“A la carte” management of recreational resources: Evidence from the US Gulf of Mexico

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1 Abstract

Externalities from recreation scale at both the extensive and intensive margins of resource interaction. Recreators have differentiated demands for these margins, so unbundling the prices of access and intensive depletion could improve upon traditional management. We use choice experiment data from US Gulf of Mexico recreational headboat anglers to estimate structural models of trip and red snapper retention demand, then simulate aggregate harvest across a range of trip and harvest tag prices. In our simulations, the red snapper harvest tag market equilibrates at $15 per tag and generates $760,000 in management revenues per year while more efficiently allocating harvest.

2 Introduction

Outdoor recreation plays an important role in the lives of North Americans and in the United States economy; an estimated 97% of U.S. citizens aged 16 and older engage in outdoor recreation at least once in any given year (Leeworthy and Wiley, 2001). In 2019, outdoor recreation accounted for $459.8 billion (2.1%) of U.S. current-value GDP, and the sector's growth rates for real output, compensation, and employment levels were faster than those of the average sector (Bureau of Economic Analysis, 2020). Federal and state natural resource managers face two foundational challenges in facilitating sustainable recreational use: 1) the management of the impacts on natural capital from recreational use; and 2) the problem of funding resource management activities when state support is often scarce.

Outdoor recreation frequently degrades the natural capital on which it depends, whether as an objective of the activity itself (e.g., fishing and hunting) or as a side-effect of ostensibly non-extractive uses (e.g., erosion from trail degradation or fire risk from human use). In the absence of effective management, these externalities may lead to excess resource degradation, with implications for both the quality of the ongoing recreational experience and the sustainability of ecosystems.

Federal and state resource managers have the unenviable task of containing the externalities of recreation, which arise at both the extensive margin (i.e., with the number of individuals accessing the resource) and the intensive margins (i.e., the per-trip level of resource impact), even as maintenance backlogs pile up and their future funding becomes ever more uncertain.[1] Wildlife agencies and other public land and waterway managers have historically received revenues from hunting and fishing license and equipment sales (Lueck, 2000), and in 2017, 35% of funds for conservation were from state license sales (Voyles & Chase, 2017). In that same year, the second and third largest sources of conservation funding, the federal Pittman-Robertson

[1] Vincent (2019) estimates that, in fiscal year 2018, the Bureau of Land Management, Fish and Wildlife Service, National Park Service, and Forest Service had a total estimated maintenance backlog of $19.38 billion.

and Dingell-Johnson Acts, contributed only 15% and 9% of total conservation funding, respectively (Voyles & Chase, 2017). Adult hunting and fishing participation are projected to decline 11-12% and 2-3% by 2030 (White et al., 2016), which means that the largest source of conservation funding—license sales—may be at risk.

Resource managers occasionally address environmental impacts of recreation by directly regulating the quantity of natural capital consumed (i.e., output-based management). For instance, game managers may directly control harvest by allocating a limited number of harvest tags for trophy species. However, it is far more common to address spillovers indirectly by trying to limit *inputs* to the impact. Park managers may place quotas on visitation to fragile backcountry habitats, while managers of sport fisheries attempt to curb the quantity and impacts of recreational "effort" through a combination of gear restrictions, retention (bag) limits, and seasonal closures. These input-based policies, while sometimes effective at containing the impacts of recreation, do not address the individual incentive to overuse a resource, because they do not directly encourage recreators to internalize the full marginal cost of their activities. As a result, recreational decisions—from the decision of how many trips to take to how many fish to retain vs. release—can be distorted, with the result that recreational experiences and the recreational consumption of natural capital itself is inefficiently allocated (Holzer & McConnell, 2014). Furthermore, input controls (at least as commonly implemented) are not revenue-raising, so that externality control, while costly, contributes little or nothing to the coffers of resource management agencies.

For these reasons, economists have often recommended full marginal cost pricing policies to address externalities. Brown (1971) and Cesario (1980), for example, emphasize the importance of accounting not only for marginal operating costs, but also peak-time or congestion spillovers when valuing and pricing a recreation site and its substitutes. Yet, the practice of closely tying the effective price paid by a recreator to their consumption of scarce (including environmental) resources remains rare. Empirical research to guide such endeavors is similarly sparse, and has primarily focused on the potential for access fees, perhaps in combination with an annual license or permit, to balance normative revenue and equity objectives (Richer and Christensen, 1999; Williams, Vogt, and Vitterso, 1999; Holmes and Englin, 2005; Abbott and Fenichel, 2013). The literature has not considered the implications of unbundling the price of access and the price of consumptive use of scarce recreational resources.

We examine the potential for a differentiated, "a la carte" management approach to better capture users' heterogeneous marginal values of access and consumption relative to other second-best regulatory pricing policies using the case of the US Gulf of Mexico (GOM) recreational headboat fishery.[2] In general,

[2]Headboats or party boats have permits to take 15 or more fisherman to fish for reef fish in the exclusive economic zone of the US GOM. These vessels typically charge anglers "by-the-head" to take an offshore fishing trip.

recreational resource users derive utility from both experiential and consumptive trip attributes. Recreational anglers, in particular, increase their utility by selecting a fishing experience, which is priced in a market for headboat trips, and by directly consuming an environmental good (fish) in the course of that experience. This headboat fishery, therefore, is an ideal context for exploring whether unbundling the prices of experience and consumption could improve allocative efficiency.

Output-based "a la carte" management in the headboat sector could take a few different forms. For instance, access to fishing trips might be regulated through a limited entry permitting system for vessels and market-driven trip pricing (as currently) coupled with a government-levied fee for fish retention. Alternatively, harvest could be regulated through the allocation of a limited number of, potentially transferable, harvest tags to anglers (Abbott, 2015; Johnston, Holland, Maharaj, & Campson, 2007). Per-fish retention fees and harvest tags are economic duals; retention fees indirectly restrict harvest by increasing the cost of retaining a fish, while harvest tags directly limit harvest. Assuming harvest tags are distributed using a market mechanism (e.g., if tags are sold by brokers or are allocated and tradable in a frictionless market), then the market price for a harvest tag should equal the per-fish retention fee that results in the same number of fish harvested as tags distributed.

In this paper, we use choice experiment data from an online survey of anglers who took deep sea fishing trips onboard headboats in the US GOM to investigate anglers' behavioral responses to and the revenue-generating potential of trip pricing that decouples resource consumption (harvest) from the trip itself. By using stated preference data, we are able to assess behavioral responses to a range of pricing policies that do not currently exist.

Respondents in our choice experiment data were presented with a two-part tariff of trip prices and per-fish retention fees as an alternative to the status-quo of trip prices with bag limits. We estimate structural models of extensive (trip-taking) and intensive (per-trip retention) margin behavioral responses to a change from bag limits to retention fees for red snapper. We then show how these two models can be used to perform *ex ante* behavioral analyses of trips demanded, fish harvested, and revenues generated for a variety of policy counterfactuals. Because retention fees and marketable harvest tags are economically equivalent, we interpret our policy simulations in terms of harvest tags, even though the survey on which our models were based asked respondents about retention fees. We explain our choice to focus on harvest tags in section 6.2.

In the next section, we provide some context both on recreational fisheries management, generally, and on the US GOM recreational red snapper headboat sector, specifically. Then, in section 4, we explain how our data were collected, cleaned, and weighted. In section 5, we build our extensive margin model of trip demand and our intensive margin model of per-trip red snapper retention demand, and then explain how we calibrate those margins together for our policy simulations. We analyze and discuss both models plus the resultant simulations in section 6.

The trip taking model shows that anglers are more likely to take trips with lower trip prices and lower per-fish retention fees, as well as higher expected catch of fish other than red snapper and higher expected catch of red snapper that they are allowed to retain. Additional red snapper caught that must be discarded under a bag limit do not impact trip-taking, which suggests that replacing the bag limit constraint with retention fees may be welfare improving. We also find that replacing a bag limit with retention fees does not impact the probability of opting-out of a trip along any particular demographic margins, and that anglers may even be agnostic between trip prices and maximum expected fee bill (i.e., trip price plus the retention fee times the number of red snapper the angler expects to catch on a given trip) when deciding to take a fishing trip. Furthermore, anglers retain fewer fish at higher retention fees, and become fee elastic in their within-trip retention demand when they must pay more than $56 to retain a red snapper.

In section 6.2, we calibrate our trip-demand and per-trip retention demand models together to predict aggregate harvest demanded and revenues generated by harvest tag sales across a grid of trip prices and per-fish retention fees. Resource managers can use this simulation tool to back out a demand curve and associated revenues for harvest tags. We show that, under logbook-derived representative conditions, a market for harvest tags would equilibrate at $15 per red snapper on GOM headboats in our sample, generating just over $760,000 in management revenues per year (assuming fixed catch limits based on historic logbook data) while more efficiently allocating harvest and addressing the fishing mortality externality that recreational anglers impose on one another through their fishing behaviors.

3 Research context

3.1 Management of recreational fisheries

We explore "a la carte" pricing in the case of marine recreational fisheries. Innovation in recreational fisheries management has been relatively slow given the scale of these fisheries' impacts on fish stocks and on the welfare of recreational anglers. Marine recreational fisheries, in particular, accounted for 4% of all marine finfish landings in 2002, and 64% of landings in the Gulf of Mexico (GOM) in that same year were recreational (Coleman, Figueira, Ueland, & Crowder, 2004). The majority of recreational fisheries are governed as regulated open access systems in which total effort is limited only through technical mechanisms (Homans and Wilen, 1997). As a result, anglers do not have an incentive to preserve stock today to ensure the fishery is available to other anglers in the future.

Managers of open-access fisheries have long sought to restrict effort by imposing size or daily bag limits on fish retained or by reducing season lengths. However, these methods are not effective at limiting total effort. Bag limits may reduce landings in the short-run by capping per-trip retention for current anglers but neither prevents those anglers from taking more trips nor blocks new anglers from entering the fishery (Cox, Beard, & Walters, 2002). Furthermore, bag limits may exacerbate harvest spillovers—especially in fisheries with higher levels of discard mortality—by encouraging anglers to high-grade their catch (Woodward & Griffin, 2003).[3] Similarly, imposing shorter fishing seasons provides no incentive to reduce effort, and instead concentrates fishing effort into a reduced number of days (Cox et al., 2002). Fisheries with abridged, intensive fishing seasons suffer welfare losses, both because they are more congested and because they become inaccessible to some time-constrained anglers who would otherwise participate in the fishery (Arlinghaus et al., 2019). For instance, Abbott, Lloyd-Smith, Willard, and Adamowicz (2018) estimate that trading season closures for reduced per-angler retention under a rights-based policy in the US GOM red snapper fishery would increase the average angler's welfare by \$139 a year. Given that more than 30% of people 16 years and older in the U.S. participate in recreational fishing, the potential scale of welfare loss due to regulated open access management is staggering (Leeworthy & Wiley, 2001).

A corollary to these welfare losses is the fact that access to fishing opportunities and fish harvest under season closures is inefficiently allocated across heterogeneous anglers (Holzer & McConnell, 2014). Rather than allocating scarce recreational goods according to their marginal valuation, as for a typical market good, bag limits and season closures create "rationing rules" that allocate recreational goods in ways that may bear little relation to how anglers actually value them. For example, seasonal fishery closures may allow anglers with low willingness to pay (WTP) for a trip to access fishery resources for the simple reason that they happen to be in the region at a particular time of year, whereas others with a high WTP but less flexible schedules are excluded. Similarly, bag limits may allow anglers with low WTP for fish to retain them even as other, relatively high-skill, anglers may value retaining the same fish more highly but are not allowed to do so due to the bag limit. These potential gains from trade are left on the table under regulated open access, suggesting that some sort of price signal, whether through a tax/fee or market mechanism could improve welfare.

McConnell and Sutinen (1976) and Anderson (1993) extended commercial fisheries bioeconomic models to the recreational context, demonstrating that the negative effect of present-day harvest on future fish stocks must be internalized by anglers in the present so that they will not engage in over-fishing. If resource managers knew the full, intertemporal social marginal cost of harvest, then they could charge all resource users one price for harvest that internalizes any spillovers and efficiently allocates harvest through time and

[3] High-grading is when anglers discard lower value fish so that they may retain more high-value fish under a harvest constraint.

across users. Importantly, if discarded catch suffers positive mortality, then the price must be differentiated across harvest and discards in order to ensure efficiency (Abbott & Wilen, 2009; Anderson, 1993), a policy that could potentially be implemented via individual transferable quotas or cooperatives in the case of recreational for-hire fisheries (Abbott, Maharaj, & Wilen, 2009). Fenichel and Abbott (2014) consider the possibility that such an "output based" policy is infeasible due to prohibitive costs of monitoring discards and landings (or the "inputs" that determine these outputs.) Abstracting from questions of endogenous discard behavior, they show how efficiency can be improved relative to the unregulated case by levying differentiated trip fees along observable correlates of fishing mortality such as distance traveled, age, income, or fishing tackle and/or mode. Nevertheless, this approach is second-best due to an imperfect mapping between *ex ante* predictions of individual fishery impacts based on observable factors and the realized fishing mortality.[4] The extent of inefficiency declines as the correlation between the observable heterogeneity used to target fees and realized fishing mortality per trip increases.

Given the shortcomings of status-quo management in recreational fisheries, it is plausible that even clearly second-best forms of output-based policies could improve allocative efficiency, better regulate fishing mortality, and support revenue-raising goals (Abbott, 2015). Johnston et al. (2007) suggest that harvest tags may be a feasible way to control harvest by assigning short-term, seasonal harvest rights to recreational anglers. Similar to tags frequently used in game management, harvest tags are limited in number and may be allocated through market mechanisms such as auctions and resale provisions to optimize efficiency or raise revenues. In this case, the market also provides a clear signal of the implicit regulatory price of harvest – creating a clear duality between quantity and price-based management. Alternatively, tags can be allocated through some combination of lotteries and set-asides in order to achieve distributional objectives (Johnston et al., 2007). Harvest tags are capable of achieving first-best efficiency if the number of tags is optimally set, perfectly enforced, and if all discarded catch survives. However, their efficiency is potentially compromised by high-grading behavior under positive discard mortality (Johnston et al., 2007). In this latter case, it is an empirical question whether harvest tags or alternative forms of management will be more efficient. The high-grading concern is also present in commercial fisheries where total catch is imperfectly observed. Regardless, ITQ fisheries tend to be more efficient than their baseline under regulated open access management.

3.2 The GOM headboat fishery

Red snapper is a favorite target of recreational anglers in the US GOM and is among the top 10 recreationally-landed saltwater species in the United States (Figueira & Coleman, 2010). The GOM recreational red snapper fishery extends from Texas through Southwest Florida and is accessed both by private boat anglers and by a

[4] "Second-best" refers to a social welfare maximizing outcome under binding information or policy constraints.

for-hire sector of over 1300 vessels, most of which are charter boats and 72 of which are headboats (National Oceanic and Atmospheric Administration, 2016).

In 1988, GOM red snapper was declared overfished and subject to overfishing due to combined stock pressure from the commercial and recreational red snapper fisheries, as well as excess bycatch of red snapper by the commercial shrimp fishery. In the years that followed, NOAA required shrimp fishermen to install devices on their trawl nets that reduced bycatch of juvenile red snapper. The commercial and recreational red snapper fisheries were subject to seasonal and daily harvest caps, as well as gear and minimum size restrictions, and both the commercial and for-hire recreational sectors were accessible through a limited number of licenses. In 2007, the commercial fisheries transitioned to IFQ management with year-round federal seasons. In response to these rebuilding efforts, the catch per unit effort (CPUE) and size of red snapper increased. The increased CPUE induced additional fishing trips (i.e., effort), even as larger fish more quickly exhausted biomass-delimited harvest caps. These two trends paired with extended state seasons that further depleted the available total recreational quota meant federal seasons for the recreational sector needed to be cut ever shorter, even as the stock recovered. In 2014, the season for recreational red snapper fishing was just nine days long, and the accelerating race to fish sparked disputes between the commercial and recreational sectors (Gulf of Mexico Fishery Management Council, 2014; National Marine Fisheries Service, 2018; Abbott, 2015). Even with regulators' efforts to control recreational harvest through abridged seasons, the recreational sector exceeded its harvest cap every year from 2007-2013, except during the 2010 Deepwater Horizon oil spill.

In 2014 and 2015, a subset of the headboat sector opted into a two year rights-based management pilot program called the Gulf Headboat Collaborative (GHC).[5] As in a commercial fishing cooperative, participating headboat owners were allocated red snapper and gag grouper quota to trade amongst themselves according to each vessel's 2011 landings. In exchange for adhering to their quota allocations, GHC participants were exempt from federal red snapper seasons, and could offer year-round retention for their clients. GHC clients still faced daily bag limits of two red snapper during federal seasons, and most GHC captains imposed a one fish bag limit on their clients outside of the federal season in order to stay within their quota allotments. The GHC program increased access to red snapper over a much longer season and number of anglers while remaining within binding harvest limits. It also reduced regulatory discards and increased industry profits (Abbott & Willard, 2017)

[5] Nineteen of the 72 headboats participated in the GHC in one or both years of the pilot.

4 Data

Anglers who took deep sea fishing trips aboard GHC vessels in 2014 and 2015 were asked to fill out an onboard survey at the conclusion of their trip. The GHC vessels hail from 8 ports in Panhandle and Southwest FL, AL and TX and represent the diversity of the headboat market well, with some vessels operating out of well-known tourist destinations (e.g., Clearwater and Destin, FL) and others operating in more remote areas (e.g., Pt. St. Joe, FL and Dauphin Island, AL). As a condition of their participation in the pilot program, vessels were required to make the onboard survey available to all passengers throughout the two-year policy experiment. Therefore, the sampling effort was approximately constant across vessels and across seasons within the year.

In the brief onboard survey, anglers were asked to provide feedback on their trip experience, some sociodemographic information (including age, income, gender, zip code, and saltwater fishing experience and avidity), and their email address if they were willing to participate in a follow-up survey.[6] Around 50% (5,330 out of 10,719) of those who completed the onboard survey provided a valid, unique email address for follow-up. The primary value of the onboard survey in our analysis is to identify and control for differences in characteristics between respondents to the online choice experiments and the the population of anglers taking trips on GHC vessels. An online follow-up survey was sent to those 5,330 email addresses in two waves in order to minimize recall bias (December 2, 2015 through December 22, 2015 and February 11, 2016 through March 7, 2016).[7,8] The response rate for both waves was 15%, with a total of 813 respondents, after excluding 10 surveys due to missing information or unreasonable trip recall responses.

Two versions of the online survey were distributed—one that focused on red snapper as a target species and one that focused on gag grouper. Our data includes only those 537 surveys that focused on red snapper. Of those anglers included in our final dataset, 34% live in the GOM region year-round, 16.57% belong to an angler organization, and 83% are male. The average respondent is 49.45 years of age ($sd = 13.56$), has 16.87 years of experience fishing in the US Gulf of Mexico ($sd = 15.14$), and has an annual household income of nearly \$108,000 ($sd = \$60.46$).[9]

There were five sections to the online survey. In the first section, respondents were asked about their vacation and recreational activities over the past year, as well as their degree of familiarity with the GOM.

[6] Anglers who provided their email were entered into a drawing for a free fishing trip.

[7] In order to ensure the wording and experimental design of the internet survey were effective, two focus groups were conducted with local anglers in Pensacola, FL in August 2015. A pretest of the online survey was conducted in October 2015 and received 39 responses.

[8] The full survey can be accessed at http://wpcareyschool.qualtrics.com/jfe/form/SV_7ZMU08RRoqoSkF7.

[9] 7% of respondents in the final sample failed to provide household income data, while 18% did not provide data on the number of years of fishing experience in the GOM. Lloyd-Smith, Abbott, Adamowicz, and Willard (2019) impute the missing income and experience data with multiple imputation using chained equations (MICE), and we included this imputed data in our summary statistics.

Many recreational fisheries, including red snapper, are managed through bag limits to help ensure the fishery is not depleted. An alternative management option used in some fisheries is where fishermen pay a fee per fish they retain. For the next two choices, assume that there is an alternative fishery management in place where there are no limits on the number of red snapper you can retain (i.e. no bag limits), but rather a fee for each red snapper retained.

The fee would be collected by the headboat operators as people leave the vessel at port. The money collected by the headboat operators would be used to fund habitat enhancement projects in the Gulf of Mexico and Gulf of Mexico fishery research.

How acceptable do you find the fishery management option where there are no limits on the number of red snapper you can retain (i.e. no bag limits), but rather a fee for each red snapper retained?

	Definitely Acceptable	Somewhat Acceptable	Neither Acceptable nor Unacceptable	Somewhat Unacceptable	Definitely Unacceptable
Management option with a fee for each red snapper retained	○	○	○	○	○

Figure 1: Fee acceptability question, showing the version of the question where fees are used to fund research and habitat enhancement.

The second section had anglers report how many headboat trips they took in the previous year, and asked them to recall some characteristics of those trips. The remaining three sections were presented to respondents in randomized order and we use data from one of these sections that included a choice experiment.[10]

In the choice experiment, respondents were first introduced to a hypothetical per-fish retention fee as an alternative to traditional bag limits. In two different experimental arms, individuals were told either that any retention fees paid would be retained by the headboat captain or that they would be invested in conservation or research within the fishery.[11] Respondents then rated the fee-based program from “definitely acceptable” to “definitely unacceptable” (see Figure 1). In our final sample, 34.82% of respondents said retention fees were a somewhat or definitely unacceptable alternative to bag limits, while 47.67% said those fees were somewhat or definitely acceptable.[12] Following this fee acceptance question, anglers were then presented a series of four choice scenarios. In one pair of experiments, retention was governed through bag limits, while the other pair featured retention fees. The order in which respondents faced each experimental pairing (i.e., the two bag limit or fee scenarios) was randomized. In each of the four scenarios, respondents were asked

[10]The other two sections asked contingent trip behavior and time valuation questions, respectively, and are utilized in other research (Abbott et al., 2018; Lloyd-Smith et al., 2019, 2020).

[11]Exactly 50% of respondents in our final data received each of the two treatment arms.

[12]The remaining 17.51% of respondents said replacing the status quo bag limit with retention fees was neither acceptable nor unacceptable.

Table 1: All variable levels included in the choice experiment survey.

Features	**Levels**
Total expected number of red snapper caught per trip (*target*)	1, 3, 5, 7
Red snapper bag limit (*retain*)	1, 2, 3
Per-fish retention fee for red snapper (*fee*)	\$10, \$25, \$35, \$50
Number of other species caught per trip (*other*)	1, 2, 4, 6, 8
Vessel is congested? (*congest*)	Spacious, Crowded
Price for half day trip (*price*)	\$50, \$80, \$120, \$150, \$200
Price for full day trip (*price*)	\$80, \$120, \$130, \$200, \$250

to choose between taking one of two fishing trips (with experimentally-varied trip characteristics as denoted in Table 1) or the outside option of not going on a headboat trip (see Figure 2).[13] Anglers were presented with either partial day or full day trip prices throughout their four scenarios. We pool partial and full day trips in our analyses, based on evidence that angler behavior and preferences are not significantly different between partial day and full day trips.[14]

Respondents who indicated they would take one of the two trips on either of the fee version choice scenarios were then asked how many of the red snapper they would retain given the expected catch and the per-fish fee on their chosen trip. We use this contingent behavior data to model the intensive margin of fish retention in response to fees.

5 Methods

We utilize responses to the trip choice experiments and follow-up retention questions to estimate separate models for both the extensive (i.e., the probability of taking a fishing trip aboard a GOM headboat) and intensive (i.e., the number of fish retained conditional on having chosen to take a trip) margins of demand for retained fish. We then calibrate those models together in order to simulate total trip and harvest demand

[13] The choice experiment experimental design was based on results of the pilot survey. Responses from the pilot survey were used to estimate a conditional logit model and these parameters were used as priors in a D-efficient experimental design for the main survey.

[14] We estimate a conditional logit, which includes all regressors (X) from table 2 and interactions between these variables and an indicator for *fullday*. We then perform a Wald test in which we fail to reject the null hypothesis that all *fullday* interaction terms are equal to zero ($\chi^2 = 9.13$, $p = 0.3318$).

Features	Trip 1	Trip 2	No trip
Total expected number of red snapper caught per trip	1 red snapper	7 red snapper	Do something else, but do not go saltwater fishing on a headboat
Cost per each retained red snapper	$50	$10	
Number of other species caught per trip	8 fish	2 fish	
Congestion	Spacious	Crowded	
Price for full day trip	$80	$200	

I would choose...

Trip 1 ○ Trip 2 ○ No Trip ○

Figure 2: A choice experiment question from the online survey in which respondents faced retention fees.

across a range of "a la carte" policies.

In order to model trip demand as a function of trip prices and retention fees, we estimate a conditional logit model of individual and alternative-specific characteristics and their interactions on trip choice. Each respondent faced four different choice sets including two bag limit and two fee scenarios, so we group observations by respondent. Underlying each choice for this conditional logit is a random utility model in which individual i chooses to take one of the two trips (j=1,2) presented to them or an opt out (j=3) option. Let the utility of choosing alternative j for individual i in any given choice scenario c be

$$U_{icj} = \begin{cases} \beta' X_{icj} + \varepsilon_{icj} & j = 1, 2 \\ \psi' Z_i + \varepsilon_{ic3} & j = 3 \end{cases} \tag{1}$$

where X_{icj} indexes the characteristics of each fishing alternative, Z_i are individual-specific characteristics, β and ψ are parameters to be estimated, and ε_{icj} is a stochastic, type I extreme value error term.

The trip characteristics in X_{icj} are the price (i.e., trip price and retention fee) and quality (e.g., whether or not a trip was congested or the expected catch of red snapper or other species) attributes included in the choice experiment design. The covariates in Z_i are individual-specific observable demographics (e.g., household income or Gulf residency) and belief or preference variables from the survey (e.g., the belief that retention fees are "acceptable" or "unacceptable") that may capture heterogeneity in anglers' probabilities of opting-out of a trip that demographic data alone cannot.[15] Table 2 describes the variables included in vectors X and Z, including the trip attributes that are specific to the fee or bag limit versions of the choice experiments.

We pool bag limit and retention fee choice experiment data in the above utility function, and therefore assume that price and non-catch trip attributes have the same effect in both scenario types. There is more than one way to represent the catch and retention attributes under the bag limit scenario; we have chosen to represent them in terms of retention (*retain*) and discards (*discard*) using the expected catch of red snapper and the bag limit for a given trip choice. If expected catch exceeds the bag limit, then *retain* equals the bag limit and *discard* equals expected catch less the bag limit. However, if the bag limit is not binding, then *retain* equals expected catch and *discard* equals zero.

To account for the potential of unobserved preference heterogeneity, we also estimate a panel random parameters logit in which we let parameters for the alternative-varying covariates differ across individuals (Train, 2009). We assume all random preference parameters are both uncorrelated and normally distributed, with the exception of *price*. We consider model specifications with a fixed price coefficient and a specification allowing for heterogeneous price responses by assuming β_{price} is distributed log-normally so that $-\beta_{price}$ (reported) is strictly negative. The random parameter specifications are estimated using maximum (simulated) likelihood.

We use our extensive margin models to draw population-scale conclusions and to simulate policy scenarios. We therefore use inverse probability weights in estimation. These weights account for non-response and sampling design bias and ensure our data are spatially and temporally representative of the headboat

[15]Past iterations of the model (not shown) also included indicators for gender, whether a respondent was told that retention fees would stay within the headboat sector or go toward research and conservation, and whether the respondent belongs to an angler organization. None of these Z_i covariates were significant in explaining trip choice and were not included in the final models.

Table 2: Alternative & individual-specific variables in the extensive and intensive margin models.

X	price^{E,I}	Price of the trip
	other^{E,I}	Number of other species caught per trip
	congest^{E,I}	Vessel is "Crowded" (=1) or "Spacious" (=0)
	optout^{E}	An ASC for the outside option
Fee	target^{E,I}	Expected catch of red snapper on a trip
Version	fee^{E,I}	Fee per retained fish
Bag Limit	retain^{E}	The number of red snapper an angler catches and may retain
Version	discard^{E}	The number of red snapper an angler catches above the bag limit
Z	gom_resident^{E,I}	=1 if an angler is a Gulf of Mexico resident
	acceptable^{E,I}	=1 if the angler said retention fees are acceptable
	unacceptable^{E,I}	=1 if the angler said retention fees are unacceptable
	income^{E,I}	Annual household income (in $10,000s)
	gomfishing_years^{I}	Tens of years of experience an angler has fishing in the GOM
	Vfeetoboat^{I}	=1 if an angler was told fees would go to the headboat captains
	knew_pilot^{I}	=1 if the angler knew about the GHC pilot program at the time of his trip
	org_angler^{I}	=1 if the angler is a member of an angler organization

Variables superscripted with E or I are included in the extensive or intensive margin models, respectively.

population. Appendix 1 provides details on the calculation of these weights.

We use data from the retention fee scenarios in which individuals choose a fishing trip to estimate a censored Poisson model of the number of fish anglers retained conditional on having chosen to take a fishing trip (i.e., intensive margin demand). This Poisson regression is top-censored by the expected catch of red snapper (*target*) presented in the chosen option of the previous choice experiment, because anglers cannot retain more fish than they catch. Let y_{ijc} be the observed, top-censored retention count, and y^*_{ijc} the uncensored, latent retention count. The top censoring point (i.e., expected catch of red snapper) is U_{ijc}. If $y_{ijc} < U_{ijc}$, then $y_{ijc} = y^*_{ijc}$. This censored Poisson can thus be represented as

$$E(y^*_{ijc}|X_{ijc}, Z_i) = exp(\beta' X_{ijc} + \gamma' Z_i) = exp(\zeta_{ijc}) \quad (2)$$

with a weighted log likelihood of

$$LL = \sum_{i=1}^{N} \left\{ w_i \left[d_{ijc} \left(-exp(\zeta_{ijc}) + y_{ijc}(\zeta_{ijc}) - ln(y_{ijc}!) \right) + (1 - d_{ijc}) ln \left(1 - \sum_{k=0}^{U_{ijc}-1} f(k|X_{ijc}, Z_i) \right) \right] \right\} \quad (3)$$

where $d_{ijc} = 1$ if $y^*_{ijc} < U_{ijc}$ and w_i denotes inverse probability sampling weights.

As in the extensive margin model, X_{ijc} and Z_i are vectors of alternative-specific and individual-specific characteristics that drive retention decisions. We include several additional covariates in Z_i that may matter for retention decisions but not for trip-taking decisions in this extensive margin model. For example, we hypothesize that anglers with more years of experience fishing in the GOM have a stronger preference for red snapper retention than other, less experienced anglers (Table 2).

The probability that an observation is included in the censored Poisson estimation is the joint probability that individual i was included in the extensive margin estimation (this is captured by the extensive margin inverse probability weights discussed in section 5) and the predicted probability (from the extensive margin model) that individual i chose a non-opt-out option in the choice experiment question. We weight the estimation of the intensive margin model using the product of the extensive margin weights and the inverse probability that individual i selected $j \neq 3$ for each included scenario (see Appendix 2).

The trip demand and retention demand models, when combined, provide an architecture to predict the effects of alternative policies on aggregate angler behavior, welfare, and impacts to fishery resources. Given our primary interest in this paper on the interactions between trip-level pricing vs. "a la carte" pricing for individual removals from the resource stock, we use our extensive and intensive margin models to predict trip and per-trip retention demand across a grid of policy-relevant trip prices and tag prices (or, equivalently, retention fees). We use trip-level logbook data to calibrate these predictions so that they reflect actual trips taken and red snapper harvested aboard GHC vessels in the two years prior to the pilot program (2012-2013) under a set of representative conditions and trip attributes. For a complete description of the simulation and calibration procedure, please refer to Appendix 4.

6 Results

6.1 Modeling Results

Table 3 presents the estimation results for a conditional logit model (column 1) and two random parameters logit (RPL) model specifications (columns 2 and 3). All three models are estimated with cluster-robust standard errors which are clustered by individual respondent to allow for possible correlation between responses.

The non-price random parameters in both RPL models are drawn from normal distributions,

Table 3: Conditional logit and random parameters models of trip choice.

			(1) clogit	(2) rp logit (fixed price)	(3) rp logit (ln price)
price[16]		μ	-0.00698***	-0.01103***	-4.49913***
			(0.00108)	(0.00199)	(0.24597)
		σ			1.06657***
					(0.13825)
other		μ	0.07749***	0.11278***	0.14822***
			(0.01935)	(0.03104)	(0.04478)
		σ		0.16914***	0.16368*
				(0.04341)	(0.0638)
congest		μ	-0.81713***	-1.33397***	-1.49132***
			(0.10879)	(0.21852)	(0.28366)
		σ		1.12175***	1.14397**
				(0.27886)	(0.35745)
optout		μ	-1.22352**	-2.50251*	-2.82661*
			(0.41718)	(0.97388)	(1.3825)
		σ		2.79362***	2.81591***
				(0.42085)	(0.52788)
	gomresident		-0.08123	-0.10628	-0.2129
			(0.35884)	(0.494)	(2.58804)
	income		-0.00058	0.00111	0.00065
			(0.00226)	(0.00167)	(0.00361)
vbag	retain	μ	0.37398***	0.67008***	0.73978**
			(0.08569)	(0.15329)	(0.25241)
		σ		0.42388	0.64788
				(0.24951)	(0.39382)
	discard	μ	0.06674*	0.07278	0.10376
			(0.03361)	(0.05346)	(0.0582)
		σ		0.22361	0.1598

[16] To restrict price effects to be negative, the negative of price is included in model 3. The estimated mean and standard deviation of the negative price coefficient are in log scale. De-logged, the estimated μ and σ are 0.01964 and 0.02859, with robust standard errors of 0.0033 and 0.0069, respectively. The formulas for finding these values are: $mean = exp(\mu + \sigma^2/2)$ and $sd = \sqrt{exp(2\mu + \sigma^2)[exp(\sigma^2) - 1]}$.

Table 3 continued from previous page

				(1)	(2)	(3)
				clogit	rp logit	rp logit
					(0.14238)	(0.35309)
vfee	target		μ	0.04699*	0.05777	0.09356*
				(0.0222)	(0.0395)	(0.04159)
			σ		0.19928**	0.17906
					(0.07194)	(0.11073)
	fee		μ	-0.02359***	-0.0396***	-0.04446**
				(0.00348)	(0.00791)	(0.01497)
			σ		0.01654	0.01356
					(0.01663)	(0.03694)
	optout			-0.28141	-0.03516	-0.04209
				(0.41082)	(0.18729)	(1.04215)
		gomresident		0.48189	0.83708	0.9431
				(0.35267)	(0.6266)	(1.12054)
		income		-0.00114	-0.00192	-0.00167
				(0.00205)	(0.0027)	(0.00553)
		unacceptable			0.13684	-0.08957
					(0.8946)	(0.58371)
		acceptable			-2.16461*	-2.76009***
					(0.89996)	(0.67615)
Number of individuals				537	537	537
Number of choice occasions				4	4	4
Number of observations				2148	2148	2148
LL				-2053.874	-1826.447	-1778.609
Pseudo R2				0.1241	0.2167	0.2365

Cluster robust standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

while β_{price} is either included as a fixed parameter (column 2) or estimated as the negative of a log-normal distribution (column 3).[17] Many of the estimated standard deviations of the random parameters in models 2 and 3 are large relative to their estimated means and statistically significant, which suggests that it is important to allow for unobserved heterogeneity when modeling the trip-taking behavior of recreational anglers. We use the estimated coefficients of model 3 in our policy simulations (section 6.2).

The estimated coefficients for both trip-cost variables (*price*, *fee*) are negative across the conditional and random parameters logit models. The estimated standard deviation of *price* (model 3) is large relative to its mean, which suggests there is substantial heterogeneity in anglers' responses to trip price. Conversely, the estimated standard deviation for *fee* (models 2 and 3) is small relative to its mean, which indicates little heterogeneity in fee sensitivity when it comes to trip choice.

In each of the models in table 3, we investigate whether anglers were more likely to opt out of fishing trips for which retention is governed through fees rather than bag limits. The uninteracted base covariate *optout* has a negative and significant estimated mean and an estimated standard deviation that is both significant and large relative to its mean. In other words, holding alternative-varying attributes constant, anglers tend to opt out less often than they opt in, but this response is heterogeneous between anglers. The coefficient for *optout* under "Fee Version" is small and insignificant, which suggests that anglers were no more or less likely to opt out of a trip conditional only on their red snapper retention being governed by fees rather than bag limits. Anglers who found retention fees to be acceptable were less likely than those who were either ambivalent toward (the omitted base interaction) or opposed to retention fees to opt out of a trip conditional only on it being a "fee trip." This finding suggests that there were behavioral consequences (at least in terms of stated preferences) of professed attitudes toward the use of retention fees.[18] Understanding the mix of these attitudes in the angler population is therefore important for understanding the overall scale of demand under this proposed policy. Nevertheless, this heterogeneity may be of limited usefulness for policy targeting since fee attitude is not a verifiable attribute on which policy can be differentiated.

If fee acceptance tends to vary along certain demographic margins (e.g., income) then we might be concerned about the distributional implications of the differential impact of retention fees on trip-taking as discussed above. In order to investigate potential distributional concerns and to identify observable, policy-relevant attributes with which fee acceptance might be correlated, we estimate an ordered logit model of fee acceptance on angler characteristics (see Table 6 in Appendix 5) which reveals that younger, male anglers with higher annual household incomes are more likely to be accepting of retention fees. These findings suggest

[17]Past iterations of model 2 included an unmixed *price* coefficient, as well as either $ln(price)$ or $price^2$, neither of which were significant. Thus, we are confident that our random parameters logit models capture the true, linear relationship between price and trip-taking probability.

[18]Note that all respondents were asked about fee acceptance prior to their exposure to the choice experiment section of the online survey, so that it can be treated as exogenous to the level of the fee in the extensive and intensive margin models.

Table 4: Conditional logits of trip choice (non opt-out) under the fee version.

	(1)	(2)
price	-0.00655***	-0.00677***
	(0.00183)	(0.00182)
other	0.0420	0.0294
	(0.0275)	(0.0264)
congest	-0.826***	-0.741***
	(0.192)	(0.183)
target	0.0333	0.186***
	(0.0277)	(0.0530)
fee	-0.0227***	
	(0.00502)	
fee × target		-0.00541***
		(0.00126)
N	1486	1486
LL	-386.56691	-384.10395
$Pseudo\ R^2$	0.0896	0.0954

Cluster robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

that uncoupled pricing could promote elitism if, as a result of being less approving of retention fees, lower income individuals are induced to take relatively fewer fishing trips. Even though income is a significant determinant of fee acceptance, we found in Table 3 that only fee acceptance and not income significantly impacted the probability of taking a fee version headboat trip.

In addition to looking at differential opt-out behavior between bag limit and fee trips, we also investigate how trip-taking depends upon on marginal changes in fee magnitude. At first impression, the coefficients in Table 3 suggest that trips hinge more on changes in the retention fee than on changes in trip price. The average marginal effects presented in the "trip-taking" panels of Figures 3 and 4 are the effects of a change in each trip attribute on the probability of an angler choosing alternative one, while the "opt-out" panels indicate how changes in the listed trip attributes impact the probability of a respondent choosing the outside option over one of the two listed trip alternatives. Given that our data comes from an unlabeled choice experiment in which the trip alternatives are differentiated by randomized attributes, the average marginal effects should be the same for trip alternatives one and two.[19] A one dollar increase in the retention fee for trip one reduces the probability of that alternative being chosen 3.4 times more (0.0051 vs 0.0015) than does a one dollar increase in alternative one's trip price (see Figure 4). Furthermore, respondents are willing to

[19]We also calculate these marginal effects for alternative two to confirm that there was no systematic difference between the two trip alternatives, and confirm that there are trivial numerical differences between the two sets of marginal effects.

pay an average of \$3.68 (sd =\$1.56) more in trip price to avoid a \$1 increase in retention fee.[20] Perhaps anglers are so averse to the idea of retention fees that they will accept higher trip prices to avoid higher retention fees. Alternatively, the average angler may anticipate catching and retaining approximately four red snapper on a fee-based trip, so that a \$1 increase in either retention fees or trip price is equivalent in welfare terms. The latter hypothesis suggests that anglers are agnostic about whether their dollars are spent on trip prices or retention fees.

To investigate the latter hypothesis, we estimate two additional conditional logit models of trip-choice using only fee version observations for which anglers did *not* choose the outside option. In other words, we model anglers' decision about which of the two trips to take conditional on having decided to take a "fee version" fishing trip (Table 4). The first model in Table 4 includes retention fee magnitude as a regressor (*fee*), while the second model replaces this regressor with the maximum expected fee bill for a given trip under the assumption of full retention of catch ($fee \times target$). In the first model, the fee coefficient is 3.47 times that of the price coefficient, agreeing with the pattern noted in the RPL models in Table 3. In the second model, a Wald test confirms that the coefficients for fee bill ($fee \times target$) and trip price are not statistically different ($\chi^2 = 1.11$, $p = 0.2929$). These results demonstrate that, conditional on having decided to take a trip, anglers appear to treat the maximum fee bill and trip price in an equivalent fashion, suggesting that the seemingly disproportionate effect of fees in the trip choice model is rooted in expectations of retention.

Not only are respondents more likely to choose trips that cost less in aggregate (*price*, *fee*), but Table 3 reveals that they also gravitate toward trips that promise: 1) a higher expected catch of non-red snapper fish (*other*); 2) less congestion on the vessel (*congest*); 3) higher expected catch of red snapper (*target*, fee version); and 4) more red snapper retained (*retain*, bag limit version). The estimated standard deviations for *other* and *congest* are significant and large relative to their means (models 2 and 3), which indicates a meaningful degree of heterogeneity in how anglers' trip-taking behaviors respond to changes in non-price and non-catch trip quality attributes. The average marginal effect of a trip being "crowded" (*congest*) on its probability of being chosen is -0.184 and -0.171 for bag limit and fee trips, respectively. The marginal effect of congestion is relatively large and variable, so we omit *congest* from our AME visualizations in Figures 3 and 4 to preserve meaningful scale for the other variables.[21,22] See section 3 of the appendix for details on

[20] All WTP estimates were calculated via bootstrapping using 1,000 draws of each of the random parameters. We used model 2 for all WTP estimates, because the estimates produced using model 3 were unrealistically large. This is because the price parameter is distributed log-normally with a near-zero mean in model 3.

[21] The bars around the average marginal effect point estimates represent the range of all average marginal effect estimates across 1,000 sets of individual-specific draws for each random coefficient.

[22] The 5th percentiles, means, and 95th percentiles of AMEs for congest in figures 3 and 4 are as follows: Trip-taking behavior, bag limit version: (-0.237,-0.184,-0.131); Opt-out behavior, bag limit version: (0.007,0.042,0.086); Trip-taking Behavior, fee version: (-0.223,-0.171,-0.103); Opt-out behavior, fee version: (0.015, 0.058, 0.102).

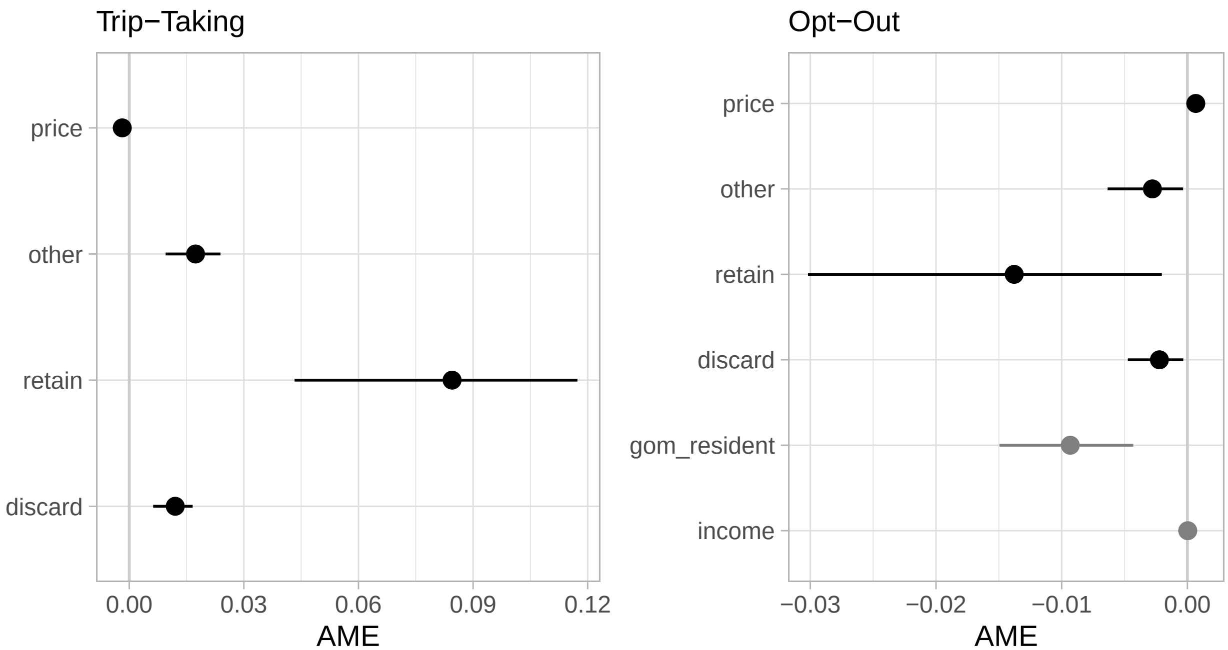

Figure 3: Calculated using model 3 (Table 3). Mean and coverage (5th to 95th percentiles) of average marginal effects on trip choice and opt-out behavior for the bag limit questions.

how we calculated AMEs.

While all three models suggest that the number of red snapper an angler expects to catch and retain is a significant and positive determinant of trip choice for bag limit trips, any fish that anglers catch and discard (i.e., red snapper caught in excess of an angler's bag limit) yield little to no marginal utility. Figures 3 and 4 show that a one fish increase in retention on a "bag limit trip" increases the mean probability of an angler taking a particular trip by 0.085. If, however, that same angler expects to discard that additional fish, then the probability that they will take that same trip only increases by 0.012. The average marginal effect of catching an additional red snapper on a "fee trip" is also 0.012. This result is consistent with that of Carter and Liese (2012), who find that recreational anglers were willing to pay more than eight times as much to catch and retain red snapper than they were to catch and release red snapper under a bag limit. The lack of marginal utility from a discarded fish suggests that providing anglers the ability to effectively purchase a larger ex post bag limit through retention fees should be welfare improving when applied to red snapper and other GOM reef fish, particularly for more highly-skilled anglers for whom the bag limit is especially likely to bind.[23] Furthermore, if anglers with higher marginal values of retention are also more likely to be constrained by the bag limit, then a switch to retention fees could further improve allocative efficiency by inducing anglers with higher marginal values to take relatively more trips now that they can enjoy a higher

[23]This finding that discarded fish yield no marginal utility likely would not generalize to an inland freshwater fisheries with a strong catch-and-release ethic.

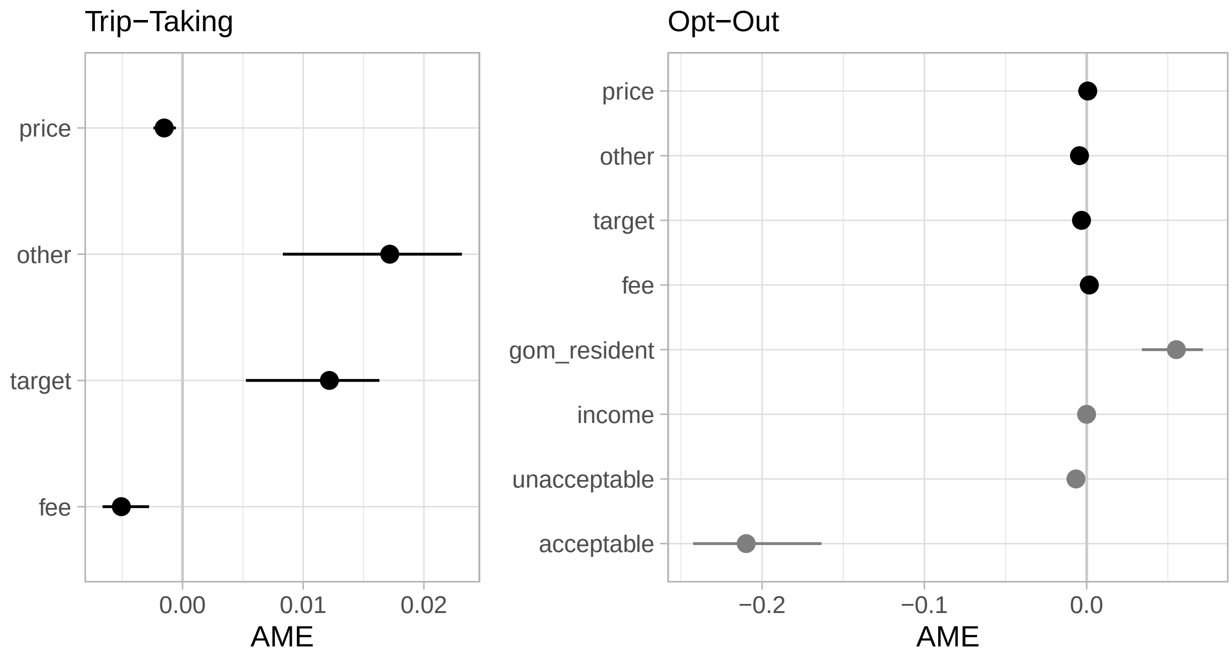

Figure 4: Mean and coverage (5th to 95th percentiles) of average marginal effects on trip choice and opt-out behavior for the fee version questions. Calculated using model 3 (Table 3).

measure of trip quality.

Table 5 reports the results of top-censored Poisson regression of the number of red snapper respondents claimed they would retain, where the top-censoring is determined by the number of fish they catch in the previous choice experiment, conditional on having chosen to take a fee-based trip. Anglers who found fees to be acceptable are not only less likely to opt-out of fee-governed trips, but also tend to retain about 49% more fish on those trips, subject to not being catch-censored, than do those who are ambivalent or averse to retention fees. Anglers who like the idea of retention fees may have overstated the number of fish they would retain if they believed that such a response could increase the probability of such a policy being adopted. However, it is also possible that anglers who approved of retention fees did so because they have a stronger baseline preference for retention than do other respondents. We cannot, with our data, determine to what degree strategic behavior may have played a role in this result, but the acceptability indicators clearly capture some latent difference in anglers who approved of or were ambivalent or opposed to retention fees.

The fee coefficient in table 5 is negative and significant, suggesting each $1 increase in fee reduces retention by 2.3%.[24] However, neither of the interactions between fee and fee acceptance are significant, suggesting that, while fee acceptance can act as a retention shifter, it is not a significant determinant of fee elasticity.

Figure 5 shows that anglers exhibit inelastic retention behavior at low fee levels ($10 per fish) but behave

[24] A past version of the censored Poisson (not shown) included a fee^2 term, which was found to be insignificant.

in a more fee-elastic manner when faced with high retention fees ($50 per fish). Above $56, demand becomes elastic, so that further increases in the retention fee will induce relatively larger reductions in retention on a given trip. However, this result does not provide the "switchpoint" fee level for overall demand, since fee magnitude impacts both extensive and intensive margin behavior. For this we must combine the two demand functions (see below).

Interestingly, the trip quality attributes that are not related to target species retention (i.e., *congest*, *other*, and *price*) are all insignificant in the trip retention demand equation. This suggests that anglers treat the utility maximization decision from retention under fees in a separable manner from these predetermined trip attributes. Demographic characteristics such as income or Gulf residency also do not explain fish retention behavior, and other specifications (not shown) revealed that gender, employment status, and whether or not a fisherman was a member of an angler organization are similarly insignificant.

The only demographic characteristic that influences per-trip retention demand is how many years of fishing experience the angler has in the GOM. On average, an additional 10 years of experience fishing in the Gulf translates to an 8.69% increase in fish retention. While GOM residents tend to have more years of experience fishing in the Gulf than non-residents (two-sample t test, $p = 0.0000$), angling experience, not residency, is the relevant mechanism of the two for predicting retention behavior.

Table 5: Top-censored Poisson model of number of fish retained.

		(1)
congest		0.0649
		(0.101)
other		-0.00900
		(0.0189)
target		0.183***
		(0.0274)
price		-0.000108
		(0.000728)
gom_resident		-0.0355
		(0.104)
gomfishing_years (10 years)		0.0869*
		(0.0361)
income		0.000972
		(0.000741)
Vfeetoboat		0.0902
		(0.101)
unacceptable		-0.106
		(0.250)
acceptable		0.401**
		(0.182)
fee		-0.0231***
		(0.00589)
	× unacceptable	0.00308
		(0.00766)
	× acceptable	0.00125
		(0.00704)
_cons		0.348
		(0.277)
N		736
LL		-643.79706

Cluster robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

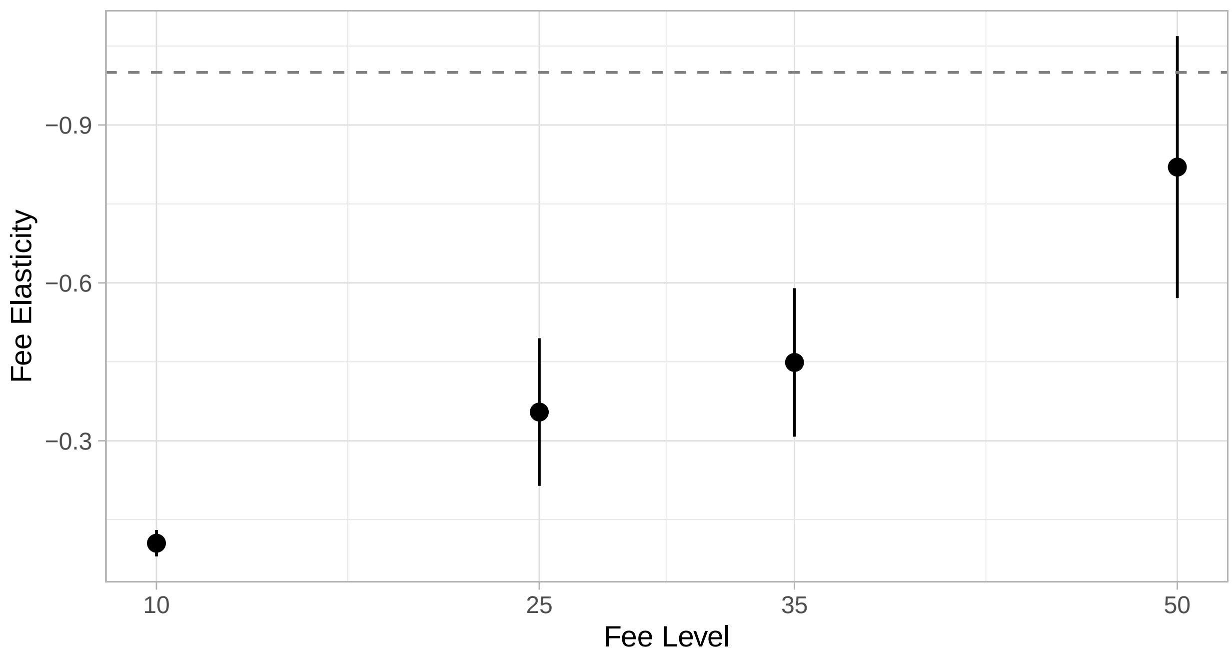

Figure 5: Fee elasticity at the four randomized fee levels with 95% error bars.

Target, or the number of red snapper that an angler expects to catch on a trip, is a trip-attribute that is both a regressor and a censoring point for this regression. We include *target* as a regressor because the number of red snapper that anglers expect to catch may influence the number they decide to retain even if their desired retention is not censored by catch. In other words, target retention may increase as catch goes up, even if catch was not "binding" on the retention decision (i.e., some catch was previously discarded). This could occur due to heuristic decision making (e.g., retaining a fixed proportion of catch) or due to an angler having a distaste for discards that leads them to increase their retention as their luck in catching fish improves. Indeed, we find that a one fish increase in target catch increases uncensored retention by approximately 18% (Table 5). However, we find that the estimates of all coefficients, save for *congest* and *other*, are insensitive to the inclusion or exclusion of *target* as a regressor.

6.2 Policy Simulations

In our policy simulations, we assume GOM headboats remain a limited access sector whose trip prices are determined in a market, and we interpret retention fees as the cost of a harvest tag. For the sake of simplicity, we assume that these tags are uniquely allocated to harvest in the GHC subset of the headboat sector and not usable outside of it, thereby ignoring any spillovers between the private, non-GHC headboat, and for-hire recreational sectors or between recreation and commercial fishing. These tags must be traded in a competitive market, either through brokers (including, potentially, headboats themselves) and/or through resale markets.

The way in which we interpret our policy simulations is just one of multiple ways in which pricing for fish retention could be implemented. Another possibility that works in the specific case of for-hire vessels such as headboats is to allocate vessels proportional rights to a share of the annual total allowable catch in the fishery, as in an ITQ. This is exactly what happened during the GHC pilot, although allocation technically occurred to to the GHC as a cooperative, with vessel-level allocation resolved by GHC members (Abbott & Willard, 2017). Vessels are then free to allocate their scarce fish quota to customers in whatever way they like, including implementing retention pricing. In this case retention pricing would be similar to a leasing arrangement in commercial ITQ fisheries, where vessel owners "lease" quota to customers according to their desire to retain fish, in addition to charging for the trip itself. If annual allocation is freely transferable across vessels, then the resulting market clearing price (and the price charged to customers) should equal the marginal WTP of customers for retention of an additional fish. Note, however, that an ITQ or cooperative allocation to headboats may not be sufficient to guarantee such "a la carte" pricing, as vessels may elect to utilize other approaches to rationing their allocation – including creation of differentiated trips with higher bag limits and attendantly higher prices – either out of concern for alienating customers or due to the transaction costs of implementing individualized retention pricing on individual trips (Abbott & Willard, 2017).

While most consistent with the GHC policy experiment, this ITQ/cooperative approach has limited applicability beyond for-hire recreational providers. Allocation of a finite number of durable share rights to harvest is would likely be problematic for recreational fishing where participation and catch history are often lacking and, even if present, the allocation of shares to thousands of claimants may be infeasible and not worth the administrative costs. Furthermore, unless quota are auctioned annually or subject to some form of royalty tax, "quota rents" would go to the for-hire headboat sector. Resource managers may instead wish to receive supplemental "a la carte" pricing revenues on top of the permit fees already collected from headboat operators.

An alternative, more generally applicable, approach is to consider the distribution of a finite number of harvest tags per season which must be surrendered for every unit of recreational harvest. These tags may be physical, virtual, or a mix of the two, and can be allocated in a number of ways, each with different distributional, efficiency, and revenue-raising implications. For example, tags could be auctioned off directly to anglers or to brokers such as sporting goods stores who then provide a ready spot market for anglers – either of which provides a source of revenue for resource management. In other cases where equity concerns dominate, particularly when tags are scarce (as for trophy species), tags may be allocated, at least partially, by lottery. To maximize efficiency within this tag market, Johnston et al. (2007) suggest allowing tag resale.

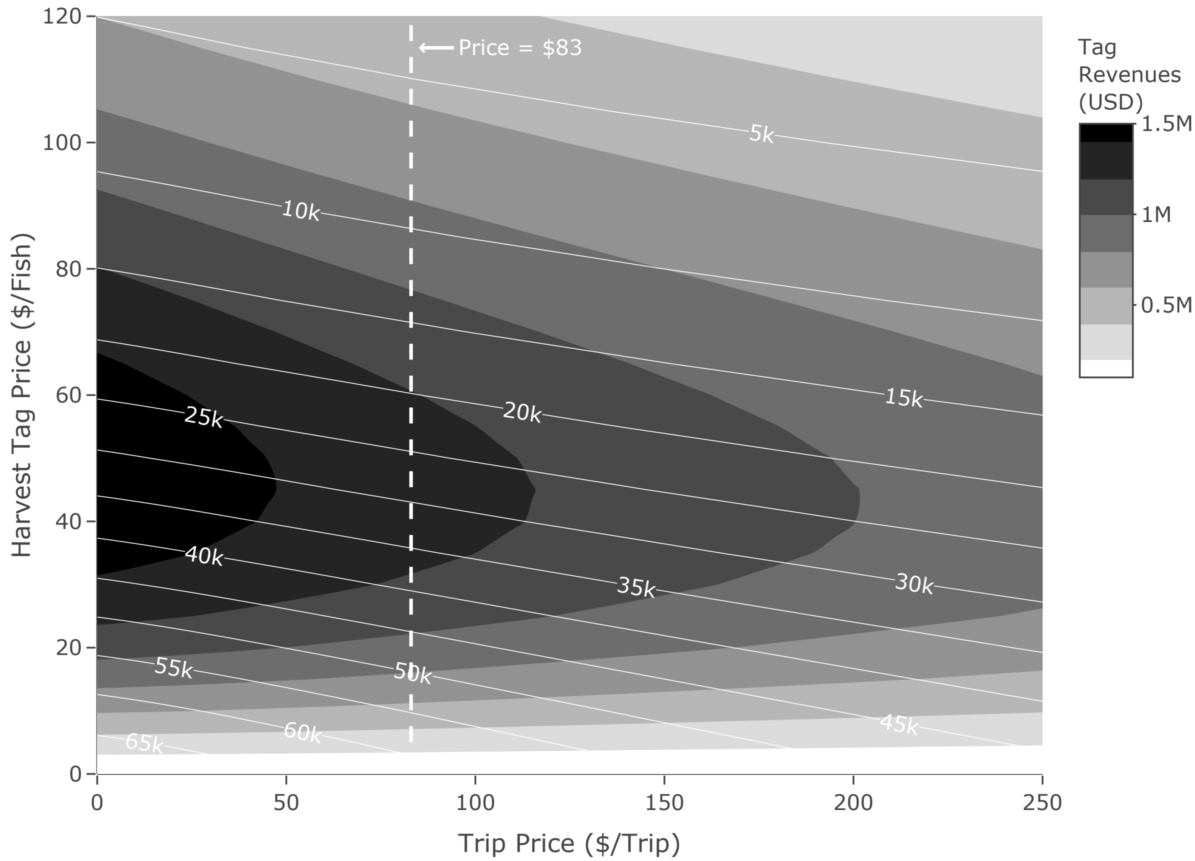

Figure 6: Harvest tags demanded (white lines) and revenues generated from tag sales (gray bars) at different bundles of trip prices and harvest tag prices.

Tags are not without their challenges, including the challenges of enforcement and the problem of accounting for discard mortality, both of which are common challenges of fisheries management and not endemic to harvest tags alone (Abbott, 2015; Johnston et al., 2007). Nevertheless, their widespread use in game management and for some freshwater fisheries suggests they could be more widely adopted in marine contexts. Indeed, bag limits already impose quantitative limits on individual anglers' harvest, so the marginal enforcement costs of a tag program may not be much higher. Finally, unlike recreational ITQs, tags have the potential to work across both the for-hire sector and for anglers fishing from their own private boats. In spite of these challenges and for the reasons discussed above, we believe that representing our simulations in terms of market-based trip prices on the extensive margin and harvest tags on the intensive margin makes sense in this context.

Figure 6 illustrates how different combinations of trip and tag prices affect both predicted harvest of (represented by white curves) and tag-based revenues (captured by the gray contours) generated by GHC clients. Not surprisingly, tag revenues and total harvest fall as trip prices increase for a given tag price.

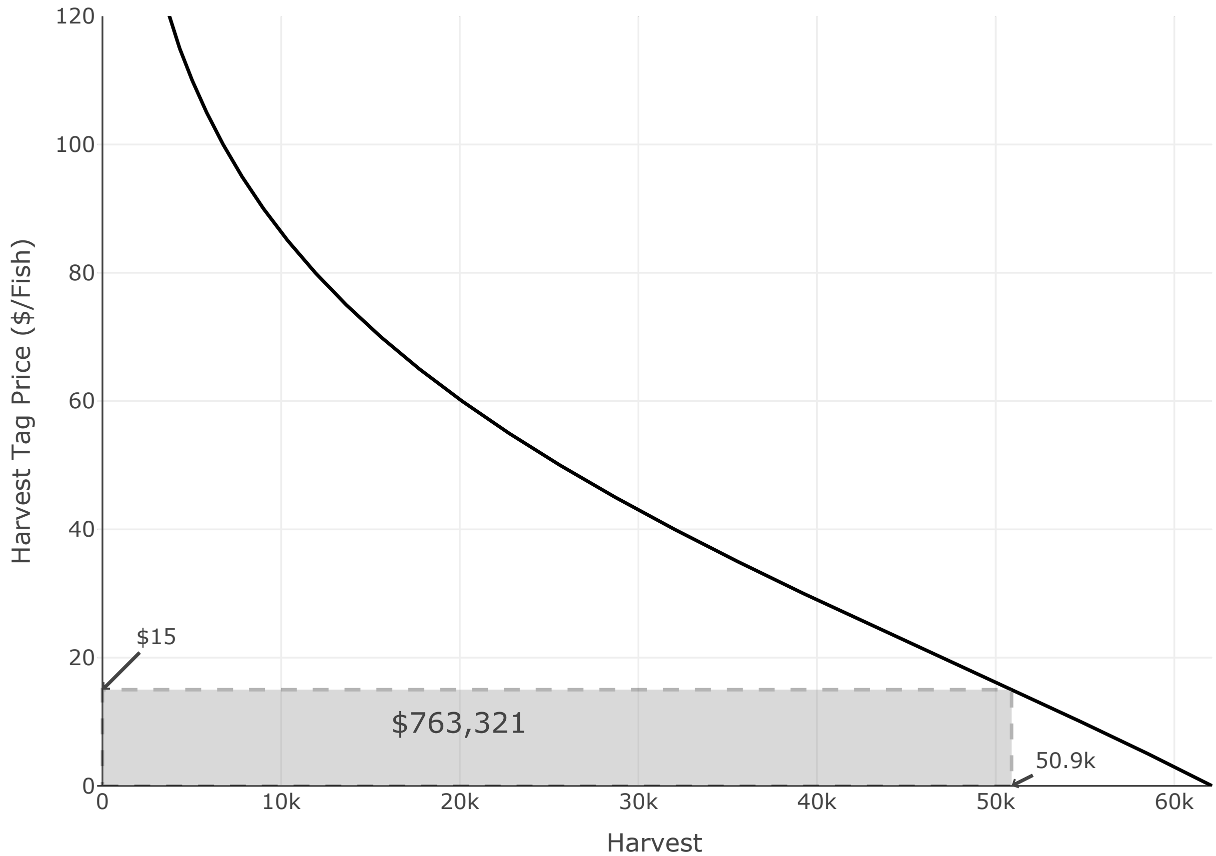

Figure 7: Demand curve for red snapper harvest tags and revenue from tag sales (gray box) when the price of a headboat trip is $83.

Nevertheless, predicted trips are inelastic to trip prices, so that harvest is relatively unresponsive to even large pricing changes on the extensive margin. Incentives on the intensive margin, therefore, are especially valuable. The backward-bending revenue contours demonstrate that there is a range of low tag prices where retention is inelastic, but that eventually a breakpoint is reached where retention responds disproportionately to further increases, leading to reduced revenues. This breakpoint tag price declines, albeit slowly, as trip prices increase. The relatively close vertical spacing of the harvest contours, particularly at lower tag prices shows the sensitivity of harvests to pricing changes on the intensive margin. Of course, in practice resource managers have no direct control of the trip pricing itself as this will depend on market-clearing outcomes in the headboat sector, which is outside the scope of our model and data. Nevertheless, these economically grounded simulations can help managers anticipate how pricing shifts from demand shifts (aside from the fish stock itself) or supply shocks (e.g., hurricane damage to the headboat fleet) may influence harvest or tag market outcomes. Indeed, if a finite number of harvest tags (say 50,000) are allocated for a season, then the harvest contour associated with this quantity represents the locus of trip prices and tag prices that support equilibrium in the tag market.

Figure 7 is the simulated Marshallian demand curve for red snapper harvest tags by anglers on GHC vessels when the market price of a headboat trip is \$83—the median price of a headboat trip aboard GHC vessels in 2012-2013—under the distribution of catch rates (and hence abundance) in those years. It reflects *overall* demand for red snapper as harvest tag prices (or retention fees) vary, accounting for both trip decisions and retention decisions by anglers. Demand for harvest tags is inelastic below prices of \$45 per tag, and becomes elastic above that level. In 2012-2013, anglers aboard the 19 GHC vessels harvested approximately 50,000 red snapper per year. Therefore, if just over 50,000 harvest tags were allocated to anglers fishing on GHC vessels and trip price remained at \$83, then the market-clearing price for a harvest tag would be \$15, generating \$763,321 in tag revenues from this subset of the recreational headboat sector alone (excluding other recreational anglers), which could accrue either to fisheries management or brokers depending on the means of allocation. For context, the commercial red snapper IFQ program collects a 3% ex vessel tax on revenues in order to recover the incremental management costs of the program, and in 2020, \$950,396 of cost recovery taxes were collected (National Marine Fisheries Service, 2021). The commercial sector has historically received 51% of the annual red snapper quota, while the for-hire sector, which is partially-comprised of Gulf of Mexico headboats, receives only 20.73% of the red snapper quota each year (National Oceanic and Atmospheric Administration, 2021). Our policy simulations are scaled to represent the sub-segment of the headboat for-hire sector that participated in the GHC. Thus, our estimate of \$763,321 in tag sale revenues is not insignificant.

An allocation of 27,000 harvest tags, on the other hand, would maximize tag revenues (\$1.22 million) under 2012-2013 harvest conditions and result in a market price for a tag of \$45. However, this finding assumes that there is no feedback between tag scarcity and the pricing of headboat trips, which is less likely as tag prices rise.

Figure 7 is also of interest for informing often contentious discussions about allocation of harvest between sectors (Abbott, 2015). Previous allocation studies have used estimates from recreation demand models to estimate the marginal value of increasing allocation to the recreational sector vs. the commercial sector. One challenge of these studies is that they are predicated on the existing regulatory structure and therefore must come up with some story for how "new" fish would be allocated to anglers (i.e. through increasing bag limits on existing trips, new trips under existing bag limits, etc.), where this "rationing" approach must be linked to the manner in which recreational values are recovered. For example, in their study of red snapper allocation in the GOM, Agar and Carter (2014) find that anglers in the broader recreational sector would be willing to pay the equivalent of \$71 a fish (or \$11.21/lb.) for moving from zero to 2 fish bag limits for red snapper. These values are then compared to lease prices in the commercial ITQ market to argue that reallocation of harvest to recreational harvesters is consistent with allocation according to the equimarginal principle. However, these estimates are predicated on the existing, inefficient allocation of fish under the regulated open access, season-length/bag limit regulatory approach, which does not allocate harvest according to diminishing marginal valuation (Holzer & McConnell, 2014). Therefore, these values do not answer the question of whether existing allocations to the sectors are efficient if allocation *within* the recreational sector were allocated efficiently, as in a tradable tag market. However, our estimates—by being predicated on price-based allocation among headboat passengers—do allow for this comparison

We find that a hypothetical harvest tag market among GHC anglers in 2012-2013 would have cleared at a price of approximately \$15 a fish. Given a mean weight of 6.3 pounds per fish (Agar & Carter, 2014), this implies a price of \$2.38/lb in the headboat sector. However, the lease price of allocation in the GOM red snapper fisher—a value of the marginal profitability of an additional pound of allocation to commercial fishers—was approaching \$3 in approximately the same time period (Gulf of Mexico Fishery Management Council, 2013). Therefore, the efficiency case for reallocation to recreational anglers (or at least those in the headboat sector) is hardly as clear-cut as the previous analysis might suggest. Opening up trade in allocation between commercial fishers and the headboat sector may not lead to reallocation away from commercial fishing, particularly if quota is efficiently allocated *within* the headboat sector itself. Indeed, the high valuation reported by Agar and Carter for additional red snapper may exist for the very reason that bag limits and season constraints are currently misallocating fish to many anglers with low valuations, so that the *marginal* value of loosening the allocation constraint is artificially high (Holzer & McConnell, 2014). Our model shows how the outcomes of market-based allocation between sectors can be addressed by explicitly modeling the allocation of recreational harvest via market mechanisms.

7 Conclusion

Our policy simulations show that "a la carte" pricing has the potential to address multiple management goals within the US GOM recreational red snapper fishery, including: meeting biological objectives, generating efficiency gains, and providing supplemental revenue for resource managers. The exact form that "a la carte" management may take will depend on the unique political climate of individual fisheries. The general approach laid out in this paper can aid policymakers in determining how successful or unsuccessful a policy counterfactual may be in their respective fishery based on the representative anglers' relative responsiveness to trip prices, retention prices, and non-price trip attributes on both the extensive and intensive margins of harvest.

The combination of stated preference data and structural modeling is a powerful tool for ex ante analysis of unbundled pricing in recreational contexts, especially because we find that the impact of price and non-price trip attributes on trip-taking and retention behavior is subject to unobserved heterogeneity. Specifically, anglers' views about the acceptability of pricing the resource influence opt-out behavior and per-trip red snapper retention on fee version trips. This behavior-shifting heterogeneity is unobserved so it cannot be targeted with policy. It is therefore important to utilize structural modeling that accounts for unobserved heterogeneity in order to understand how a body of anglers might adapt their trip-taking or retention behavior in aggregate in response to any policy instruments under consideration.

The modeling approach in this paper could be used to investigate policy contexts beyond the intra-sectoral allocation of harvest tags to brokers and headboat anglers. In this paper, our policy modeling is restricted to include retention demand only from the recreational headboat sector; we do not model a unified tag market for the private and for-hire recreational sectors, because we do not have information on private angling demand, and therefore do not know how this unified market would equilibrate. However, it seems likely that establishing a single harvest tag market across recreational sectors would enable inter-sector allocation to resolve itself through the tag market. Furthermore, by accounting for the impacts of pricing the resource on both the trip-taking and retention margins, we find evidence that allocating tradable short-term rights that are transferable between recreational anglers (or at least passengers of headboat vessels) and commercial harvesters may result in quota flowing toward the commercial sector, in contrast to the current narrative that recreational anglers have higher marginal values for harvest.

Our findings are not directly applicable for intensive resource use that is not extractive (e.g., trail degradation from hiking, mountain biking, or ATV use) because the information and enforcement costs associated with pricing non-extractive use are likely prohibitively high. However, unbundled pricing could yield similar benefits to resource managers whose resources are subject to extractive uses on the intensive margin, and the data collection, and modeling approaches illustrated in this paper could provide insight on how differentiated pricing mechanisms may actually play out in their specific contexts. For instance, harvest tags are already common in hunting, and especially for trophy species. This type of model may aid game managers in allocating the correct number of tags to meet their objectives, as well as to anticipate how the market clearing price for tags may change in response to changes in demand (suppose the population of a substitute species surges, leading to decreased demand for the target species) or in supply (say, through climate shocks or fire.)

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Appendix

1 Preparing Extensive Margin Estimation Weights

We use the inverse probability sample weights developed by Abbott et al. (2018) in our extensive margin model estimation, as well as in scaling the extensive margin policy simulations up to the full headboat sector. These weights are products of three inverse probability weights to collectively account for selection along dimensions of survey version, survey non-response, and spatiotemporal variables – thereby producing estimates that are as representative of the population of Gulf of Mexico headboat anglers as possible.

The first component of these estimation weights is the inverse probability that a respondent received the survey version that they did. Anglers in Texas, Alabama, and Northwest Florida encounter more red snapper than gag grouper, so respondents who filled out onboard surveys in those regions received the red snapper version of the follow-up survey with 80% probability and the gag grouper version with 20% probability. Anglers in Southwest Florida encounter relatively more gag grouper, and so received the gag grouper version with 80% probability and the red snapper version with 20% probability. We use only the red snapper surveys, so this first part of the extensive margin weights is 0.80^{-1} for Texas, Alabama, and NW Florida anglers, and 0.20^{-1} for SW Florida anglers.

The second component of the estimation weights control for non-response bias, where non-response is defined as either failing to complete the Internet survey or failing to provide a valid email address on the initial onboard survey. We estimate a logistic regression of survey completion (i.e., whether an individual provided a valid email address on their onboard survey and completed the follow-up survey) on gender, age, income, years of experience an angler has fishing in the GOM, how often an individual goes fishing, and a dummy for home state (Alabama, Florida, Texas, Louisiana/Mississippi, other) to predict the probability that each respondent would have completed the survey. The inverse of these "propensity scores" control for non-response bias based on selection-on-observables assumptions.

The third and final component of the estimation weights are spatial-temporal post-stratification survey weights that ensure the spatial and temporal distribution of the respondents to the onboard survey (after adjusting for survey non-response and survey version) reflects the headboat angler population. Abbott et al. (2018) used logbook data from all Gulf Headboat vessels to account for the percentage of total anglers who took trips during each of the four seasons (January through May, June, July through August, September through December) and four regions (Texas, Alabama, NW Florida, SW Florida) included in the sample. We then use these percentages to compute spatial-temporal post-stratification survey weights – effectively up-weighting responses in space-time cells that are underrepresented in on our sample while down-weighting responses in cells that are overrepresented.

The final weights for the trip choice model are the product of these three components, normalized in the sample.

2 Preparing Intensive Margin Estimation Weights

The intensive margin model estimates per-trip demand for red snapper retention for those respondents who chose one of the two trip alternatives in at least one of the fee version choice experiments. Thus, the probability of appearing in the intensive margin estimation sample is the product of the probability of being included in the extensive margin sample (captured by the inverse of the extensive margin estimation weights described above) and the probability of having chosen to take a trip on the fee version choice experiments.

We use the final mixed logit model (Table 3, column 3) to generate estimated probabilities that each individual i would have chosen to take a trip on the fee version choice scenarios. The probability that individual i chooses to take one or the other of the fee version trips is the complement of the probability that they choose the outside (no-trip) option, $Pr(Opt\text{-}out)$. Our final intensive margin estimation weights are, therefore, the product of the extensive margin estimation weights (above) and $[1 - Pr(Opt\text{-}out)]^{-1}$. We also estimated the censored Poisson using the extensive margin weights, but it had no notable effect. The estimation results from this alternative weighting are available upon request.

3 Estimating Average Marginal Effects and Elasticities

We use the prediction functions from the Apollo package in R to estimate both the average marginal effects (AME) and elasticities for the extensive margin model (Hess & Palma, 2019a, 2019b). The procedures for estimating AMEs and elasticities from a random parameters logit are nearly identical, but we indicate two places where these procedures differ. We use Monte Carlo simulation to consistently estimate these marginal effects and elasticities of the random parameters in our model.

Let X represent a variable whose AME and elasticity we are estimating. For each choice occasion faced by individual i, we first drew 1,000 β_i values and then calculated the corresponding baseline choice probabilities using the original, unaltered data for all variables aside from X. For X, we use the original unaltered data for continuous variables, and set $X = 0$ across all trip alternatives for discrete variables.

We then perturb X in trip alternative one for each choice occasion n and re-estimate the choice probabilities across the same individual and choice-occasion specific 1,000 $beta_i$ draws as used for the baseline choice probabilities. When estimating the AME of a continuous variable, we perturb variable X by adding

Δ_c for continuous variables or $\Delta_d = 1$ for discrete variables to each X_n. Δ_c is defined as .001 of the standard deviation of a continuous variable. [25,26]

We estimate both *own* marginal effects and elasticities of alternative-specific attributes (e.g., price, congestion) and *cross* effects on the probability of opting-out (i.e., of choosing the outside option). For demographic variables that only enter the regression through interactions with "optout", we estimate *own* marginal effects and elasticities with the choice to not take a trip, as well as *cross* effects with alternative 1.

In order to estimate the average marginal effects of each observation for each of the 1000 draws for a given alternative, we perform the following calculation for each of the 1000 draws j

$$AME_j = \sum_{n=1}^{2148} \frac{Pr_{nj}^{new} - Pr_{nj}^{baseline}}{\Delta} \tag{4}$$

where 2148 is the total number of choice occasions in the sample, n is the choice occasion, j is the draw, and Δ is the amount by which the variable was perturbed.[27] This transformation leaves us with a matrix of AMEs or elasticities by alternative for each of the 1,000 sets of draws. When discussing average marginal effects and elasticities, we describe the distribution of effects across all draws of unobserved heterogeneity.

4 Trip-Taking and Aggregate Retention: Policy Simulations

We investigate trip-taking and retention behavior across a grid of trip prices and per-fish retention fees. The trip prices over which we run simulations range from \$0 to \$250 in \$5 increments, while the fees range from \$0 to \$150 in \$5 increments. In order to maintain consistency across estimates, we fix trip-attributes to common values for both trip alternatives across all observations. Congestion is always set to "spacious" and the expected catch of fish other than red snapper to eight (the median number of fish other than red snapper actually caught by headboat passengers from 2012-2013).

4.1 Extensive Margin: Trip-Taking

4.1.1 Simulating the Extensive Margin

We use Apollo's prediction tools to generate a matrix of predicted trip probabilities for each price-fee combination. Our extensive margin predictions are drawn from a random parameters logit, so we draw 1,000 predicted probabilities per observation (i.e. choice occasions) and price-fee combination. Some adjustments

[25] We perturb only the X_n of alternative 1, not that of alternative 2. As a robustness check, we also tried perturbing only alternative 2 attributes, and found only trivial differences in our results, as expected in an unlabelled choice experiment.

[26] When estimating elasticities for a continuous variable, $\Delta_c = 0.01X_{old}$.

[27] When estimating elasticities, Δ is replaced with $0.01 \times Pr_{nj}^{baseline}$.

to the simulation are needed to accommodate for the fact that each simulation concerns a single set of trip attributes vs. the opt-out option, whereas the underlying choice experiments utilize two trip alternatives plus the opt-out. To maintain congruity with our estimation model, we simulate by setting the attributes for alternatives one and two to be always identical. However, this will overstate the probability of the trip alternative and understate the probability of the opt-out without an algebraic adjustment. The necessary adjustment directly follows from the Independence of Irrelevant Alternatives (IIA) assumption, which holds for a given draw of the random preference parameters.

To implement the correction, we extract a matrix of predicted probabilities of opting-out (P_3) for each draw of the random coefficients and price-fee combination, and calculate the true probability of opting-out (P_o) using equation 5 below.

$$P_o = \frac{2P_3}{1 + P_3} \tag{5}$$

The probability of the trip option is then $1 - P_o$. We then store the mean probability of taking the trip over 1,000 random coefficient draws for each individual and price-fee combination in an (N×F×P)×1 "prediction vector," where N is the number of observations, and F and P are the number of fees and prices simulated over.

4.1.2 Scaling the Extensive Margin

We use logbook data from GHC vessels in the two years prior to the GHC experiment (2012 and 2013) to create a representative "status-quo" scenario with which to scale each respondent's predicted probability of taking a trip up to total predicted trips aboard Gulf headboat vessels. Of all 2012-2013 headboat trips taken aboard these vessels, we used data from only those 1,850 that occurred within the federal red snapper season (i.e., when red snapper could be retained) and for which we had data on trip price for fishing passengers. We omitted trips for which payment type was "per group" or "no charge," leaving 1,756 trips for which payment type was either "per person" or unspecified. After dropping multi-day and specialty trips (identified through a combination of high trip prices and captain comments), we were left with 1,716 partial or full-day trips.

The trip price for a fishing passenger on those 2012-2013 trips ranged from \$40-\$145, with a mean price of \$83 per head. The mean number of fish other than red snapper caught per angler day is 13, while the median is 8. The long right tail on this distribution has a clear and significant impact on the mean, so we assume 8 fish other than red snapper caught per angler day is more representative of a typical headboat trip. Average red snapper catch per angler trip is distributed normally with a mean of 2.14 fish per angler day. In 2012-2013, the daily bag limit was two red snapper per angler, which implies an average discard of 0.14

red snapper per angler day. The average number of trips (i.e., total angler counts) taken per year between those two years was 39,265.[28]

We plug these status-quo trip attributes into each trip alternative from the bag limit choice experiment scenarios and use the mixed logit model in which price is a random parameter (Table 3, column 3) to estimate predicted probabilities of trip-taking under representative 2012-2013 conditions. We then calculate *scale* such that the weighted mean (weighted with the extensive margin weights from appendix section 1) of those predicted probabilities times *scale* equals the actual average annual trips taken during the 2012-2013 red snapper seasons (39,265). We multiply *scale* by the (weighted) mean predicted trip probabilities for each fee version simulation to visualize aggregate trip demand for the GHC vessels.

4.2 Intensive Margin: Retention Per Angler Day

We estimate the top-censored Poisson model of retention using the post-estimation command *margins* from the *rcpoisson* package in Stata (Raciborski, 2011). So that our retention predictions can be consistently multiplied by our extensive margin trip predictions to generate aggregate harvest and revenue predictions, we integrate them over a representative distribution of catch rates from 2012 and 2013 GHC vessel logbook data. For each trip taken, we know the total number of red snapper caught, the number of anglers on board, and trip length. We assign each passenger a catch rate equal to the average number of red snapper caught on their trip, using only trips on which at least one red snapper was caught. For instance, if 12 red snapper were caught on a single trip for which there were six anglers, the data frame from which we sample catch rates represents this trip as six observations for which two red snapper were caught. We then take $N \times j$ (where $N=736$ equals the the number of observations in our intensive margin estimation and $j=100$ is the number of draws per observation) draws of catch rate from the full angler population and save those draws in a catch rate matrix.

By integrating over draws of average catch per trip, we assume that catch in excess of the bag limit for high-catch anglers is given to anglers with catch rates below the bag limit, as opposed to discarded. In other words, we implicitly assume that bag limits are enforced at the vessel level, rather than at the individual level. This is consistent with our interviews with headboat captains. We also considered a model of individual accountability under bag limits by fitting an intercept-only negative binomial model to trip-level catch data with number of anglers per-trip included as an exposure variable. We then applied bag limits to angler-specific draws from the catch distribution. However, the unrealistic level of regulatory discards (relative to the headboat survey data) combined with our prior interviews lead us to reject this individual

[28] We scale to "trips" rather than to angler-days because the units match our extensive margin model, which pools full- and part-day trips and is thus agnostic about trip-length.

bag limit model.

We generate retention predictions over a price-fee grid as in our extensive margin simulations, integrating over 100 draws of catch per observation for each unique combination of price-fee. We then average over these averages for each observation, weighted by the intensive margin weights from appendix section 2, to provide an expected retention prediction for each pricing bundle. Population-level harvest is the product of predicted trips (scaled to the population as described above) and predicted retention-per-trip at any given price-fee bundle. Expected revenues are calculated for each price-fee combination as the number of predicted trips times the trip price (trip revenues) plus total harvest times the retention fee (fee revenues).

5 Ordered Logit of Fee Acceptance on ISCs

This ordered logit model in Table 6 reveals that Gulf residency, whether the collected fees go to the headboat operators or are invested in conservation research (*Vfeetoboat*), if respondents were aware of the GHC pilot program while on their trip (*knew_pilot*), and several indicators of angler avidity (e.g., if a respondent is a member of an angler organization) are not significant determinants of fee acceptance.[29] Instead, only the sociodemographic variables *income*, *age*, and *gender* are significant, with younger, male, and higher income individuals being more likely to support retention fees. Our findings hold when the left-hand side variable is replaced with with a binary indicator for "acceptable" (= 1) or for "ambivalent or unacceptable" (= 0).

[29] Of the respondents included in our analysis, 57.17% were aware of the GHC pilot program when they took their recalled fishing trip.

Table 6: Ordered logit coefficients and cluster robust se for fee acceptance.

knew_pilot	-0.448
	(0.254)
gomfishing_years	-0.127
	(0.105)
org_angler	-0.654
	(0.446)
gom_resident	0.155
	(0.300)
age	-0.0166*
	(0.00825)
male	0.708*
	(0.311)
income	0.00465*
	(0.00230)
Vfeetoboat	-0.158
	(0.253)
cut1	-2.058***
	(0.475)
cut2	-1.163*
	(0.478)
cut3	-0.185
	(0.491)
cut4	1.862***
	(0.535)
N	6360
LL	-6067.762
$Pseudo\ R^2$	0.0338

Cluster robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

org_angler is a binary variable that indicates membership in an angler organization.