groupings

To implement the choice structure, we had to make some aggregations over species. As shown by Haab et al. (2008), it isn't possible to include species-specific choice nodes for every (or even many) species, because for each choice node we must calculate expected catch for each site and wave. This places high data requirements and to overcome this problem, past studies (e.g. McConnell and Strand (1994) and Hicks et al. (1999)) have aggregated over many species for which there is insufficient data.

We employ the McConnell and Strand (1994) aggregation scheme shown in Figure 3.1, with two notable exceptions.[3].

[2]Other species groups such as big game, other flat-fish, non-specific targets are ommitted from our analysis based on our analysis of catch profiles for recreational trips involving summer flounder.

[3]The reader may notice some species listed which are rarely, if ever, caught in the study area. This is

1. Because we have (a) a policy interest in summer flounder and (b) summer flounder is one of the most targeted and caught species in the United States, we break summer flounder out of the flat fish group

2. After breaking summer flounder out of the flat fish group, we don't have enough data to include an "other flatfish" category, so all other flatfish are dropped for our analysis.

3. When conducting our species composition analysis, we found that there was virtually no overlap between McConnell and Strand's "big game" category and summer flounder, so it is dropped from the analysis.

because McConnell and Strand (1994) examined the entire Atlantic seaboard as well as the panhandle of Florida. However, their species group assignment is valid for the study area as it embodies both biological characteristics and recreational fishing experience when categorizing species.

Table 3.1: The McConnell-Strand Species Groupings Employed in this Study

	Small Game	
Striped Bass	Bluefish	Jack
Pompano	Seatrout	Bonefish
Bonito	Snook	Red Drum
Barracuda	Mackerel	
	Bottom Fish	
Sandbar Shark	Dogfish Shark	Cat Shark
Sand Tiger Shark	Smooth Dog Shark	Carp
Catfish	Toadfish	Cod/Codfish
Pollack	Hake	Sea Robin
Sea Bass	Sawfish	Grunt
Kingfish	Mullett	Tautog
Butterfish	Nurse Shark	Brown Cat Shark
Porgy/Scup	Sheepshead	Pinfish
Snapper	Grouper	Perch
Black Drum		
	Flat Fish	
Summer Flounder	Winter Flounder	Southern Flounder
Sole	Founders	
	Big Game	
Blue Shark	Tuna	Marlin
Thresher Shark	Great Hammerhead	Swordfish
Shortfin Mako Shark	Tiger Shark	White Shark
Smooth Hammerhead	Scalloped Hammer	Tarpon
Billfish	Sailfish	Dolphin
Cobia	Wahoo	
	Other Fish	
Herring	Eel	Skate
Puffer	Blacktip Shark	Requiem Shark
Dusky Shark	Atlantic Sharpnose	Bull Shark
Smalltail Shark		

3.1.2 Limiting the Choice Set Based on Distance

From the MRIP intercept survey data we have approximately 30,000 trips (in NC-MA in 2018) $\times$ 720 choice alternatives.[4] Past studies (e.g. McConnell and Strand (1994) and Hicks et al. (1999)) have limited the choice structure by only modeling single-day trips where the one way travel distance is less than 150 miles from the recreator's home. We use the NOAA Fisheries S&T distance files (these files calculate the distance from each intercepted angler's home to every coastal county within 150 miles), and therefore, we continue with past practices for limiting the choice structure to those sites within 150 miles of the respondents home. This necessarily eliminates all persons in the MRIP sample living far away (>150 miles) from their chosen site. Practically speaking, this reduces the size of the choice set from 720 to approximately 220 choices per individual in the intercept survey.

It is important to note that there are *very good* behavioral reasons for reducing the choice set in this way. Individuals on single-day angler trips are making decisions in a way consistent with our theoretical model. Multiple day trips (e.g. an angler from NC going to Maine who takes a marine fishing trip) are probably engaging in a plethora of other activities and this makes the link between travel cost and the resource we are valuing tenuous at best.

3.1.3 Summary Statistics Weighting

This study uses the MRIP data, which has information enabling proper weighting for summary statistics (e.g. mean catch of summer flounder per wave). Since strata are potentially over or under sampled in MRIPS, we use the supplied sample weights for calculating **any** summary statistic (e.g. average per site catch for summer flounder) in this study unless noted otherwise.[5] The weights we employ for this report uses the "New Method" described elsewhere in this document.

3.1.4 Opportunity Cost of Time and the Price of the Trip

In the valuation of recreational resources, we need to link a non-market resource like trip quality (which for our case is catch) to a trade-off made by recreators. This study makes

[4]When we estimate the model, this would equate to 21.6 million rows of data

[5]We use the R Survey package for all summary statistics weighting in this chapter Lumley et al. (2004).

this link using the travel cost method. The choice set describes the trip quality along the coast and we construct the price of the trip as travel cost to each site s for individual i based on distance as follows:

$$tc_{is} = \$0.545 \times dist_{is}$$

where \$.545 is the federal reimbursable rate for 2018 per mile. In this study we don't have access to an economic add-on information for discerning what the literature terms "opportunity cost of time" (McConnell and Strand, 1981). Past studies using MRFSS data such as McConnell and Strand (1994) and Hicks et al. (1999) employed data for which there was a complementary economic add-on for discerning if the individual took time off work, without pay as a signal for whether the time spent traveling or on-site had costs to the individual by way of foregone wages. Gentner et al. (2010) also don't have an available economic add-on survey but does follow a similar methodology to ours. They however, approximate the "opportunity cost of time" using Census data. In this and our prior report (Hicks and Schnier, 2017) we don't attempt the approximation and agree with Gentner et al. (2010) that our model without benefit transfer techniques presents a lower-bound estimate. Later in this chapter we present a benefits transfer technique (also used in (Hicks and Schnier, 2017)) to adjust our estimates to include opportunity cost of time effects.

3.2 Random Utility Model of Recreational Site Choice

We assume an individual will choose species group g, mode m, and site s by comparing the alternative specific utilities if it is the best one:

$$U(g, m, s) + \epsilon_{g,m,s} > U(i, j, k) + \epsilon_{i,j,k} \forall i \in G, j \in M, k \in S$$

where all species groups are denoted by G, all modes M, and all sites S. In this study we need to be able to alter landings (keep) of SF, so we calculate mean landings and release rates (numbers of fish) for each mode and site for summer flounder.

Ignoring subscripts indexing individuals, we have for summer flounder the utility at each site k and mode j:

$$
\begin{aligned}
U(SF,j,k) =& \beta_{tc}TC_k + \beta_{lnm,k}log(M_k) \\
& + \beta_{SH}(mode_j == SHORE) \\
& + \beta_{PR}(mode_j == PRIVATE/RENTAL) \\
& + \beta_{SF,K}\sqrt{Keep_{SF,j,k}} + \beta_{SF,R}\sqrt{Release_{SF,j,k}}
\end{aligned} \tag{3.1}
$$

For the other two species, we have similar specifications. For example, for bottom fish the utility at each site k and mode j:

$$
\begin{aligned}
U(BT,j,k) =& \beta_{tc}TC_k + \beta_{lnm,k}log(M_k) \\
& + \beta_{SH}(mode_j == SHORE) \\
& + \beta_{PR}(mode_j == PRIVATE/RENTAL) \\
& + \beta_{BT}\sqrt{Catch_{BT,j,k}}
\end{aligned} \tag{3.2}
$$

Following normal conventions on assumptions about site, mode, and species specific errors (ϵ), we can model the probability that an individual chooses g (species), m (mode), and s (site) as

$$P(d^i_{g,m,s}|\beta,\mathbf{X}) = \frac{e^{U(g,m,s)}}{\sum_{l\in G}\sum_{m\in M}\sum_{k\in S} e^{U(l,j,k)}}$$

Using likelihood contributions like this for each individual, we define the log-likelihood function using the Weighted Exogenous Sample Maximum Likelihood Estimation (WESMLE) approach that accounts for on-site sampling (see Lovell and Carter (2014) and Manski and Lerman (1977)),[6]

$$LL(\mathbf{d}|\beta,\mathbf{X}) = \sum_{i\in N}\sum_{g\in G}\sum_{m\in M}\sum_{s\in S}\frac{Q_s}{H_s}d_{igms}logP(d^i_{g,m,s}|\beta,\mathbf{X})$$

where the weight ($\frac{Q_k}{H_k}$) is comprised of

$$Q_k = \frac{T_k}{T}, H_k = \frac{s_k}{S}$$

and where d_{igms} is equal 1 if individual i chooses alternative $[g,m,s]$ and T_k are total (population) trips taken to site k, T are total trips (across all sites), s_k are sampled trips from site k and S is the survey sample size.[7].

[6] We didn't attempt a nested estimation of this model.

[7] Using Monte-Carlo techniques generating toy data consistent with the MRIP data collection method (where sites are over and under sampled), we found the WESMLE to out-perform the choice-based sampling weight approach outlined in Haab and McConnell (2002)). These results are unreported but available from the authors.

3.3 Estimation Methods

We experimented with using classical maximum likelihood techniques for estimating the model but due to the size of the dataset, we resorted to using Bayesian Sampling techniques for recovering the posterior distribution of our parameters by constructing Monte Carlo Markov Chains. From Bayes Rule, the posterior of our parameters ($P(\beta|\mathbf{d}, \mathbf{X})$) is

$$P(\beta|\mathbf{d}, \mathbf{X}) \propto P(\mathbf{d}|\beta, \mathbf{X})P(\beta|\beta^0)$$

where $P(\mathbf{d}|\beta, \mathbf{X})$ is the likelihood function where $P(\beta|\beta^0)$ are our priors on the model parameters. In this work we assume flat priors (any real numbered parameter vector is equally likely based on our prior knowledge), making our posterior

$$P(\beta|d^i_{g,m,s}, \mathbf{X}) \propto P(\mathbf{d}|\beta, \mathbf{X})$$

consequently, when we use sampling techniques to sample from the posterior distribution of parameters, we are sampling exactly from the distribution of parameters that maximizes the likelihood. When constructing our Markov Chain, we used the weights employed by WESMLE to account for on-site sampling. Sampling from the posterior in this way allows us to construct the distribution of our parameter estimates directly and all inference (e.g. parameter estimates and standard errors) are self weighting.

We implemented this approach in Python using the `tensorflow` package. This package is capable of very fast sampling when likelihood functions are computationally expensive and datasets are very large.

3.4 Results

Summaries of the posterior distribution of the parameters are reported in Table 3.3.[8] Note that our Monte Carlo Markov Chain is comprised of 1000 samples (after burn-in) from the posterior distribution of the parameters. We summarize these samples in this table. We report the mean, the standard deviation (analogous to standard errors), and various percentiles. Looking at the parameters, we can see that the the 99% confidence intervals never overlap zero. For example, for travel cost (β_{tc}), the 99% confidence interval is [-0.1038,-0.1004]. P-values (not shown) for each of these variables shows these

[8] Recall that in our specification, catch rates (and keep rates for summer flounder) enter in square root form.

are all significant at the 5% (and 1%) levels. We also see that the dummy variables on mode (normalizing on party charter) are positive with shore mode being slightly higher. This indicates that anglers are more likely to choose something besides party/charter trips and are more likely to choose the shore mode over private rental mode.

All of the parameters are also of the expected sign. The travel cost coefficient is negative, the aggregation term (β_{lnm}) correcting for the number of sites in each county is positive. All of the catch coefficients for each of our species/species groups are also positive. Note that in relative terms, the bottom fish has the smallest mean estimate, whereas summer flounder is the highest (landed). Summer flounder landed ($\beta_{sf,land}$) is significantly higher than summer flounder caught and released ($\beta_{sf,rel}$). This indicates that while anglers might enjoy catching summer flounder and releasing them, they are much happier keeping landed summer flounder.[9]

For comparison sake, we include tables for our prior parameter estimates in the 2017 study (Table 3.3) alongside our current estimates in Table 3.2. A convenient way to compare results across different time periods and data sets is to compare *ratios* of parameters rather than parameters in levels as in the tables.[10] Since the focus of this work is on summer flounder, we will compare the ratios $-\frac{\beta_{sf,land}}{\beta_{tc}}$ and $-\frac{\beta_{sf,rel}}{\beta_{tc}}$ across the two studies which we present in Table 3.4. Haab, Whitehead and McConnell (2001) show that parameter ratios like this when we divide by the travel cost coefficient can be interpreted as the marginal value of the attribute (e.g. summer flounder landings), but this interpretation isn't appropriate for our case since the catch data enters as being transformed by the square root. Despite this we can say from Table 3.4 that summer flounder was likely valued more based on the prior study (which would tend to lower the current marginal willing to pay schedule), *but* the current results show that anglers are less happy having to substitute away from landed to released catch (which would tend to increase the current marginal willing to pay schedule relative to our previous study when recreational catch and seasonal limits are tightened). Despite these differences, the prior and current model results are revealing very similar angler preferences for how sites are chosen.

---

[9] It bears mentioning again that all of the catch rate variables included in the model are calculated from *sample weighted* MRIPS data that accounts for the problems with on-site sampling.

[10] A well known property of random utility models like this one is that model parameters can't be independently identified from the scale of the error distribution. Hence it is necessary to examine ratios of parameters since the error scale cancels out for valid cross-model comparisons (Louviere, Hensher and Swait, 2000)

Table 3.2: Recreational Random Utility Model Estimates

	β_{tc}	β_{lnm}	β_{bt}	β_{sg}	$\beta_{sf,land}$	$\beta_{sf,rel}$	β_{pr}	β_{sh}
Mean	-0.1021	1.3513	0.0748	0.4797	1.5162	0.4745	2.7368	3.4791
Std Dev	0.0006	0.0123	0.0088	0.0085	0.0940	0.0346	0.0456	0.0465
min	-0.1051	1.3028	0.0410	0.4466	1.0887	0.3528	2.5737	3.3155
0.5%	-0.1038	1.3205	0.0522	0.4574	1.2764	0.3842	2.6216	3.3585
2.5%	-0.1034	1.3275	0.0576	0.4628	1.3314	0.4053	2.6475	3.3883
5%	-0.1032	1.3312	0.0603	0.4656	1.3624	0.4170	2.6621	3.4028
50%	-0.1021	1.3512	0.0748	0.4798	1.5150	0.4748	2.7368	3.4786
95%	-0.1010	1.3720	0.0892	0.4935	1.6714	0.5316	2.8124	3.5568
97.5%	-0.1008	1.3758	0.0920	0.4960	1.7034	0.5419	2.8270	3.5733
99.5%	-0.1004	1.3837	0.0971	0.5010	1.7603	0.5632	2.8596	3.6023
max	-0.0994	1.3975	0.1082	0.5180	1.8633	0.6001	2.9183	3.6681

Table 3.3: Recreational Random Utility Model Estimates from Previous Report: (2014)

	β_{tc}	β_{lnm}	β_{bt}	β_{sg}	$\beta_{sf,land}$	$\beta_{sf,rel}$	β_{pr}	β_{sh}
Mean	-0.099572	1.261703	0.210776	0.828308	1.704043	0.730967	1.522743	1.690098
Std Dev	0.000687	0.013695	0.010831	0.014509	0.087752	0.032410	0.027029	0.029306
min	-0.102108	1.216995	0.169941	0.777885	1.384343	0.628437	1.433269	1.584659
0.5%	-0.101449	1.227577	0.184025	0.789383	1.471976	0.647675	1.454465	1.614740
2.5%	-0.100980	1.235180	0.189104	0.799830	1.531269	0.665325	1.469813	1.631867
5%	-0.100733	1.238977	0.192635	0.804790	1.561199	0.677568	1.479011	1.640069
50%	-0.099575	1.261834	0.210678	0.828181	1.702743	0.731825	1.522283	1.690711
95%	-0.098457	1.284005	0.228427	0.852046	1.850422	0.784601	1.566065	1.736475
97.5%	-0.098255	1.287781	0.231412	0.856292	1.877102	0.796230	1.574819	1.747441
99.5%	-0.097822	1.296705	0.238011	0.865643	1.932048	0.815577	1.593135	1.765785
max	-0.096878	1.315996	0.250116	0.877409	2.004679	0.841560	1.621508	1.788339

Ratio	2017 Study	Current Study
$-\frac{\beta_{sf,land}}{\beta_{tc}}$	17.11	14.85
$-\frac{\beta_{sf,rel}}{\beta_{tc}}$	7.34	4.65

Table 3.4: Summer Flounder Parameter Ratios for Model Comparison

3.5 Welfare Estimation

The standard welfare calculation (defined as compensating variation (CV)) for a change in policy affecting site-specific variables from $\mathbf{x}^0$ to $\mathbf{x}^1$ for individual i is defined as:

$$CV(\mathbf{x}_i^0 \rightarrow \mathbf{x}_i^1) = \frac{log\left(\sum_{i \in S} e^{\mathbf{x}_i^0 \beta}\right) - log\left(\sum_{i \in S} e^{\mathbf{x}_i^1 \beta}\right)}{\beta_{tc}} \tag{3.3}$$

This gives us the mean compensating variation *per trip*.[11]

3.5.1 Modeling Policy Changes

For our purposes, all $\mathbf{x}_i$'s will remain as observed in the data from year 2018, except for landings and released historical catch averages for summer flounder. Note that by assumption the allocation policy

- Does not alter expected total catch (combined keep and release)[12]
- Does alter the distribution of expected total catch between keep and release categories.

Pre-policy expected Keep and Release rates for summer flounder at site s, mode m is $Keep^0_{SF,s,m}$ and $Release^0_{SF,s,m}$. Following the policy change (for example giving the fraction Δ more Keep to recreational anglers) Keep and Release change to

$$Keep^1_{SF,s,m} = Keep^0_{SF,s,m} \times (1 + \Delta) \tag{3.4}$$
$$Release^1_{SF,s,m} = Release^0_{SF,s,m} - \Delta \times Keep^0_{SF,j,k} \tag{3.5}$$

Note that: $Keep^1_{SF,s,m} + Release^1_{SF,s,m} = Keep^0_{SF,s,m} + Release^0_{SF,s,m}$.

[11] Recall that since there is no economic add-on in 2018, the results presented in this section are lower bound estimates.

[12] This analysis doesn't consider cases where total recreational and commercial TAC *and* allocations are changed. Consequently, we can think of the Welfare estimation as from a 2018 baseline and TAC.

To make this more concrete, consider summer flounder landings and release averages in the Table 3.5, before (denoted as Policy 0) and after (Policy 1) a 10% increase in summer flounder landings at some site. Under policy 1, more of the released fish are allowed to be kept. So the way we model the policy, total catch (combined catch and release) is unchanged, but the policy alters the distribution of that total between catch and release categories.

Table 3.5: Example Policy Impacts on Catch and Keep Rates

Policy	Total Catch	Landings	Release
0	5	3	2
1	5	3.3	1.7

Equation 3.3 is the compensating variation for angler i on an intercepted trip. Since angler i is part of the on-site sample, she might be over or under-represented compared to a population based random sample. Taking the simple mean across all CV_i's gives us an incorrect mean welfare effect. Consequently, we again used R's Survey package and the provided MRIP weights to calculate a weighted and correct mean CV. We have to do this for *every* allocation rule under consideration. We also sample from our posterior parameter values to calculate these weighted CV's for a wide range of likely parameter vectors. In the end, we are able to construct confidence intervals around our mean CV estimate.[13]

3.5.2 Aggregation to Population

Once we have recovered the correct mean compensating variation per trip, we perform aggregations to project our estimates into total economic values and total economic values per pound. Since policies impact the distribution of catch between kept and released summer flounder, we perform the following simple steps in our analysis for computing the totals described in our results below.

1. For a Δ% change in quota, change every expected catch and keep rate for summer flounder as described above.

[13]In addition to our uncertainty about parameter estimates, our confidence intervals also include uncertainty associated with 1) total landings and 2) summer flounder weight per fish.

2. Using this change calculate CV for each observed trip in the dataset as described above. For each geographic unit and wave associated with the trip, using weights from "New Method" MRIPS, calculate mean CV. Calculate TWTP by scaling this mean CV for effort levels (also calculated using weights from the "New Method"). Note that when performing this calculation, we include the uncertainty associated with effort.

3. From the NOAA Fisheries website, we know the total harvested summer flounder and total weight harvested (along with standard deviations) for each state. Draw randomly from each states distribution and sum for total harvest and total harvested weight.

4. For the $\Delta\%$ change in quota, scale total harvest and total harvested weight.

5. Calculate changes in compensating variations and changes in quota allocations across each subsequent quota allocation[14]. We then approximate the marginal value for the region between each policy step t and $t+1$ as $MWTP_{t+1} = \frac{TWTP_t - TWTP_{t+1}}{Landings_t - Landings_{t+1}}$ and for graphing purposes center at the mid-point between the two quota amounts $\frac{Landings_t - Landings_{t+1}}{2}$.

Note that this method explicitly assumes that what fishermen value *ex ante* is exactly what will be observed with respect to aggregate harvests and weights.

3.5.3 Results

In Table 3.6 we show compensating variation for divergences from the 2018 allocation baseline. So a change in quota of 50,000 means that +50,000 more pounds are given to the recreational sector for total harvest of 7,599,646 + 50,000 pounds of fish. A negative change in quota is taking pounds away from the recreational sector. In Table 3.7 we calculate the marginal willingness to pay for quota allocation levels (rather than changes in quota as in Table 3.6). In Table 3.7 we also report quota allocation levels in metric tons for more direct comparison to the commercial chapter.

Based on estimation available from NOAA National Marine Fisheries Service, the total summer flounder harvested weight (in the study region) in 2018 was 7,599,646.

[14] In our work, we examine the following quota changes: -100%, -80%, -60%, -40%, -20%, -5%, +5%, +20%, +40%, +60%, +80%, +100% relative to the *observed* 2018 landings

Consequently, in our analysis, we consider a 100% reduction and 100% increase to the summer flounder recreational allocation.[15]

Notice that as quota for the recreational sector approaches zero, the required total compensating variation gets larger (more negative) at a non-linear rate. This is consistent with what economists call "diminishing marginal returns" and supports intuition about how fishermen value summer flounder quota: the less quota the angler community has, the higher the relative value a pound of quota. Conversely, if we increase quota to the recreational sector, the angler community benefits, but the incremental benefit for a pound of quota enjoyed by the community is less than the first pound of quota they receive.

Figures 3.1 and 3.2 show visually the total economic value and the marginal value, respectively, of quota for the recreational sector. In Figure 3.1 at a quota change of 0 pounds, Compensating Variation is zero. In Figure 3.1, we see that doubling the recreation quota leads to a gain in economic value for recreational anglers of approximately \$30 million per year. By contrast, reducing the recreational sector leads to a loss in economic value of approximately \$75 million per year.[16]

We see similar patterns in Figure 3.2. For very small quota allocations in the recreational sector, the value per pound of summer flounder is approximately \$18. As quota is increased, the value per pound declines (this is due to diminishing marginal returns as discussed above), so that after a doubling of recreational quota, the value per pound is approximately \$2.

It should be noted that in both of these figures, the confidence intervals flare out from the Change in Pounds Allocated at 0 (for Figure 3.1) and for Pounds Allocated at approximately 7.4 million pounds (for Figure 3.2) because both of these points represent the baseline observed levels in 2018. As we move further from that baseline, the uncertainty of our estimated economic values increase.

[15] Note that unlike our 2017, where recreational landings were nearly exactly consistent with the 60/40 commercial recreational allocation, that is not the case for 2018.

[16] While the model can be used for analyzing these large swings in quota relative to 2018, we are more confident in our model for analyzing smaller quota changes.

Table 3.6: Total Compensating Variation for Recreational Sector by Quota Change from 2018 Observed Landings

Change in Quota (Pounds)	Change in Quota (Metric Tons)	Lower 95% CI	Mean CV	Upper 95% CI
-7,599,646	-3,447	-81,165,294	-74,643,236	-68,851,695
-6,079,717	-2,758	-50,115,403	-46,047,998	-42,567,134
-4,559,788	-2,068	-34,478,624	-31,401,552	-28,766,333
-3,039,858	-1,379	-21,797,828	-19,553,460	-17,614,314
-1,519,929	-689	-10,404,505	-9,276,259	-8,206,977
-379,982	-172	-2,419,453	-2,203,018	-1,971,192
379,982	172	1,936,479	2,136,466	2,414,549
1,519,929	689	7,148,273	8,123,191	9,174,749
3,039,858	1,379	13,331,367	15,235,856	17,612,860
4,559,788	2,068	18,408,451	21,480,839	24,894,448
6,079,717	2,758	22,055,045	25,921,972	30,108,073
7,599,646	3,447	24,450,751	29,432,205	35,080,946

3.6 Caveats

As with any model, we make assumptions and simplifications over very rich economic and biological systems in order to distill important impacts due to policy changes in the fishery. Below we list the major caveats with our work:

1. This analysis focuses *only* on recreational fishermen and ignores changes in economic value in related sectors (e.g. party/charter owner operator profits, bait and tackle shop profits, etc.) that can be solely attributed to summer flounder quota changes. Consequently, this means the estimates presented here are *lower bound estimates*.

2. As discussed previously, our estimates ignore the opportunity cost of time and again means we are providing *lower bound estimates*. We discuss this in more detail in the following section where we present our preferred model.

3. Our analysis *does not* account for changes in trips due to quota changes. We might imagine that as quota is lowered trips decrease (via bag, seasonal restriction, bag and size limit changes, etc.). We hold trips constant at 2018 observed levels. This again means that our estimates are *lower bound* estimates.

Table 3.7: Marginal Willingness to Pay by Quota Allocation

Quota (Pounds)	Quota (Metric Tons)	Lower 95% CI	Mean CV	Upper 95% CI
759,965	345	13.51	18.75	24.03
2,279,894	1,034	6.73	9.54	13.05
3,799,823	1,724	5.90	7.98	10.32
5,319,752	2,413	5.30	6.68	8.13
6,649,690	3,016	5.29	6.16	6.96
7,599,646	3,447	5.25	5.71	6.15
8,549,602	3,878	4.44	5.27	6.28
9,879,540	4,481	3.09	4.71	5.93
11,399,469	5,171	1.58	3.80	6.09
12,919,398	5,860	-0.46	3.22	6.11
14,439,327	6,550	-2.08	2.11	6.75

4. When altering expected catch and release of summer flounder as described in Section 3.5.1, we assume that there is some combination of bag, size limit, and season limit that could be changed to meet quota goals. Whether this tends to push our estimate towards an upward or lower bound is unknown.

3.7 Discussion

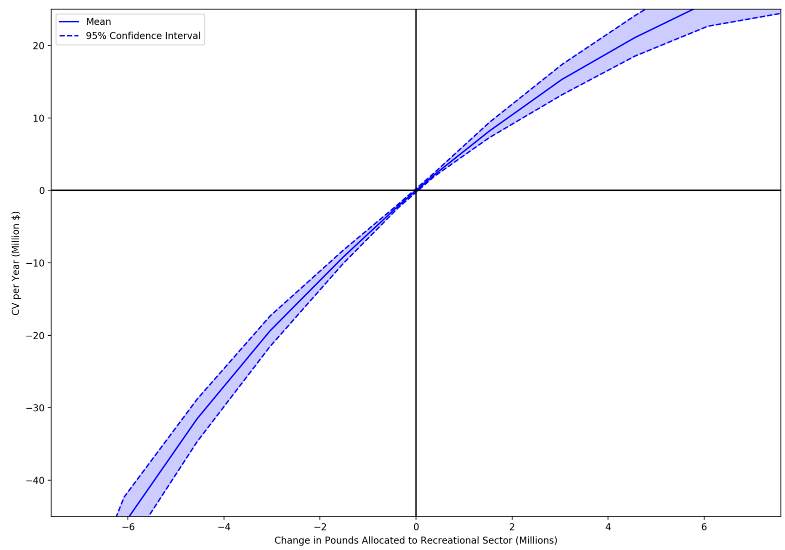
Despite the limitations of our work mentioned in the above section, the provided estimates are a very defensible *lower bound* estimates for the change in economic value associated with quota changes in the Summer Flounder Fishery. Table 3.8 lists several other studies and point estimates for marginal values associated with summer flounder.

To compare the results, it is important to note that all of the values per pound reported in Table 3.8 except ours, calculate a +1 fish change in expected catch *at each site for all trips.* Consequently, the policy change examines a case where every summer flounder trip probably catches and keeps an additional summer flounder. This change is much larger in magnitude than any considered in this study[18]. The most comparable estimate we produce to either Gentner et al. (2010) or Massey, Newbold and Gentner

[17] Calculated by dividing +1 fish estimate ($4.22) by 2.77 (Average weight of summer flounder used by (Gentner et al., 2010)). Also uses a sample of Maryland anglers who fished and not NOAA Fisheries MRIP data.

[18] 4,061,024 trips (MRIP estimated Summer Flounder directed trips along the Atlantic Coast) $\times$ + 1 fish $\times$ 2.77 pounds per fish = 11,249,036 additional pounds of recreational harvest.

Figure 3.1: Recreational Total Change in Economic Value



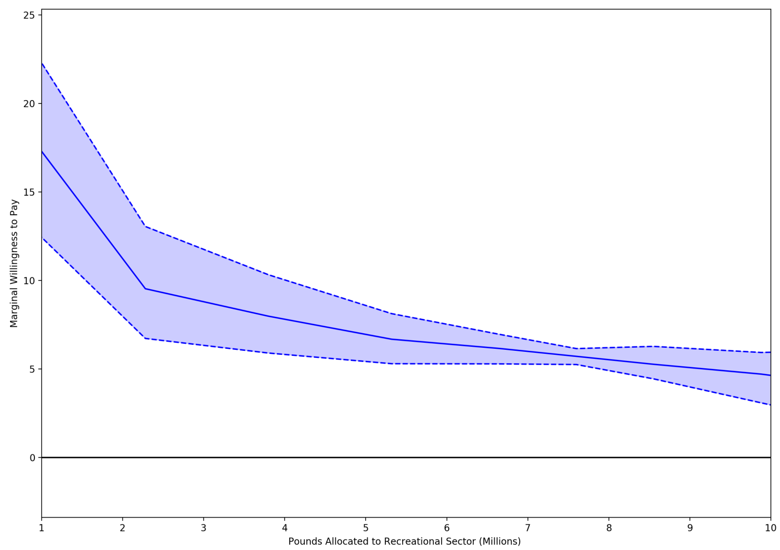
(2006) is $2.11 which corresponds to an allocation of an additional 7.5 million pounds of recreational quota from this study.

Due to data constraints we were unable to estimate a model that fully accounts for the travel cost of recreation trips because a lack of data precluded us from accounting for the opportunity cost of time. It is well known and an established finding in the recreation demand literature that failing to include the opportunity cost of time in recreation demand models will bias welfare results (Bockstael, Strand and Hanemann (1987)). Examining the results in Gentner et al. (2010), they find that after using their opportunity cost of time correction, their economic value estimate was approximately 1.85 times higher for their preferred model which includes opportunity cost of time via an estimation method.[19] Since we don't have access to data allowing us to include time in the construction of travel costs, we perform a benefits transfer by applying Gentner et al. (2010) scaling ratio to our estimates to approximate the results we would have found given complete data.[20] After applying the benefits transfer to approximate a situ-

[19] From Table 5.15 page 59.

[20] There is a well established literature on benefits transfer and the conditions under which it is a valid technique to use, particularly in a random utility model context (Parsons and Kealy (1994)). Given that both our study and Gentner et al. (2010) are using the same data (except for the including travel

Figure 3.2: Marginal Willingness to Pay Time Costs Excluded



ation where the opportunity cost of time had been included in our model, the marginal willingness to pay would have resided in the range [$18.24 to $3.83] depending on the quota level being analyzed. Consequently, our preferred marginal williness to pay estimates include the opportunity cost of time and are given in Figure 3.3 and are calculated by scaling either Figure 3.2 or the values in Table 3.7 by 1.85.

While not mentioned in the 2017 report, the benefit transfer presented in Figure 3.3 inherently adds uncertainty to our marginal willing to pay schedule since the value 1.85 is derived from a ratio of estimated parameters.[21] Given the information contained in Gentner et al. (2010) it is possible to approximate the full 95% confidence intervals around the mean willingness to pay with opportunity cost of time included and we can use some properties of the model allow us to incorporate uncertainty from the benefits transfer more formally. Consider the following:

1. We know that the 95% confidence interval for the willingness to pay estimate from

cost), the same study region, and the same modeling technique the literature shows benefits transfer to yield reliable estimates for welfare measures ((Parsons and Kealy (1994)).

[21] In the 2017 report we didn't comment on this issue since the point estimates for the recreational sector including the opportunity cost of time marginal willingness to pay schedule overlapped with the commercial marginal value schedule in large regions of the allocation cases considered.

Table 3.8: A comparison of Summer Flounder Valuation Estimates

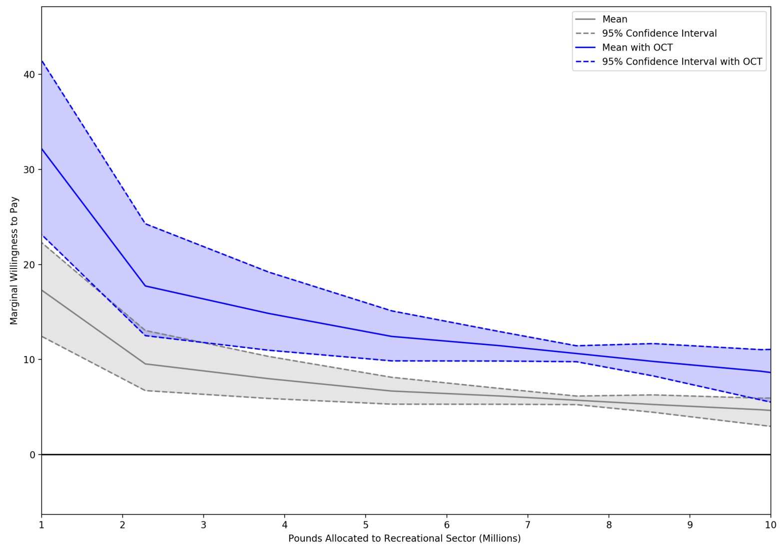
Study	Mean Value per Pound	Opportunity Cost of Time	Weighting	Nested
Current Study	\$18.75 - \$2.11	Not Included	Yes	No
Hicks and Schnier (2017)	\$9.86 - \$2.07	Not Included	Yes	No
Gentner et al. (2010)	\$3.48	Included	No	Yes
	\$2.38	Not Included	No	Yes
	\$1.45	Included	No	No
	\$0.80	Not Included	No	
	\$0.99	Included	Yes	No
	\$0.53	Not Included	Yes	No
Massey, Newbold and Gentner (2006)[17]	\$1.59	Unknown	Unknown	No

the base model that does not include the opportunity cost of time must describe the *lowest* value that willingess to pay can take on since including opportunity cost of time must increase willingness to pay. Consequently, the lower 95% from this model must be the lower bound for the 95% confidence interval for the model with benefits transfer to include opportunity cost of time.[22]

2. For the upper 95% limit of for the model with benefits transfer, we need to derive the variance of our benefit transfer estimate (1.86) which is a ratio of willingness to pay estimates. Since the variance of a ratio of random variables $\frac{x}{y}$ has no closed formed solution, it can be approximated using the Taylor series approximation: $Var\left(\frac{x}{y}\right) \approx \frac{\mu_x^2}{\mu_y^2}\left[\frac{\sigma_x^2}{\mu_x^2} - 2\frac{Cov(x,y)}{\mu_x\mu_y} + \frac{\sigma_y^2}{u_y^2}\right]$, where μ_x and σ_x^2 denotes the point estimate and variance for WTP with opportunity cost of time included and μ_y and σ_y^2 for the willingness to pay when opporunity cost of time is ignored. Applying this formula to the information available in (Gentner et al., 2010) provides information suggestive of a very large variance for the benefit transfer multiplier which we cal-

[22]This statement is valid since calculating lower 95% confidence intervals using the method described in the next item leads to *even lower* lower 95% bounds, which can't be the correct lower confidence interval.

Figure 3.3: Marginal Willingness to Pay (Time Costs Included)



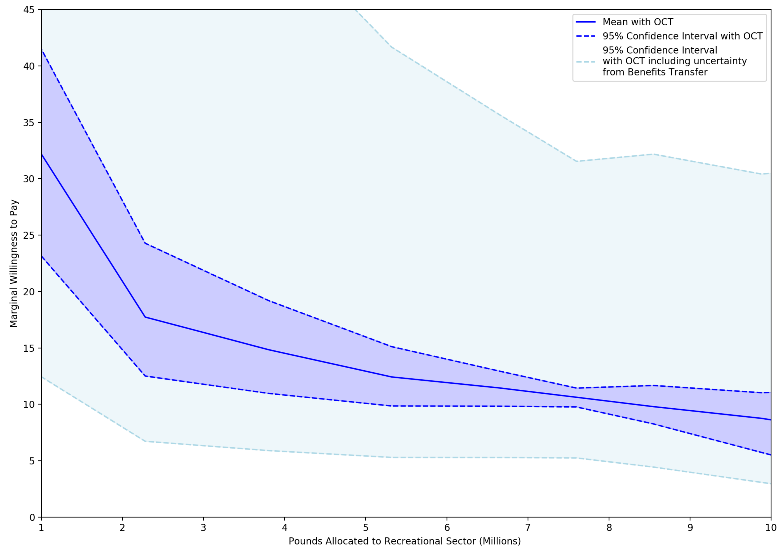
culate as a rough approximation to the upper bound of the range of willingness to pay values that incorporates uncertainty associated with estimating model parameters and the benefits transfer.[23] Consequently, applying scaling to account for the opportunity cost of time introduces noise that greatly increases the confidence interval limits around the marginal willing to pay schedule if we fully include statistical uncertainty in the model.

Figure 3.4 shows how the benefit transfer expands the confidence interval in the model accounting for opportunity cost of time as the light blue area around the mean marginal willingness to pay with opportunity cost of time included. The full confidence interval is denoted in light blue and is bounded below by the base model ignoring opportunity cost of time. If we knew the benefits transfer coefficient with certainty, we could use the smaller confidence interval associated with the darker blue area. The full light blue 95% confidence limits represent full statistical uncertainty in the model: uncertainty arises from uncertainty associated with estimated model parameters and MRIPS estimated

[23]We note that the upper 95% bound we calculate using this method is illustrative and a rough approximation since the information in Gentner et al. (2010) is incomplete for this calculation since it lacks information on covariances between the two willingness to pay estimates which we assume is zero.

number of trips. This is our preferred model.

Figure 3.4: Marginal Willingness to Pay (with Time Costs and Full Uncertainty Included)



Our results show that the recreational summer flounder fishery is extremely valuable notwithstanding our caveats above. Furthermore, our results clearly show that this value responds to allocation decisions made by managers and responds in ways that we think is reasonable: when recreational anglers don't have very much quota they value an additional pound of quota more than if the sector had lots of quota. However, even as sector allocations for the recreational sector get large (relative to observed catches in 2018), they continue to have a high value per pound for summer flounder.

Chapter 4

Commercial Model

Our analysis of the commercial sector substantially differs from the previous work that has been conducted on sector allocation Gentner et al. (2010), Carter, Agar and Waters (2008). However, the modeling structure closely follows the empirical methodology used in our analysis of the recreational sector, as the random utility model is the foundation (McFadden (1978)), and it is exactly the methodology used in our prior report submitted in 2017. Our modeling efforts consist of four distinct steps that allow us to estimate the marginal value per a pound of summer flounder within the commercial sector. In the first stage we estimate trip-level costs for the trawl fleet targeting summer flounder. In the second stage we estimate a site choice model for vessels that caught summer flounder between 2000 and 2018. In our third stage we combine the trip-level cost estimates with site choice estimates to simulate fleet activity and the execution of the summer flounder fleet allocation. Lastly, using a convolution method we estimate the marginal value per a pound of summer flounder by determining the incremental profits earned when the allocation is increased for the commercial summer flounder fleet. In the following description we divide up each estimation step and discuss them in more detail.

4.1 Estimating Trip Costs

The first step in our analysis is estimating the expected trip-level costs using the trip-level cost data from 2000 through 2014. This data has been collected by the Social Sciences Branch (SSB) of the NMFS Northeast Fisheries Science Center on an annual basis as part of Northeast Fishery Observer Program's (NEFOP) data collection efforts Das (2013). The data are obtained either through the direct observation of the observer or through interviewing the vessel captain. The data used to construct our expected costs is a subset of the broader data set constructed by the NEFOP as it focuses on just those vessels who have landed summer flounder between 2000 and 2014 and are trawl vessels. Therefore, our estimation techniques and data utilized are slightly different from those used by Das (2013). In our updated analysis we were unable to obtain revised trip-level cost data, however we were able to impute trip-costs for the post-2014 trips in our anlaysis by assuming that all trips taken between 2014 and 2018 have them same structural constant in the regression model.

Given the narrowly defined subset of vessels that we elected to use in our analysis we extracted the tons of ice, the price of ice, the gallons of fuel purchased, the fuel price, costs incurred for vessel damages, general supply costs, food costs, water costs and bait costs from the NEFOP cost data to construct a total trip level cost. We also extracted information on the number of crew members employed, the month and year of harvest, vessel characteristics (i.e., gtons, hp, hold, length), the vessel's state, the days on the trip and the number of hauls conducted on the trip. This data was used to estimate a log-log ordinary least squares regression for trip-level costs. The covariates used to explain the total trip level costs included year fixed effects, month fixed effects, vessel-state fixed effects, vessel capital (i.e., vessel characteristics), crew, days fished and hauls conducted. The parameter estimates from our regression are contained in Table 4.1.

The regression results indicate that trip-level costs were the lowest in the early 2000s, which is most likely driven by the substantially lower fuel costs during this time period. Costs are also lower during the months of August and October which roughly corresponds with the seasonal fishing patterns within the summer flounder fishery. Vessels fishing from Connecticut, Maryland, New York and Rhode Island have lower trip level costs. This roughly corresponds with the areas that have the largest concentration of summer flounder. The fixed inputs that have an impact on trip costs are vessel length and gross tonnage. The horsepower and hold capacity do not have a statistically significant effect. The parameter on vessel length suggests that larger vessels have lower costs, but the statistically significant second order term indicates the contrary for larger vessels. The first-order effect is similar for gross tonnage and the second order term is not statistically significant. However, given the large positive effect for the second order term on vessel length this indicates that for exceptionally large vessels the trip costs are increasing. As far as the variable inputs of production, the larger the crew size the higher the costs, but the second order effect is negative. The number of days fished also increases the trip-level costs and the second order term is positive and statistically

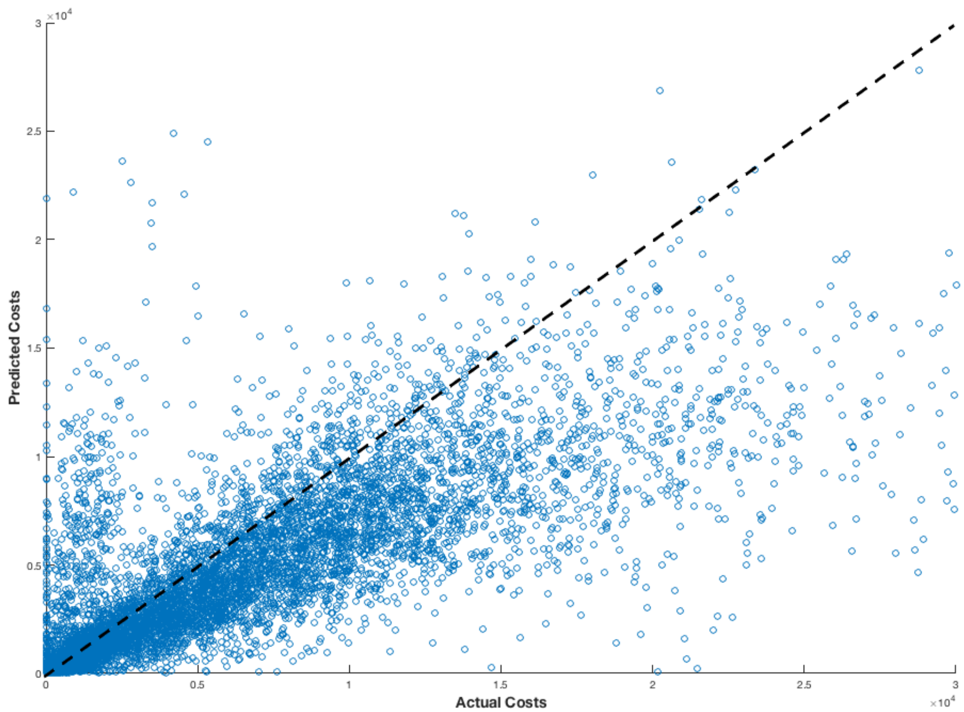
Table 4.1: Trip-Level Cost Estimates

Parameter	Estimate	Parameter	Estimate	Parmeter	Estimate
Constant	18.9721**	March	0.0140	Rhode Island	-0.3104***
	(7.0374)		(0.0919)		(0.1344)
Year 2000	-0.6996***	April	0.0057	ln(length)	-10.9003**
	(0.2001)		(0.1000)		(0.40198)
Year 2001	-0.8467***	May	-0.0676	ln(length)*ln(length)	1.4261**
	(0.1895)		(0.0926)		(0.4881)
Year 2002	-0.4229**	June	-0.1121	ln(gtons)	-1.1406***
	(0.1798)		(0.0894)		(0.5065)
Year 2003	-0.3323*	July	-0.1646	ln(gtons)*ln(gtons)	-0.0890
	(0.1704)		(0.0854)		(0.0602)
Year 2004	-0.4365**	August	-0.2499***	ln(hp)	0.9521
	(0.1597)		(0.0875)		(0.9991)
Year 2005	0.0706	September	-0.1483	ln(hp)*ln(hp)	-0.0777
	(0.1541)		(0.0903)		(0.0816)
Year 2006	0.2230	October	-0.1788**	ln(hold)	0.1214
	(0.1610)		(0.0893)		(0.1369)
Year 2007	0.1721	November	-0.0655	ln(hold)*ln(hold)	-0.0066
	(0.1598)		(0.0882)		(0.0074)
Year 2008	0.3392**	Connecticut	-1.7617***	ln(crew)	0.3485**
	(0.1598)		(0.1977)		(0.1408)
Year 2009	-0.2320	Maine	0.3041*	ln(crew)*ln(crew)	-0.1346
	(0.1554)		(0.1595)		(0.0834)
Year 2010	0.1428	Maryland	-1.0385***	ln(days)	0.9889***
	(0.1583)		(0.1845)		(0.0980)
Year 2011	0.2754*	Massachusetts	0.1374	ln(days)*ln(days)	0.0646***
	(0.1582)		(0.1293)		(0.0517)
Year 2012	0.1012	New Hampshire	-0.1005	ln(hauls)	0.7033***
	(0.1600)		(0.1732)		(0.0708)
Year 2013	0.1264	New Jersey	-0.0288	ln(hauls)*ln(hauls)	-0.1340***
	(0.1594)		(0.1356)		(0.0224)
January	-0.1078	New York	-0.3329***		
	(0.0888)		(0.1470)		
February	-0.0716	North Carolina	0.0330		
	(0.0916)		(0.1785)		
	Number of Obs.		13,667		
	Adjust. R^2		0.4057		

significant, indicating that days increase costs at an increasing rate. Lastly, the number of hauls increases costs but the statistically significant second order term indicates that they do so at a decreasing rate.

Using these parameter estimates we will estimate the expected costs per a haul within our simulation. Given the need for an accurate profile of costs we plot the actual and expected costs resulting from our regression estimates in Figure 4.1. In general our predicted trip-level costs are closely in line with those observed in the trip cost data. However, our estimates do tend to underestimate the expected trip level costs. This can be easily observed by noting that clustering of the data in Figure 4.1 below the 45-degree line. Although this does introduce a bias into our simulation results, as long as this bias permeates all of the trips within the simulation this will not introduce a substantial bias to our marginal valuation estimates. This will become more evident in our discussion of the simulation results.

Figure 4.1: Predictive Accuracy for the Trip-Level Cost Estimates



4.2 Random Utility Model

The random utility model has been extensively used in the fishery economics literature focused on spatial discrete choices Curtis and Hicks (2000), Hicks and Schnier (2008), Haynie, Hicks and Schnier (2009), Holland and Sutinen (1999), Holland and Sutinen (2000) and Smith and Wilen (2003). Assuming that there are N different sites that a fisherman can select from, they will select location i in time period t if the utility of selecting location i exceeds the utility they can derive from all other locations. This is expressed as,

$$U(i,t) + \epsilon_{i,t} > U(j,t) + \epsilon_{i,t} \forall j \in N$$

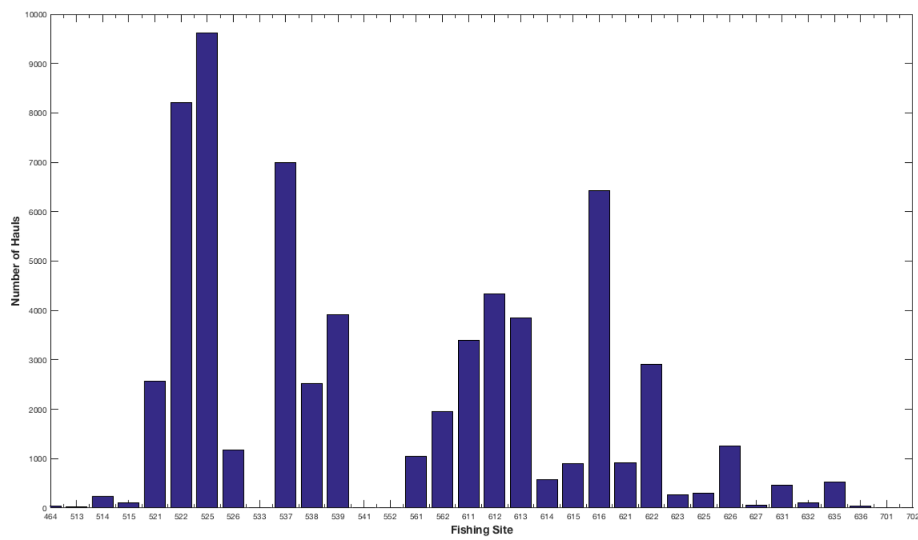
The error structure $\epsilon_{i,t}$ is assumed to be known by the decision agent (the fisherman) but not by the researcher. Ignoring the subscripts indexing locations and time the utility specification we utilize for our model is,

$$\begin{aligned} U(i,t) =& \gamma_i + \beta_1 Distance + \beta_2 SF_{Catch} + \\ & \beta_3 BSB_{Catch} + \beta_4 SCUP_{Catch} + \\ & \beta_5 Other_{Catch} + \beta_6 No_{Choice} + \epsilon \end{aligned} \tag{4.1}$$

The model selected is identical to our model utilized in prior analysis. In this model γ_i are site specific constants to control for site-specific factors that are unobserved in our data set, but that drive site choice selection. The use of these alternative specific constants have proven to be exceptionally valuable in the fishery economics literature (Timmins and Murdock (2007), Smith (2005) and Hicks, Horrace and Schnier (2012)). $Distance$ is the expected distance that a vessel will travel from the current location to all other potential locations. Within the data set on a vessel's first haul we calculated the distance using their home port as the point of origination. SF_{Catch} is the expected summer flounder catch that a fisherman will obtain if they visit the site in question in the current time period. BSB_{Catch}, $SCUP_{Catch}$ and $Other_{Catch}$ are similar variables constructed for black sea bass, scup and all other species landed. All expected catch calculations are constructed using a 60-day lag of the observed catch earned in the respective locations. We elected to partition out black sea bass and scup from the other species as these two species are jointly managed with summer flounder. The variable No_{Choice} is a dummy variable that indicates whether or not a location has not been visited within the past 60-days (the time window used for the catch expectations). This helps to control for temporal variations in the sites that vessels fish, which is important given the seasonal trends that exist within this fishery.

To estimate our model we use observer data from 2000 through 2018. The data used is different than that in our prior report and we focused our analysis on vessels that landed summer flounder during this time period. However, we ran three different empirical models, which varied the percentage of summer flounder revenues derived on the trip. This is different from our prior analysis. In the largest unrestricted data set (those vessels that landed any summer flounder) there were 34 distinct 3-digit NMFS zones that were fished by vessels during this time period, 64,703 unique hauls conducted and 8,759 unique fishing trips. Figure 4.2 plots a histogram of the number of hauls that were conducted in each of these sites within our sample. The top five most visited sites were locations 525, 522, 537, 616 and 612.

Figure 4.2: Histogram of Hauls per a Site



As mentioned earlier, three separate models were estimated using the data. We will report the regression estimates for all three models separately. The first model utilizes all of the data within the data set and the results are contained in Table 4.2. The second model only utilizes those fishing trips for which the total revenues derived from summer flounder exceeded ten percent. The results are contained in Table 4.3. The third model only utilizes those fishing trips for which the total revenues derived from summer flounder exceeded thirty-three percent. The results for the third model are contained in Table 4.4.

The parameter estimates across all three models are remarkably consistent. The

Table 4.2: Model 1: Random Utility Model Site Choice Estimates

Parameter	Estimate	Parameter	Estimate	Parmeter	Estimate
Site 521	3.4287***	Site 514	1.2626***	Site 627	0.6229***
	(0.1092)		(0.1266)		(0.1752)
Site 522	4.5107***	Site 635	1.5234***	Site 614	2.3805***
	(0.1084)		(0.1199)		(0.1167)
Site 525	4.7492***	Site 515	1.3765***	Distance	-1.9235***
	(0.1086)		(0.1476)		(0.0082)
Site 562	3.3350***	Site 625	1.8503***	SF Catch	0.1603***
	(0.1105)		(0.1245)		(0.0134)
Site 613	3.2694***	Site 612	3.3935***	BSB Catch	0.1038***
	(0.1088)		(0.1095)		(0.0306)
Site 537	4.0580***	Site 623	1.2394***	SCUP Catch	-0.1717***
	(0.1081)		(0.1242)		(0.0306)
Site 616	4.0270***	Site 632	1.0924***	Other Catch	0.0114**
	(0.1084)		(0.1478)		(0.0046)
Site 539	2.9286***	Site 538	3.0467***	No Choice	-13.0645*
	(0.1087)		(0.1095)		(6.9011)
Site 626	2.8357***	Site 561	2.9081***		
	(0.1116)		(0.1125)		
Site 621	2.3563***	Site 526	2.8566***		
	(0.1137)		(0.1115)		
Site 622	3.5309***	Site 615	2.2304***		
	(0.1094)		(0.1131)		
Site 631	1.7674***	Site 611	2.9393***		
	(0.1195)		(0.1089)		
	Number of Obs.		64,703		
	Log Likelihood (parameters=0)		-228,166		
	Log Likelihood (estimates)		-90,232		

Table 4.3: Model 2: Random Utility Model Site Choice Estimates

Parameter	Estimate	Parameter	Estimate	Parmeter	Estimate
Site 521	3.3215***	Site 514	0.9708***	Site 627	0.5375**
	(0.1623)		(0.1896)		(0.2520)
Site 522	4.3075***	Site 635	1.5272***	Site 614	2.4943***
	(0.1614)		(0.1728)		(0.1700)
Site 525	4.5188***	Site 515	1.3143***	Distance	-1.9375***
	(0.1619)		(0.2116)		(0.0116)
Site 562	3.0967***	Site 625	1.8910***	SF Catch	0.1909***
	(0.1650)		(0.1799)		(0.0175)
Site 613	3.3727***	Site 612	3.4327***	BSB Catch	0.1624***
	(0.1614)		(0.1621)		(0.0473)
Site 537	4.1359***	Site 623	1.3105***	SCUP Catch	-0.1184***
	(0.1606)		(0.1786)		(0.0398)
Site 616	4.0299***	Site 632	1.1252***	Other Catch	0.0125*
	(0.1608)		(0.2095)		(0.0066)
Site 539	2.9873***	Site538	2.9457***	No Choice	-12.7467
	(0.1613)		(0.1628)		(9.5574)
Site 626	2.8317***	Site 561	2.4508***		
	(0.1640)		(0.1705)		
Site 621	2.4844***	Site 526	2.7941***		
	(0.1662)		(0.1658)		
Site 622	3.5227***	Site 615	2.3131***		
	(0.1618)		(0.1662)		
Site 631	1.4713***	Site 611	2.9870***		
	(0.1771)		(0.1616)		
	Number of Obs.		32,122		
	Log Likelihood (parameters=0)		-112,315		
	Log Likelihood (estimates)		-45,143		

Table 4.4: Model 3: Random Utility Model Site Choice Estimates

Parameter	Estimate	Parameter	Estimate	Parmeter	Estimate
Site 521	2.7074***	Site 514	0.0950	SF Catch	0.2167***
	(0.1111)		(0.1725)		(0.0220)
Site 522	3.6834***	Site 635	0.8766***	BSB Catch	0.1678**
	(0.1096)		(0.1475)		(0.0682)
Site 525	3.7933***	Site 625	1.2181***	SCUP Catch	-0.1695***
	(0.1110)		(0.1419)		(0.0504)
Site 562	2.1079***	Site 612	2.7505***	Other Catch	0.0207**
	(0.1207)		(0.1108)		(0.0079)
Site 613	2.7012***	Site 623	0.7722***	No Choice	-10.4726***
	(0.1093)		(0.1384)		(0.3.9012)
Site 537	3.4373***	Site 538	2.2920***		
	(0.1077)		(0.1125)		
Site 616	3.4126***	Site 561	1.2246***		
	(0.1079)		(0.1427)		
Site 539	2.2969***	Site 526	2.1616***		
	(0.1093)		(0.1187)		
Site 626	2.1145***	Site 615	1.6837***		
	(0.1146)		(0.1190)		
Site 621	1.7538***	Site 611	2.2891***		
	(0.1189)		(0.1100)		
Site 622	2.8662***	Site 614	1.9035***		
	(0.1087)		(0.1261)		
Site 631	0.9821***	Distance	-1.9456***		
	(0.1392)		(0.0142)		
	Number of Obs.		21,626		
	Log Likelihood (parameters=0)		-74,263		
	Log Likelihood (estimates)		-30,022		

site-specific constants are consistent with the patterns of site visitation and those sites with more visitation predominately having a larger site-specific constant. The sites with the largest site-specific constants are sites 525, 522, 537, 616 and 622, four of which are the top five most visited sites. Location 612, which is one of the top five most visited locations, has a large site-specific constant as well. All of the coefficients on distance traveled are negative and highly significant, indicating that distance traveled is a significant factor in site selection. The expected catch coefficients indicate that a higher expected summer flounder catch as well as black sea bass catch increases the probability that a vessel will fish in a given location, whereas a high expected catch for scup reduces the probability that one will fish in a given location. The expected catch for other species did not influence the site visitation probability. Lastly, the coefficient on No_{Choice} indicates that vessels are less likely to visit a location that they have not visited in the past 60-days. The parameter estimates from this regression provides the foundation for the simulation model that will be discussed in the upcoming section.

4.3 Simulation Model

The simulation model utilizes the parameter estimates to simulate fleet activity and the execution of the total allowable catch within the commercial fishery sector. The simulation is a multi-step process that invokes different elements of existing policy limitations and seasonality to reflect the true fleet activity within the fishery. This model replicates the simulation model used in our prior report submitted in 2017. Each step is discussed in detail below.

Step One: We initialize the current total allowable catch to the commercial sector. Within the simulation we initialize the allocation at 1,000 metric tons and increase it by 1,000 metric tons until the allocation reaches 24,000 metric tons. Although 24,000 metric ton is substantially higher than recent allocations, it is near the peak catch levels observed in the 1980s and it is reasonable to assume that it is highly unlikely that future allocations will ever reach that level.

Step Two: We take a random draw from the parameter distribution resulting from the random utility model. The random draw uses the parameter estimate vector as well as the variance covariance matrix for the estimates to generate a new parameter vector. This is conducted to ensure that our parameter estimate draws reflect the underlying parameter distribution.

Step Three: We randomly draw a fishing trip from the observer data and use the parameter vector from *Step Two* to predict the site visitation probabilities for each haul on the randomly drawn trip. The estimated probabilities are calculated using the following equation

$$P(i,t) = \frac{e^{U(i,t)}}{\sum_{j \in N} e^{U(j,t)}}$$

This estimated probability surface is then multiplied by the expected catch rates, $SFExp_{i,t}$ (estimated using 60-day lags) at each location in time period t, $P(i,t) * SFExp_{i,t}$, and then is summed up across all locations, $Catch_t = \sum(P(i,t) * SFExp_{i,t})$, to determine the expected catch in time period t. These expectations are also estimated for black sea bass as well as scup.

Step Four: We reduce the allocation of summer flounder to the commercial fleet by the $Catch_t$ to determine the remaining allocation of summer flounder. In addition, we set the total allowable catch of black sea bass to 2.5 million pounds and the total allowable catch for scup to 22 million pounds. If the catch for either or these species exceeds this allocation the expected catch is set to zero to reflect that they must be discarded.

Step Five: We calculate the expected revenue from each haul using the following formula $Rev_t = \sum(P(i,t) * (SFRevenues_{i,t} + BSBRevenues_{i,t} + SCUPRevenues_{i,t} + OtherRevenues_{i,t})$.[1] To account for the costs incurred on the trip we subtracted the expected costs from fishing that trip using our cost estimates (see Table 4.1) discussed earlier to get a profile of trip-level profits. These profits were then added up for all fishing activity that occurred within the simulation to determine the fleet wide profits for the given allocation of summer flounder.

Step Six: We determine whether or not the current aggregate catch of summer flounder for the fleet has exceeded the allocation and if it has not we return to *Step Two* until the allocation of summer flounder is exhausted.

The above mentioned six steps represent the core of the simulation, which we refer to as *Model One*, however additional complexities have been added to make the simulation more realistic. The additional features are summarized below.

[1] Revenue expectations are calculated using a 60-day lag.

Table 4.5: State Allocations for Summer Flounder, Black Sea Bass and Scup

State	Percentage SF	Percentage BSB	Percentage SCUP
ME	0.05%	0.12%	0.50%
NH	0.01%	0.00%	0.50%
MA	6.82%	21.59%	13.00%
RI	15.68%	56.19%	11.00%
CT	2.26%	3.15%	1.00%
NY	7.65%	15.82%	7.00%
NJ	16.72%	2.92%	20.00%
VA	21.33%	0.17%	20.00%
NC	27.44%	0.025%	11.00%

4.3.1 State Allocations for Summer Flounder, Black Sea Bass and Scup

The commercial fleets allocation of summer flounder is further subdivided among the states that harvest summer flounder. This is also true for the allocations of black sea bass and scup. The state allocations we used for each of the three species are indicated in Table 4.5.

In order to incorporate the state allocations into the simulation model we tracked the catch of summer flounder (SF), black sea bass (BSB) and scup through the simulation. In the case that state allocation for summer flounder was exceeded we removed all vessel-trips originating from that state. This way only those vessel-trips that were eligible to fish for summer flounder, per the state allocation rules, were eligible for random selection. If a states allocation for black sea bass or scup were exceeded, we still allowed for the vessel-trip to be selected, but we zeroed out the catch of the species that had already exceeded its state allocation limit.

4.3.2 Seasonal Patterns in Fishing Behavior

The summer flounder fishery is a seasonal fishery with a large percentage of the catch occurring in the winter months. To preserve this pattern we allocated a bulk of the quota to be executed during the months of November, December, January, February and March. Given that we are randomly generating a vessel-trip from the set of all vessel-trips, we added a seasonal constraint to the model that ensures that the simulated fleet behavior mirrors the temporal distribution of catch within the fishery. This was achieved by first randomly sampling a month from the distribution of monthly landings and then randomly selecting a vessel-trip from within that month. This is consistent with the seasonal simulation variation conducted in our prior report in 2017.

4.4 Construction of Marginal Values

For each of the different summer flounder allocations we conducted 40 different simulations. This allows us to construct confidence intervals on our estimates of the marginal value per a pound of summer flounder. To calculate the marginal value we estimated the following equation

$$\text{Marginal Value}_k = (Profit_k - Profit_{k-1})/(1000 * \text{Metric Ton})$$

where, Marginal Value_k is the marginal value when one increases the allocation of summer flounder to allocation level k, $Profit_k$ is our estimate of fleet profits when the allocation is k and $Profit_{k-1}$ is the estimated profit prior to the increase in the allocation from level $k-1$ to k. Given that our unit of increase is 1,000 metric tons, we divide the difference in the change in profits by the incremental change in pounds landed to get a marginal value per a pound of summer flounder. Since we have 40 different simulations for each level of k, through the convolution of all 40 at one level of k with the 40 observed at level $k-1$ we obtain 1,600 different comparisons. These 1,600 comparisons allow us to construct 95% confidence intervals by dropping the top and bottom 40 estimates of Marginal Value_k.

One important feature of the marginal value calculations is that they are derived from the total profits that a vessel earns while fishing. This is the sum of all species landed and not just summer flounder. Therefore, although the ex-vessel price for summer flounder ranges between two and four dollars it is possible that the marginal value for summer flounder can exceed this value. This is because summer flounder is a complement in production. When a vessel targets summer flounder they also catch other species that have market value. Therefore, the marginal value of summer flounder is not only the value they derive from summer flounder but also the additional value they derive from the other species that are caught in conjunction with targeting summer flounder. This is an important feature of the simulation because if one reduces the allocation of summer flounder to the commercial fleet it will also impact the revenue flows that they derive from the other species that they would have caught if they were able to target more

Table 4.6: Marginal Values for Model 1

Allocation (MT)	Mean	Lower 95% CI	Upper 95% CI
2,000	8.0837	6.6434	10.0050
3,000	7.8794	5.7456	10.2290
4,000	7.6322	5.2120	9.6532
5,000	7.8306	5.8239	9.8945
6,000	7.9398	5.4417	10.5880
7,000	7.8914	4.7764	10.8080
8,000	8.0042	4.9359	11.1390
9,000	7.4341	4.5038	11.0120
10,000	7.6704	4.4112	10.6230
11,000	8.2476	5.0243	11.7240
12,000	7.5556	3.8001	10.5620
13,000	7.9397	4.6933	11.3300
14,000	7.6558	3.8278	11.8150
15,000	8.1222	4.1306	11.8650
16,000	7.5456	4.1502	10.4990
17,000	7.8381	4.9370	10.8020
18,000	8.3751	4.9105	11.7040
19,000	7.5997	3.9217	11.1480
20,000	7.9914	4.4802	12.4280
21,000	7.5688	2.5088	11.5630
22,000	7.5838	3.5554	11.6950
23,000	7.7622	3.6943	11.7010
24,000	8.2765	4.3356	12.6460

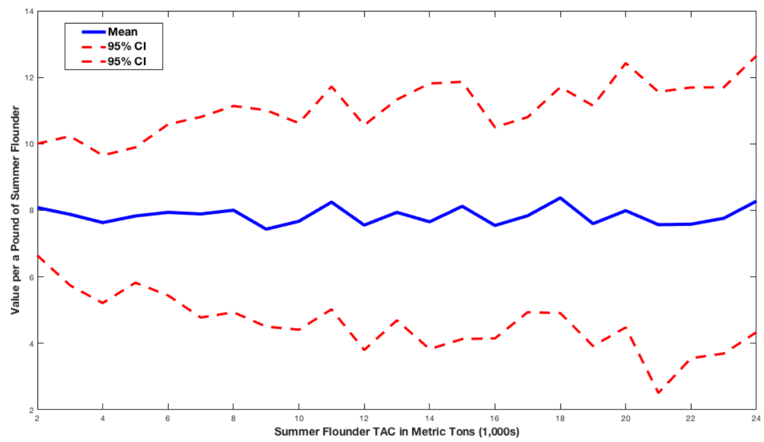
summer flounder. The following subsections discuss the results from the three different models estimated.

4.4.1 Marginal Values - Model 1

Model 1 uses the data from all the vessels that reported landing summer flounder between 2000 and 2018. It is by far the most inclusive of the valuation methods, but it also contains vessels that may not have been explicitly targeting summer flounder. The mean marginal value for each incremental increase in the allocation of summer flounder as well as the 95% confidence intervals are illustrated in Table 4.6 and graphically illustrated in Figure 4.3.

The results from *Model 1* illustrate that the average marginal value for summer

Figure 4.3: Marginal Value Estimates for Model 1



flounder ranges from around \$7.43 to \$8.38 a pound. The confidence intervals for the estimates increase as the quota allocation increases. At the lowest quota allocation, 2,000 metric tons, the 95% confidence interval is between \$6.64 and \$10.01. At the highest quota level, 24,000 metric tons, the 95% confidence interval is between \$4.34 and \$12.65. The current allocation to commercial sector has been hovering between 8,000 and 13,000 metric tons. In this range the average marginal value is between \$7.43 and \$8.25 and the 95% confidence intervals are between \$4.94 and \$11.14 at 8,000 metric tons and \$4.69 and \$11.33 at 13,000 metric tons.

4.4.2 Marginal Values - Model 2

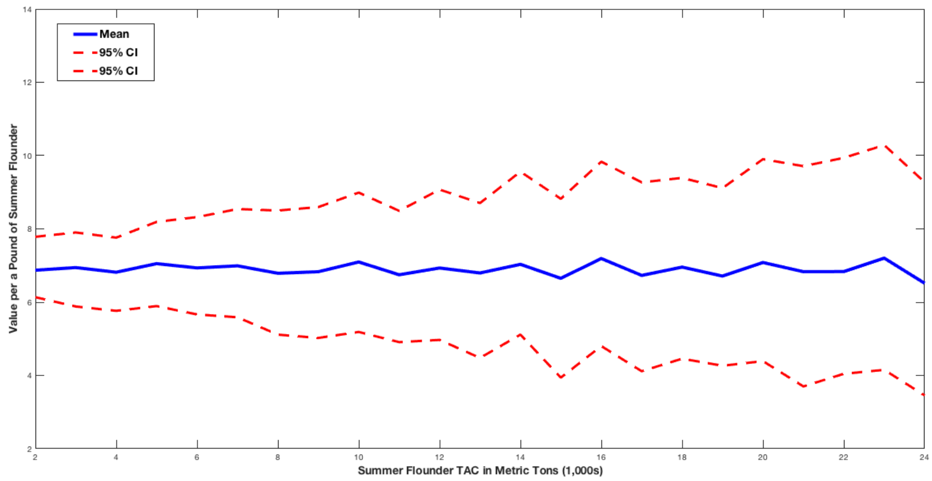
Model 2 alters *Model 1* by focusing on only those trips during which at least ten percent of the revenues were derived from summer flounder. This modification helps to ensure that the simulation focuses more on vessels that were targeting summer flounder versus those who caught it while targeting other species. The results from this simulation are contained in Table 4.7 as well as Figure 4.4.

The results from *Model 2* illustrate that the average marginal value for summer flounder ranges from around \$6.52 to \$7.20 a pound. The confidence intervals for the estimates increase as the quota allocation increases. At the lowest quota allocation, 2,000 metric tons, the 95% confidence interval is between \$6.14 and \$7.78. At the highest quota level, 24,000 metric tons, the 95% confidence interval is between \$3.45 and \$9.28. The current allocation to commercial sector has been hovering between 8,000 and 13,000

Table 4.7: Marginal Values for Model 2

Allocation (MT)	Mean	Lower 95% CI	Upper 95% CI
2,000	6.8719	6.1355	7.7838
3,000	6.9443	5.8814	7.9022
4,000	6.8172	5.7631	7.7607
5,000	7.0514	5.8927	8.1918
6,000	6.9346	5.6652	8.3214
7,000	6.9917	5.5876	8.5423
8,000	6.7883	5.1136	8.5005
9,000	6.8307	5.0238	8.5953
10,000	7.0965	5.1872	8.9903
11,000	6.7476	4.9092	8.4924
12,000	6.9326	4.9703	9.0723
13,000	6.7966	4.4783	8.7049
14,000	7.0322	5.1147	9.5608
15,000	6.6510	3.9400	8.8209
16,000	7.1914	4.8018	9.8338
17,000	6.7299	4.1135	9.2696
18,000	6.9567	4.4578	9.3923
19,000	6.7119	4.2645	9.1141
20,000	7.0825	4.3907	9.9029
21,000	6.8318	3.7005	9.7114
22,000	6.8356	4.0450	9.9384
23,000	7.2022	4.1526	10.2870
24,000	6.5162	3.4542	9.2750

Figure 4.4: Marginal Value Estimates for Model 2



metric tons. In this range the average marginal value is between \$6.79 and \$7.10 and the 95% confidence intervals are between \$5.11 and \$8.50 at 8,000 metric tons and \$4.48 and \$8.70 at 13,000 metric tons.

4.4.3 Marginal Values - Model 3

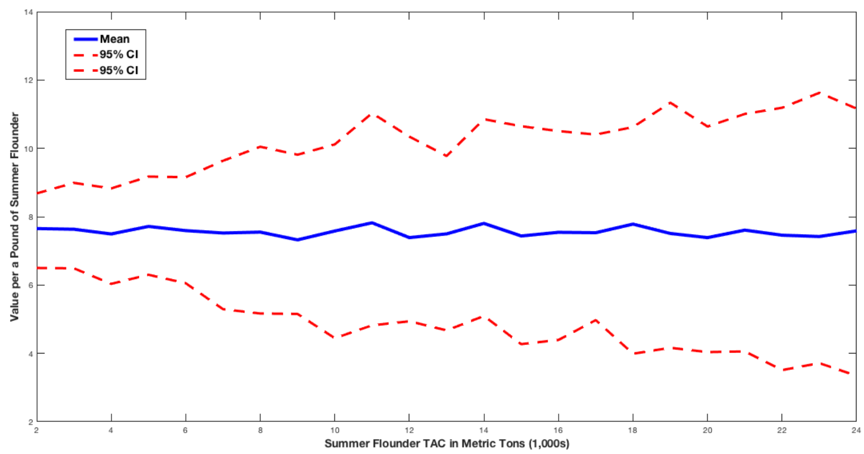
Model 3 builds on *Model 2* by further restricting the trips included to be only those on which at least thirty-three percent of the total revenues derived on the trip came from summer flounder. This additional restriction reduces the number of trips substantially and may result in trips which targeted summer flounder during the trip being excluded. The results from the simulation are illustrated in Table 4.8 and Figure 4.5.

The results from *Model 3* illustrate that the average marginal value for summer flounder ranges from around \$7.32 to \$7.82 a pound. The confidence intervals for the estimates increase as the quota allocation increases. At the lowest quota allocation, 2,000 metric tons, the 95% confidence interval is between \$7.65 and \$8.68. At the highest quota level, 24,000 metric tons, the 95% confidence interval is between \$3.34 and \$11.16. The current allocation to commercial sector has been hovering between 8,000 and 13,000 metric tons. In this range the average marginal value is between \$7.32 and \$7.58 and the 95% confidence intervals are between \$5.17 and \$10.05 at 8,000 metric tons and \$4.67 and \$9.78 at 13,000 metric tons.

Table 4.8: Marginal Values for Model 3

Allocation (MT)	Mean	Lower 95% CI	Upper 95% CI
2,000	7.6525	6.4994	8.6804
3,000	7.6325	6.4896	8.9899
4,000	7.4939	6.0342	8.8265
5,000	7.7152	6.3015	9.1737
6,000	7.5923	6.0523	9.1554
7,000	7.5222	5.2937	9.6358
8,000	7.5468	5.1669	10.0470
9,000	7.3216	5.1547	9.8134
10,000	7.5812	4.4451	10.1160
11,000	7.8210	4.8216	11.0290
12,000	7.3876	4.9387	10.3420
13,000	7.4972	4.6737	9.7765
14,000	7.8040	5.0939	10.8530
15,000	7.4352	4.2705	10.6470
16,000	7.5428	4.3928	10.5050
17,000	7.5308	4.9738	10.4040
18,000	7.7829	3.9896	10.6210
19,000	7.5092	4.1637	11.3370
20,000	7.3871	4.0383	10.6380
21,000	7.6070	4.0564	11.0070
22,000	7.4582	3.5112	11.1880
23,000	7.4192	3.7147	11.6250
24,000	7.5850	3.3440	11.1620

Figure 4.5: Marginal Value Estimates for Model 3



4.4.4 Caveats

As with any empirical study, there are limitations to our analysis. These limitations are a result of the modeling conducted as well as the available data we have used to conduct our analysis. The limitations from the prior report submitted in 2017 carry forward to this report as well. Listed below are the major caveats with our work:

1. The data used in our analysis relies on the observer data set. This data set captures only a small portion of the total summer flounder landings. Although the observer data does closely align with the vessel trip reports it is important to note its limited coverage. The vessel trip report data can not be used in our analysis because it does not contain detailed and sequenced spatial behavior. Therefore, the observer data is the best available data set for our analysis.

2. Our analysis is a short run analysis of the commercial fleet. In our model the price of summer flounder is not endogenous and we do not account for the free entry and exit of fishermen within the summer flounder fishery. These factors may result in different results, but the data does not allow us to investigate these factors.

3. Our analysis does not account for the localized depletion within the fishery. As the quota increased, and more fishing occurs one might expect that the cost per a haul increases.

Chapter 5

Allocation Analysis and Recommendations

We conclude with our allocation analysis, which examines for a particular quota level the marginal benefits (or marginal willingness to pay) for each sector if an additional unit of quota was allocated to them. Following the equimarginal principle, we examine allocation levels where each sector's marginal benefit for the last quota unit allocated to them is equalized. Economists call this optimal because once we have established the optimal allocation, any other allocation necessarily lowers total economic benefits in the fishery.[1]

5.1 Allocation Analysis

The earlier chapters clearly demonstrate that both sectors benefit when quota is allocated to them. In this section, we compare these marginal benefits to examine

1. How the current allocation (60% Commercial and 40% recreational) compares to the optimal allocation

2. The quota allocation change that could increase economic benefits in the fishery

Both the commercial and recreational methodologies produce marginal value estimates that show what the sector is "willing to pay" for an additional unit of quota. We combine the marginal value estimates from Model 2 in the commercial Chapter 4

[1]This is a strong statement and we note the caveats to our work mentioned in this chapter and elsewhere in the document.

Figure 4.4 (the preferred model) with the marginal value schedule from the recreation chapter in Figure 3.4 (also the preferred model). In order to do this, we assume a grand total allowable catch of 6453 metric tons (which is the commercial quota allocation + the estimated landings (in metric tons) from the recreational sector both in 2018) and imposed the following constraint on the commercial and recreational sectors[2]:

$$Harvest_{Recreational} + Quota_{Commercial} = 6453$$

This allows us to solve for one sector's harvest as a function of the other. The commercial harvest can be written as

$$Harvest_{Recreational} = 6453 - Quota_{Commercial}$$

to find the recreational harvest consistent with 1) a total allowable catch limit of 6453 and 2) commercial harvest equal to the quota.

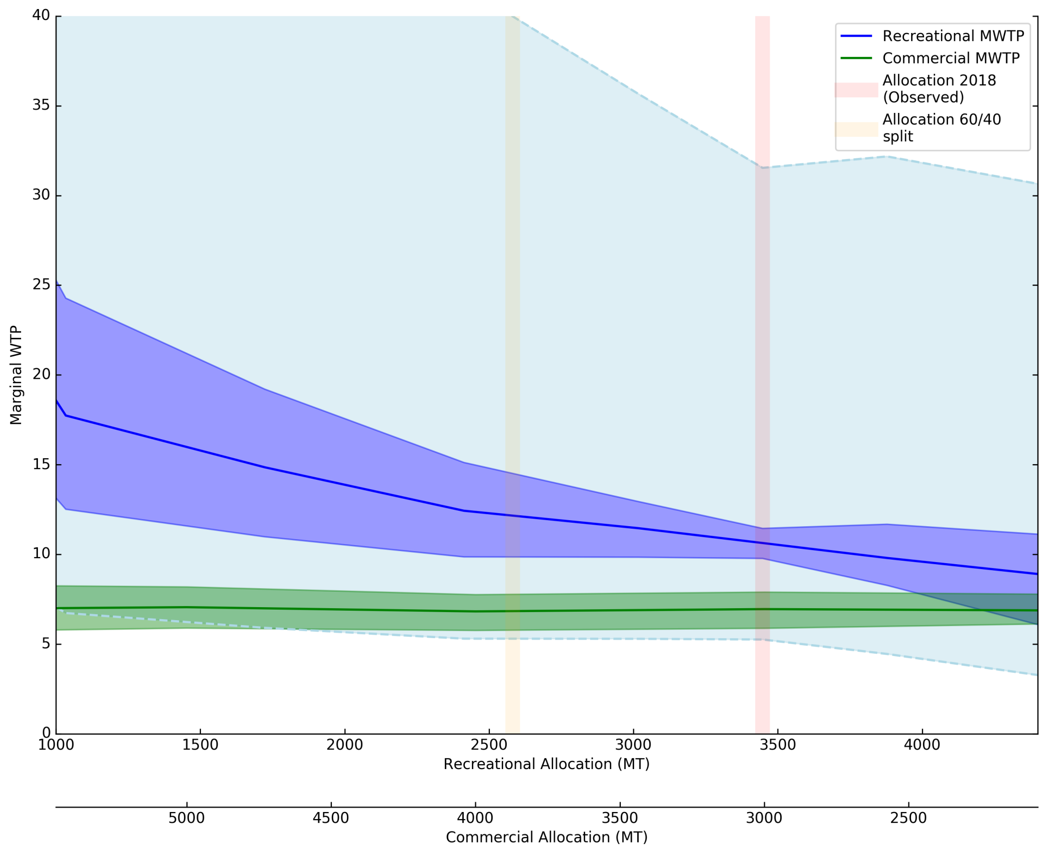
Using these constraints we combine the marginal value schedules for each sector in Figure 5.1. Note that in the figure, we use the preferred models from both the recreational and commercial sectors.

This figure shows, that once the 95% confidence intervals are included (and we incorporate the uncertainty around the benefits transfer as discussed in Chapter 3), there is no clear-cut difference in marginal value schedules for a wide swath of quota allocation levels between 1500 and 6000 metric tons allocated to the recreational sector. We can say however, that with data from the "New Method", the marginal willingness to pay schedule for the recreational sector has increased substantially and with a more precise way to estimate the model explicitly with opportunity cost of time included, or a more statistically precise benefits transfer we could recommend a shifting of quota towards the recreational sector (for example, the observed 55% recreational 45% commercial split). At this time however, the precision of our estimates given data availability do not allow us to make such a definitive recommendation. Consequently, we conclude that

- the current 60/40 allocation can't be said to be sub-optimal since stakeholders directly engaged in summer flounder fishing have a similar "Willingness to Pay" for an additional pound of fish in the neighborhood of the current allocation as the 95% confidence intervals overlap.

[2]Note this differs from our approach in the 2017 report since in that case landings in both sectors were roughly equivalent to quota allocations in 2014. Here, we choose the larger of landings and allocations for each sector for the purposes of drawing the figure.

Figure 5.1: Marginal Benefits of Quota by Sector



- modest changes from the current allocation would most likely not lower benefits in the fishery. While the point estimate (the dark lines labeled "Recreational WTP" and "Commercial WTP") of the recreational sector's marginal willingness to pay is higher and would argue for higher recreational allocations, there are allocations where the commercial sector has an even larger than 60% share where benefits from the fishery might increase since the confidence intervals overlap.

5.1.1 Caveats

The aforementioned analysis hinges on a number of key assumptions and we want to make clear some that we think are quite important to note alongside our main results. Besides the caveats broken down by sector and listed below, we also acknowledge additional caveats that impact the overall analysis:

- Both the commercial and recreational models use *past* fishing outcomes to characterize fishing quality for each of the sites in the spatial fishing model. Since past fishing outcomes are a product of past management and ecological conditions the quality measures we use may not fully capture the current quality expectations that is important for characterizing fishermen's preferences. However, since the models require fishing quality expectations that are spatially detailed, we have no choice but to use past fishing data for characterizing current expectations.

- As pointed out by Holzer and McConnell (2014), the equimarginal principle (that we use for allocation above) reaches an efficient allocation when property rights can be attached to the resource. We don't have that in this case, since once allocations occur for each sector an open access fishery ensues. We note this important caveat and argue that we can't do better without a *per-fisherman* participation model for both sectors and models of preference heterogeneity.

- Neither sector model allows for localized biological depletion.

- Our results are conditioned using the year 2018 as the baseline.

Recreation Caveats

1. By focusing on angler behavior, we ignore any other changes in consumer or producer surplus in the recreation sector that is *due to quota changes in the summer flounder fishery* such as losses/gains in profits at bait shops and boating repair and supply businesses. This means we are tending to underestimate the marginal value schedule for the recreation sector.

2. Our adjustment above in Figure 5.1 to account for the opportunity cost of time is an estimate of what the complete model might look like. In a sense, we are performing a benefits transfer with all of the issues that accompany it. We think it is a reasonable approximation since both studies examine the same resource, use the same data, and employ similar methods.

3. Our methods do not account for changes in participation and numbers of trips due to policy changes. Consequently, we are tending to underestimate the marginal value schedule for the recreational sector.

Commercial Caveats

1. The benefits accruing to commercial anglers occur in the *short-run*, since an extensive literature (see Grafton et al. (2006) for a brief overview) has shown that exogenous changes in profitability in regulated open access fisheries are often driven to low levels as commercial vessels try to out-compete each other to catch the fleet quota. Consequently, we would expect the marginal value schedule in 5.1 to decline over time.

2. Like the recreation analysis, this study only focuses on at-sea commercial behavior and ignores any changes in consumer and produce surplus in the commerical sector *solely due to quota changes* such as boating and dock services, and losses in consumer surplus for consumers of summer flounder. Consequently, we are tending to underestimate the marginal value schedule for the commercial sector.

5.1.2 Recommendations

Deciding the sector allocation of summer flounder between the commercial and recreational sectors is an impactful policy decision that alters the welfare of these respective sectors. In our analysis we have focused on making conservative recommendations regarding sector allocation because each of the models developed in our analysis possess important caveats and limitations that are relevant to policy. Although, the methods and data used are the best available we have made a concerted effort to acknowledge the limitations of our efforts and its efficacy for public policy. Given our results, there are a number of short-run implications of our analysis.

In the short-run, we don't see any statistical difference between the marginal value schedules of the two sectors using the preferred set of results. This suggests that the current sector allocations conform with our results. Although the mean estimates for the commercial sectors marginal valuation lie below the recreational sector's for the allocations shown in Figure 5.1, the confidence intervals for both sectors overlap. This indicates that our results provide little empirical support for altering the current allocation. Our results also suggest that modest changes in allocation would most likely not lower the economic benefits in the fishery noting the important caveat that we can't statistically distinguish differences in the marginal willingness to pay schedules between sectors. Large changes that severely restricted one sector over another would most likely lower the economic benefits in the fishery.

Our results can not be used to inform any long-run policy analysis as both sectors are likely to change their behavior should the existing allocation change. On the recreational side our results ignore any changes that may arise in related sectors (i.e., party/charter owners, bait and tackle shops, etc..) and changes in recreational effort that could impact their marginal valuation. On the commercial side our results do not address any changes in the prevailing market (i.e, ex-vessel prices), fleet behavior (i.e, entry and exit), or in related sectors should the allocation to the commercial sector change. Consequently, based solely on the equimarginal analysis performed here with accompanying caveats, we do not recommend changing the quota allocation as the marginal value schedules (Figure 5.1) are nearly equalized at the current allocation level.

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