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Abstract. We estimate demand models with revealed preference (RP) site selection and stated preference (SP) discrete choice experiment marine recreational fishing data. We combine RP data from the Marine Recreational Information Program (MRIP) creel survey with SP survey data from 2003/04. RP and SP data combination is motivated by two factors. Catch rate information in the RP data are often thin, and use of SP scenarios for changes in catch can improve variation while minimizing multicollinearity. The SP data can suffer from hypothetical bias, which often manifests itself as bias in the cost coefficient. There are eight SP trip decisions and one RP trip decision for each of 1928 anglers who provided enough information to be analyzed. Joint RP-SP generalized multinomial logit models are estimated. We find that the SP travel cost coefficient is much lower than the RP travel cost coefficient in absolute value, suggesting hypothetical bias in the SP data. This difference is reflected in the willingness to pay estimates, where the SP estimates for improved catch are much higher than the RP estimates. Attribute non-attendance (ANA) arises when survey respondents ignore choice experiment attributes. We use inferred ANA methods to identify respondents who may be ignoring the SP cost variable. The generalized multinomial logit model accounting for ANA is statistically preferred. The SP cost coefficient accounting for ANA is much higher in absolute value than the SP coefficient from the model that does not account for ANA. The ANA model indicates much more consistency between the RP and SP data. The smaller difference in the travel cost coefficients is also reflected in the willingness to pay estimates.

JEL: Q51, Q22, Q26

Introduction

Marine recreational fishing is an important economic activity. In the United States, anglers take 188 million trips annually and spend more than $10 billion per year (Lovell, et al. 2020). Over and above expenditures, estimating the non-market recreational value is important for several types of policy analyses (Abbott, et al. 2021). For example, estimating recreational value of catch is important when considering the allocation of fishery harvest among competing user groups. Allocation analysis uses the equi-marginal principle to compare the desirability of alternative quota allocation scenarios for key species (Edwards 1991; Carter, Agar and Waters 2008; Plummer, Morrison, and Steiner 2012). To implement the equi-marginal principle, the marginal value-per-unit (i.e., pound or fish) of landings must be estimated for commercial and recreational sectors.

Economic theory suggests that the marginal value of catch is declining along the commercial and recreational demands for quota. In the commercial sector, quota demand is downward sloping due to declining marginal profits as catch increases; with constant ex-vessel price per pound, profit is declining due to the increasing marginal costs of fishing effort. Producer surplus is a function of the supply of seafood from the harvest, processing, wholesale, distribution, and retail sectors. In the recreational sector, demand for quota is downward sloping due to the diminishing returns to the enjoyment of catching and consuming fish.[1] Consumer surplus is the difference between angler willingness to pay to catch and keep fish (i.e., recreational landings) and the amount that they must actually pay. Consumer surplus is a

[1] One can also appeal to substitution and income effects stemming from price changes to explain why demand for quota is downward sloping.

function of the demand for catch in the for-hire (i.e., charter and party boat modes) and private (e.g., boat and shore modes) recreational sectors.

The equi-marginal principle can be used to determine optimal fisheries harvest allocations (Plummer, Morrison, and Steiner 2012). The most efficient outcome (i.e., where net economic benefits are maximized) occurs when the marginal value of competing uses of a scarce resource are equalized. For example, if quota is allocated so that the marginal value of commercial harvest is greater than the marginal value of recreational harvest, then society is better off with a reallocation away from the recreational sector and towards the commercial sector. Since marginal values of both sectors are decreasing with quota, the marginal value of recreational quota will increase and the marginal value of commercial quota will decrease with a re-allocation. The economically efficient allocation is found at the quota level where marginal values converge (approximately) across sectors.

In this paper, we focus on estimation of the marginal value of recreational catch to inform allocation analysis. First, we combine data from the Marine Recreational Information Program (MRIP) on-site and add-on revealed preference (RP) data (Hindsley, et al. 2011; Haab, et al. 2012) with stated preference (SP) survey data that have been used by National Marine Fisheries Service economists to estimate recreational fishing values (Gentner 2004; Wallmo and Gentner 2008; Carter and Liese 2012). We focus on four primary species groups: dolphin, red snapper, king mackerel, and a "groupers" species aggregation. We focus on MRIP data from 2003/04, including intercept data on RP angler decisions and SP responses for the South Atlantic and the Gulf of Mexico. We abstract away from diminishing marginal returns in the value of catch for simplicity.

This paper makes a methodological contribution by exploration of ways to combine RP and SP recreational fishing data. We estimate joint models with RP/SP data that build upon the strengths of each type of data, while ameliorating some of the drawbacks (Adamowicz, Louviere, and Williams 1994; Whitehead, et al. 2008). Revealed preference data analyses may be limited by measurement error for travel costs (Haab, et al. 2012) and non-diminishing catch values (Carter, Agar and Waters 2008; Gentner, et al. 2010). Stated preference data analyses may be limited by hypothetical choices differing from actual choices. Joint estimation with combined data can mitigate many of these limitations (Whitehead, Haab and Huang 2011).

There have only been a few studies that jointly estimate discrete choice RP and SP data models in the environmental and resource economics literature (Adamowicz, Louviere, and Williams 1994, Adamowicz, et al. 1997, von Haefen and Phaneuf 2008, Abildtrup, Olsen and Stenger 2015).[2] Whitehead and Lew (2019) compare these approaches by jointly estimating RP and SP data for recreational fishing in Alaska. They constrain the RP and SP cost coefficients to be equal, taking the agnostic position that neither the RP or SP coefficients are preferred to the other. In a comparison of econometric models they find that willingness to pay estimates are not statistically different for a generalized multinomial logit model that takes account of the differences in the scale parameter across data sources and naïve scaled multinomial logit, mixed logit, and generalized multinomial logit models that ignore scale differences across data source. Willingness to pay estimates, however, are statistically different for separately estimated conditional logit RP and mixed logit SP models, jointly estimated nested logit, and error component mixed logit models.

[2] There is a large literature that combines RP and SP data but these studies use only continuous/count data (Hynes and Green 2013), a combination of discrete and continuous/count data (Huang et al. 2016), or combine data without joint estimation (e.g., Anciaes, Metcalfe, and Sen 2020).

In this paper, we reconsider these findings, focusing on recreational fishing in the US southeast, and we explore the role that attribute non-attendance may play in the SP data. Hensher, Rose and Green (2005) were the first to introduce the concept of attribute non-attendance into the stated preference literature. Attribute non-attendance (ANA) arises when survey respondents ignore choice attributes for a variety of reasons (Alemu ,et al. 2013). ANA offers a behavioral explanation for several anomalies in stated preference methods, such as hypothetical bias and insensitivity to scope (e.g., catch) (Lew and Whitehead 2020).

Several models have arisen to account for ANA. Inferred ANA models allow the empirical model to provide clues about ANA. Two types of inference have appeared in the literature: Hess and Hensher (2010) use a random parameters logit model to infer non-attendance by the dispersion of individual parameters; Campbell, Hensher and Scarpa (2011) use a latent class model to estimate separate classes of respondents who ignore attributes. In the latter, attribute coefficients are fixed at zero in the ignoring class and the model sorts respondents into attending and non-attending classes. Class probabilities provide estimates of those respondents who ignore one of the attributes. Stated ANA models rely on survey respondent statements about which attributes they ignored. Scarpa, et al. (2012) compare these approaches and find mostly similar results across the different models. Kragt (2013), on the other hand, finds that the stated and inferred approaches produce different results and that the inferred approach is statistically preferred.

Without respondent input for stated ANA we use a simple version of the inferred ANA model – the equality constrained latent class model (ECLC). Koetse (2017) uses the ECLC model to consider whether hypothetical bias, as measured by ANA on the cost variable, is responsible for differences in WTP and willingness to accept. We estimate the ECLC and use the estimated class probabilities for cost non-attendance to assign observations to attending and non-attending classes, constraining the cost coefficient to zero for respondents in the cost-non-attending class (as one would in a stated ANA model).

In the next section we describe the empirical models used to jointly estimate the RP and SP data. After a description of the subset of the 2003/4 SP data used by Carter and Liese (2012), we present the empirical results. We estimate separate RP and SP models, then a joint RP-SP model with unconstrained cost coefficients, and finally a joint RP-SP model with a constrained cost coefficient. We present and compare willingness to pay estimates with each of these models. Then, we perform a similar set of analyses after accounting for attribute non-attendance on the cost variable in the SP data.

In general, we demonstrate the gains from joint estimation of RP and SP data. The independently estimated RP model does not produce statistically significant willingness to pay estimates for catch rates due to measurement problems in the catch rate variable. An independently estimated SP model produces statistically significant estimates of willingness to pay, but these may be a result of a hypothetical exercise that is not disciplined by constraints faced by anglers. Combining data and jointly estimating the models produces statistically significant willingness to pay estimates, which are lower than those estimated from the independently estimated SP model. When ANA is introduced, the WTP estimates fall and the difference between the RP and SP willingness to pay estimates is reduced. The policy implications of this research are that a naïve reliance on SP data in marine fishery applications to estimate marginal catch values could lead to an overallocation of quota to the recreational sector, while primary reliance on RP may be inadequate for welfare analysis. Combining RP and SP data and incorporating innovations in empirical analysis offer improved reliability and better accuracy in applications of welfare economics to public policy.

Model

Since many of the benefits and costs occur outside normal market transactions, we employ the travel cost method to assess preferences for, and estimate the economic value of, outdoor recreational activities (Lupi, Phaneuf and von Haefen 2020). Recreation activities stand in stark contrast to market commodities, like seafood for example, where consumption takes place as a result of market transactions and the market price of seafood covers most of the consumer costs. Much, if not most, of the costs of access to recreation occur outside the market in the form of travel costs. With the travel cost method, an implicit price of the recreation experience is constructed, which includes the costs of travel and for-hire fishing fees. Recreation behavior, such as fishing site choice and frequency, negatively correlates with these travel costs. Anglers tend to choose sites with low travel costs, and when they choose sites further away, they tend to visit those less often and only if the distant sites offer attractive characteristics (such as greater expected catch, ease of access, better conditions, etc.). This behavior can be used to estimate preference functions for recreational fishing, but measurement problems can complicate the analysis.

The catch rate is a major factor affecting recreational fishing decisions (Hunt, et al. 2019). Current recreation demand models assume that anglers are targeting either a species complex (e.g., coastal migratory) or a specific species (e.g., red snapper) (Haab, et al. 2012). For the RP data, measures of fishing quality for individual species (e.g., red snapper, dolphin) and aggregate species groups (e.g., snapper-grouper, big game) are calculated using the MRIP creel data. Typically, catch is estimated as historical performance of anglers, or predicted levels for individual anglers at each site for relevant species (McConnell, Strand, and Blake-Hedges 1995), but the quality of the measures is highly dependent on available data. For the SP data, catch rates vary by experimental design.

We focus on discrete choice models of recreational angler behavior, modeling tradeoffs of travel cost and catch rates, while controlling for other pertinent factors. Random utility theory is the basis for recreational fishing models involving joint estimation of RP and SP discrete choices:

$$U_{ij} = V_{ij} + \varepsilon_{ij}, \tag{1}$$

where U_{ij} is the utility angler i receives from fishing alternative j, $i = 1, \ldots, I$, $j = 1, \ldots, J$, $V_{ij} = \beta' x_{ij}$ is the systematic portion of utility, β is a vector of parameters, x_{ij} is a vector of variables specific to the choice (e.g., travel cost, catch rate[3]), and ε is a random error. Given the unobserved elements of utility, the probability of individual i choosing alternative j is:

$$\pi_{ij} = Pr\left(V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik}; \forall k \in J\right). \tag{2}$$

We estimate recreation site choice models for 2003/2004, corresponding with available data for both RP and SP. Following the recent literature in analysis of recreation choices, we estimate generalized multinomial logit (GMNL) models (Fiebeg, et al. 2009; Keane and Wasi 2013). For the SP data, we also explore the issue of attribute non-attendance (ANA), which arises when survey respondents ignore certain elements of SP design when making choices (Hensher, Rose and Green 2005; Koetse 2017; Lew and Whitehead 2020).

[3] For simplicity, throughout this section we assume that catch is synonymous with harvest (i.e., recreational landings) unless otherwise noted.

The multinomial logit model assumes the error terms in (2) are independent and identically distributed (iid) Type 1 extreme value (also known as Gumbel) variates and takes the form:

$$\pi_{ij} = \frac{exp(\mu\beta' x_{ij})}{\sum_{j=1}^{J} exp(\mu\beta' x_{ij})}, \tag{3}$$

where μ is a scale parameter (that cannot be identified in a typical discrete choice setting and is thus implicitly set equal to one). The MNL has numerous convenient properties, including a closed form solution; the MNL, however, restricts site choices according to the assumption of the independence of irrelevant alternatives (IIA). This potentially restrictive assumption states that, for any two alternatives, the relative odds of choosing those two alternatives is independent of other alternatives in the choice set. The MNL formulation also assumes that the model parameters describing site choice, β, are constant across individuals, indicating homogeneous response to site characteristics. In contrast, the mixed logit (MXL) model introduces additional flexibility to the site choice model by allowing for preference heterogeneity (Hensher, Rose, and Greene 2015). In the MXL, individual angler preferences differ randomly according to a specified distribution, $f(\beta)$, such that the unconditional site choice probability takes the form:

$$\pi_{ij} = \int \frac{exp(\beta' x_{ij})}{\sum_{j=1}^{J} exp(\beta' x_{ij})} f(\beta) d\beta. \tag{4}$$

In application, (4) does not have a closed form solution so estimation of the parameters requires simulation of the integral.

When RP or SP models are estimated separately, the scale parameter of the multinomial logit model in equation (3) is arbitrarily set equal to one. When RP and SP data are stacked and estimated jointly, however, it is common for the error terms that result from the different data sources to have unequal variance leading to unequal scale parameters, a form of heteroskedasticity. Typically, the SP data have a higher variance due to the unfamiliarity of the choice task. The difference in the scale parameter will cause the multinomial logit coefficients to differ across RP and SP data sets. When the random errors are independent and identically distributed (iid) Gumbel errors, the multinomial logit (MNL) model in (3) results, but the relative scale parameter can be recovered due to the combination of data:

$$\pi_{hij} = \frac{exp(\mu_h \beta_h' x_{hij})}{\sum_{j=1}^{J} exp(\mu_h \beta_h' x_{hij})} \quad (5)$$

where μ is the scale factor, and h = RP, SP. Since both revealed and stated preference data follow the theoretical choice framework above, the multinomial model can be used to combine and jointly estimate revealed and stated preference data.

The generalized multinomial logit model can be used so that individual scale heterogeneity and preference heterogeneity can be accounted for (Fiebeg, et al. 2009).[4] First, consider the basic mixed logit model which involves individual specific coefficient estimates, $\beta_i = \beta + z_i$, where z_i is the individual specific deviation from the mean. The scaled coefficient is $\beta_i = \sigma_i \beta + z_i$, where $\sigma_i = exp\left(\frac{-\tau^2}{2} + \tau w_i + \theta SP\right)$, τ is the coefficient on the unobserved scale heterogeneity, w_i, θ is the parameter representing the difference in scale between RP and SP data (Hensher 2012), and *SP* is a dummy variable indicating stated preference data.[5]

We use the ECLC to identify respondents who may have ignored the cost variable in SP analysis and then account for ANA in the jointly estimated RP and SP models. The ECLC

[4] The ability of the GMNL to separately estimate individual-level scale and preference heterogeneity has been challenged by Hess and Rose (2012) and Hess and Train (2017), who argue that the utility specifications in GMNL models simply allow for more flexible distributions of the preference parameters.
[5] Note that this is the GMNL-I model in Fiebig, et al. (2010) where $\gamma = 1$.

involves estimation of two classes of respondents, $c = 1, 2$, with the SP data (where $h = SP$ is suppressed):

$$\pi_{cij}|c = \frac{exp(\beta_c' x_{ij})}{\sum_{j=1}^{J} exp(\beta_c' x_{cij})} \quad (8)$$

We constrain the coefficient on cost in the SP data to zero for one class to estimate the probability that an angler belongs to this non-attending class ($c = NA$). All other coefficients are constrained to be equal. Once the non-attending class is identified, we treat these respondents as non-attenders and estimate the SP cost coefficient in the GMNL model with stated ANA methods. In this case, the coefficient on the cost variable is $\beta_i = a_c(\sigma_i \beta + z_i)$, where $a_c = 0 \rightarrow \beta = 0$ when $c = NA$ and $a_c = 1$, otherwise. In other words, the cost coefficient is skipped in estimation for those identified as cost non-attenders in the ECLC model.

The independently estimated RP and SP models and the jointly estimated RP-SP models can be used to estimate a variety of willingness-to-pay measures. Haab and McConnell (2002) show that the marginal willingness-to-pay for a change in catch for each fishing trip with a linear utility function is $WTP = \frac{\beta_q}{\beta_{tc}}$, where β_q is the coefficient on catch, and β_{tc} is the coefficient on travel cost. Since the coefficient on travel cost is the denominator of the willingness to pay function, it plays a primary role in valuation. Hypothetical bias in SP cost coefficients will lead to bias in willingness to pay. For example, suppose the estimated coefficient on cost is biased downwards due to the hypothetical nature of the SP exercise (i.e., anglers pay less attention to changes in the hypothetical cost relative to the real cost of a fishing trip). Downward bias in the cost coefficient will upwardly bias willingness to pay estimates.

Data

For RP analysis, we utilize the MRIP on-site and add-on data (Hicks, et al. 1999;

Hindsley, et al. 2011). The RP choice sets were constructed based on site selection, aggregated at the county level.[6] Our analysis of SP data closely follows the work of Carter and Liese (2012), employing the econometric models described above. The stated preference survey was sent to a sample of willing anglers who participated in the economic add-on to the MRIP in the South Atlantic and Gulf of Mexico regions.[7] The SP survey was administered via mail, and 8518 anglers who fished in the South Atlantic and Gulf states returned the survey. The RP/SP dataset was constructed by merging RP site choices from the basic MRIP survey with SP responses based on angler IDs found in the MRIP.

Merging the 2003/04 SP data with the RP data reduces the number of anglers to 2637. Since the target species in the SP survey are rarely caught from shore and the SP choice experiment data describes private boat trips (the trip cost variable did not include charter fees), we exclude anglers whose intercepted trip used other modes (e.g., charter, shore). In all, we were able to account for 2210 anglers self-identified as using private/rental boats. In development of choice sets, we utilize a 150-mile cutoff for sites (Haab and Hicks 1999; Gentner 2007). After accounting for this distance cutoff as well as missing zip code data, the sample size was reduced to 1928 private/rental boat anglers.

There are eight SP trip decisions and one RP trip decision for each angler. The choice sets for the SP observations are trip A, trip B, and stay-at-home. The choice set for the RP decision range from two to nineteen sites (i.e., counties) within 150 miles of the angler's residence. Thirty-percent of the anglers were intercepted at a South Atlantic fishing site, and

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[6] Distances were calculated between individual site (INTSITE) and anglers' home zipcodes (ZIP) with ArcGIS by NMFS economists.
[7] The 2003/04 Stated Preference Survey can be found at https://www.st.nmfs.noaa.gov/Assets/econ-human/pdf/SE_SP_2003.pdf.

70% were intercepted at a Gulf of Mexico site. The data summary is presented in Table 1. The sample size for data summary is the cross section/time series over the number of alternatives faced by the respondents. In the RP site selection data each of the 1928 anglers appears in the data once (i.e., time-series = 1). In the SP choice experiment data each angler appears in the data eight times (pseudo time-series = 8). The sample size is 22,698 for the RP data (reflecting variability in the number of sites in individual choice sets) and 31,872 for the SP data (not all SP respondents answered all choice set questions).

The RP trip cost variable is constructed to be consistent with the trip cost variable in the SP survey which is described as follows: your travel cost "includes your personal share of the costs associated with gas, wear and tear on your vehicle, tolls, ferries, parking, access fees, food, ice, bait, and fishing equipment used on this trip." The RP trip cost variable is $TC = FC + VC$ where FC are fixed costs and VC are variable costs of the trip. The fixed costs are taken from Gentner and Steinbeck (2008) and include expenditures on food, access, parking, bait, ice and tackle that vary by state. The expenditures are deflated to 2004 dollars using the CPI. The variable costs are the product of the composite national average cost per mile, $0.499 rounded to $0.50 (AAA 2004) and round-trip travel distance.[8] The opportunity cost of time is not included in either RP or SP trip cost variables. The average RP trip cost over 22,698 trips is $106 with a range of $11 to $187. The average SP trip cost over 30,848 trips (excluding the stay at home alternative) is $89 with a range of $45 to $140.

[8] If we wish to produce conservative estimates, we should consider adjusting travel costs to include only operating costs (fuel, maintenance, and tires), excluding operating and ownership costs (insurance, registration & taxes, depreciation, and finance charges).

The RP model includes trip cost, the five-year site average targeted catch-and-keep rates for dolphin, grouper, red snapper and king mackerel, the five-year site average catch-and-release rates, and the log of the number of intercept sites in the coastal county site (Haab, McConnell and Whitehead 2000). The SP data includes trip cost, catch-and-keep, catch-and-release, other species catch, and an alternative specific constant for the stay-at-home alternative. Catch-and-release in the SP data is the sum of the catch-and-release resulting from size and bag limits. The catch rates are for the target species dolphin, red snapper, king mackerel, and an aggregate grouper group.

The RP catch rates are lower than the SP catch rates due to a preponderance of zero catch rates in the RP data. For example, the five-year average dolphin catch-and-keep per trip is 0.04 with a range of 0 to 1.64; the SP dolphin keep rate is 1.07 with a range of 0 to 10. The grouper, red snapper, and king mackerel RP catch-and keep rates range from 0.02 to 0.05. The SP grouper red snapper and king mackerel catch-and-keep rates range from 0.45 to 0.47. The other species catch variable in the SP data has a mean of 3.33 with a range of 1 to 6. The RP catch-and-release variable means range from 0 to 0.18. The SP catch-and-release variables range from 0.39 to 0.64.

Empirical Results

We first estimate separate RP and SP models, then a joint RP-SP model with unconstrained cost coefficients, and finally a joint RP-SP model with a constrained cost coefficient. We present and compare willingness to pay estimates for each of these models. Then, we perform a similar set of analyses after accounting for attribute non-attendance on the cost variable in the SP data as in Koetse (2017).[9] All of the models are estimated with NLOGIT

[9] We do not weight these models for onsite sampling. Previous research suggests that the MRIP weights had little effect on WTP estimation (Lovell and Carter 2014). Endogenous stratification is less likely a problem with our dataset, since only those RP observations that can be matched with the SP data are analyzed.

6 (www.limdep.com).

Generalized RP-SP Multinomial Logit

A joint RP-SP generalized multinomial logit model is presented is Table 2.[10] We fix $\tau = 0.5$ and $\gamma = 1$ (not shown above, but an additional parameter in Fiebig, et al. (2010)) as in Hensher (2012) and Whitehead and Lew (2019).[11] Each of these models is estimated with 500 Halton draws. In Model 1 we estimate cost coefficients separately for revealed preference and stated preference data as in Whitehead and Lew (2019); in Model 2 we constrain the cost coefficients to be equal. Statistically, the constrained cost coefficient models are inferior to the unconstrained models. The philosophy behind constraining coefficients across models is that both types of data have weaknesses (e.g., measurement error for RP data and hypothetical bias for SP data), and "data fusion" can contribute to an improved model in terms of the accuracy of the coefficients. We constrain all of the catch coefficients to be equal. There is little benefit to estimating models with unconstrained catch coefficients. In preliminary models with the RP catch variables set equal to zero, goodness of fit measures are almost identical. Therefore, we proceed only considering the sensitivity of constrained cost coefficients on model performance

[10] Separate conditional logit models are estimated and presented in the Appendix. In the revealed preference model only two of the four catch and keep coefficients are statistically significant and all of the catch and release coefficients have negative signs. Comparing statistically significant catch coefficients, the RP dolphin and red snapper catch-and-keep coefficients are much larger than the SP coefficients. This may be a result of the unequal size of the catch variables in the underlying data. The marginal value of additional catch when catch is low, as in the RP data, is higher than when catch is relatively high, as in the SP data. Otherwise, the pattern of results is similar to that from more complex econometric models.

[11] When these constraints are not imposed the τ and γ estimates become very large. For example, in an unconstrained τ and γ model with a constrained cost coefficient the estimated parameters are $\tau = 54$ and $\gamma = 19$. Most of the coefficients are similar across these models with all differences less than 10%. The exceptions are coefficients on dolphin release (31% increase), grouper release (37% increase) and king mackerel release (18% increase). In the unconstrained model the standard deviations are 88% to 96% smaller and none of these are statistically different from zero. Since the constrained τ and γ models conform to expectations in terms of the random parameters and there will be little difference in the willingness to pay for the catch and keep values, we proceed with the constrained τ and γ models.

and willingness to pay estimates.

Each catch coefficient is specified to be normally distributed. The other coefficients are estimated without randomness. The stated preference parameter, θ, is positive and statistically significant indicating a larger variance in the SP data. Whitehead and Lew (2019) find that accounting for this variance has little effect on willingness to pay estimates from a random parameter model. We find similar results here, but we continue to estimate GMNL models with this parameter included.[12] The individual scale parameter, σ_i, is not statistically different from zero or one. Both of these results indicate that a mixed logit (random parameters) model may be sufficient to jointly estimate willingness to pay.

All of the coefficient estimates have the expected sign and are statistically significant at the 95% confidence level. The coefficients on grouper, red snapper, and king mackerel catch are larger than the coefficient on dolphin catch. Also, each of the catch-and-keep coefficients is larger than the catch and release coefficients, except for dolphin for which the coefficients are equal. The SP cost coefficient is almost 80% lower (in absolute value) than the cost coefficient in the RP model. Given the mean values across the RP and SP data, this may indicate that anglers pay less attention to cost in the choice experiment relative to the fixed and variable costs of an actual fishing trip. All things equal, this will lead to larger willingness to pay estimates with the SP cost coefficient. From the revealed preference data, the site agglomeration variable is positive and statistically significant, which indicates that an angler is more likely to visit a county with a larger number of MRIP interview sites. From the stated preference data, the other catch

[12] The pattern of regression results for scaled and mixed logit models is similar to what is presented there. The willingness to pay estimates are 39% and 15% lower from the scaled, mixed, and generalized multinomial logit models with scale differences relative to the GMNL models with scale differences. These results are available upon request.

coefficient is positive and the stay-at-home coefficient is negative, which indicates that anglers value other catch and prefer taking fishing trips to staying home. The standard deviations on the mean catch-and-keep coefficients are large relative to the means indicating (1) significant preference heterogeneity in the data or (2) measurement error in the RP data. In the case of (2), results suggest that the joint models should favor the SP catch variables.

In Model 2 we present estimates from the same model with the cost coefficients constrained to be equal. As stated above, the unconstrained model is statistically preferred with higher McFadden's R^2 and lower AIC statistics. The SP cost variable is more influential in estimation. The constrained cost coefficient is 103% larger than the unconstrained SP cost coefficient and 175% smaller than the unconstrained RP cost coefficient (in absolute value).

Generalized RP-SP Multinomial Logit with Cost Non-Attendance

We next consider the potential for attribute non-attendance in the cost variable (Table 3). We estimate the simplest version of the inferred ANA model, the equality constrained latent class model (ECLC) with ANA imposed on the cost variable (see Appendix); this consists of a 2-class finite mixture, in which the cost coefficient is constrained to be equal in one class as in Koetse (2017). Class probabilities imply the probability that an angler is a member of the non-attending class is 79%, on average. In other words, there is a 79% probability that respondents did not pay sufficient attention to the SP cost variable. The other coefficient estimates are similar to those in the SP conditional logit model. There is less than a 5% difference in each of the catch coefficients between the two models.[13]

We use the ECLC model to identify respondents who may be ignoring the cost variable. We create a variable equal to 1 if the probability of being a member of the non-attending class is greater than 0.50 and 0 otherwise. For these anglers we estimate the GMNL models as if these anglers ignored the cost variable. The GMNL model with unconstrained cost coefficients and the ANA adjustment for the SP cost coefficient is presented in Table 3 (Model 1). In comparison to the similar model in Table 2, the ANA model is statistically preferred with a higher McFadden's R^2 and a lower AIC statistic. The RP cost coefficients are similar across the Model 1 in Tables 2 and 3. The SP cost coefficient accounting for ANA is 164% percent larger in absolute value than the SP cost coefficient that does not take ANA into account in Table 3. This suggests that the ECLC model identifies anglers for whom the cost variable has less effect on their trip taking decisions in the SP data. All other results are similar across the two models. Interestingly, the parameter on the SP variable in the scale factor (θ) changes sign. This indicates that the variance in the SP data is lower than in the RP data once ANA on the cost variable is considered empirically.

The RP cost coefficient is 4.6 times lower than the SP cost coefficient in the jointly estimated GMNL model without consideration of ANA (Table 3). In the GMNL model

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[13] The willingness to pay estimates from the ECLC model are significantly lower than the corresponding willingness to pay estimates from the SP conditional logit model presented in the appendix. The interpretation of the ECLC model as a hypothetical bias correction, as in Koetse (2017), suggests that the willingness to pay estimates that do not account for hypothetical bias are about 300% higher than those that do account for the bias (i.e., attribute non-attendance).

accounting for ANA, the RP cost coefficient is only 1.6 times larger than the SP cost coefficient. This indicates much more consistency between the RP and SP data when ANA is accounted for.

In Model 2 we present estimates from the GMNL model with the RP and SP-ANA cost coefficients constrained to be equal. The unconstrained model is statistically preferred with higher McFadden's R^2 and lower AIC statistics, but the differences are smaller than when comparing models without ANA as a consideration. The SP cost variable is more influential in estimation. The constrained cost coefficient is only 1.2 times larger than the unconstrained SP cost coefficient and only 1.3 times lower than the unconstrained RP cost coefficient, in absolute value.

Willingness to Pay Measures

The willingness to pay estimates from these models are presented in Table 4 and Figure 1 (for catch-and-keep[14]). Considering estimates that do not account for ANA, willingness to pay for dolphin catch are lower than the other target species and released catch is worth about 100% less (on average) than harvested catch. The RP cost coefficients are higher than the SP cost coefficients (in absolute value) in Tables 3 and 4, meaning that the RP costs have a higher impact on angler utility than the SP costs. This difference is reflected in the willingness to pay estimates, where the SP willingness to pay estimates are 156% larger than the willingness to pay estimates estimated with the RP cost coefficient. Comparing WTP estimates from models 1 and 2 in Table 3, the WTP estimates from the constrained model are influenced more by the repeated observations from the SP data. The willingness to pay estimates from the unconstrained revealed preference cost coefficients are 100% lower, on average, than the WTP estimates from the

[14] The pattern of WTP results for catch-and-release is similar to catch-and-keep.

constrained cost coefficient. The willingness to pay estimates from the unconstrained stated preference cost coefficients are 56% higher than the WTP estimates from the constrained cost coefficients. When ANA is employed, WTP estimates are 105% lower, on average. The pattern of differences between unconstrained (Model 1) and constrained (Model 2) WTP estimates are similar to above, but the differences are much less pronounced.

Discussion

Economics can offer an objective basis for policy analysis and resource allocation decisions, but empirical results must make use of best available data and models to provide useful guidance (Abbot 2015; Gopalakrishnan, Landry, and Smith 2020). In our application to valuation of recreational fishing, we find significant advantages in combining revealed and stated preference data and incorporating technical advances that are designed to address data problems. Revealed preference data often suffer from measurement problems, especially for important variables like expected catch, travel costs, and opportunity cost of time (Randall 1994; McKean, Walsh, and Johnson 1996; McConnell, Strand, and Blake-Hedges 1996); other difficulties relate to modeling group decisions and allocation of travel costs for multi-purpose trips. While modeling efforts have attempted to address some of these shortcomings (Larson 1993; Amoako-Tuffour and Martínez-Espiñeira 2012; Lupi, Phaneuf and von Haefen, 2020), combining revealed and stated preference data is a viable and often simpler alternative. The stated preference data, however, are not without their drawbacks, as the hypothetical nature of the choice exercises can reduce reliability and introduce bias, especially for attributes like cost (Alemu, et al. 2013; Johnston, et al. 2017).

Combining RP and SP data, while using equality constrained latent class model to address attribute non-attendance in the SP cost parameter, offers considerable advantages in producing valid measures for allocation and other types of policy analysis. Applied economists should seek to continue to incorporate methodological innovations in pursuit of combined RP-SP valuation models. For example, the use of attribute non-attendance models (Hindsley, Landry, and Morgan 2020), certainty scales (Beck, Fifer, and Rose, 2016), designs that permit learning about personal values (Cook, et al. 2007) or valuation methods (Bateman, et al. 2008), and "consequential" designs (Carson and Groves 2007; Landry and List 2007; Vossler, Doyon, and Rondeau 2012) have proven useful at addressing problems in stated preference analysis (Landry 2017). Innovations in RP analysis, such as improvements in valuation of travel time (Fezzi, Bateman, and Ferrini 2014), can be incorporated as well. Lastly, RP-SP models also permit greater flexibility in valuation modeling, for example allowing researchers to assess non-use values (Eom and Larson 2006; Landry, Shonkwiler, and Whitehead 2020) or looking for latent consistency in RP/SP responses (Jeon and Herriges 2017).

Utilizing this rich set of resulting valuations, we applied the equi-marginal principle to gain insight into optimal harvest allocations (Hindsley et al., 2018).[15] Our results are predicated by an exclusive focus on marginal values derived from recreation demand and commercial supply models and our assumption that the recreation fleet could expand to utilize additional catch (whereas commercial could not in the short run). Our results suggest that the high marginal recreation values for Gulf of Mexico anglers could justify significant reallocation away from the commercial sector. For example, our analysis indicates the recreational allocation of 13 million pounds of red snapper could increase from 49% to 91%; the 68% recreational allocation of 8.8

[15] Recent research has highlighted the importance of an efficient property right structure for the equi-marginal principal to apply and the need to focus on other important economic factors when determining the appropriate allocation (Abbott 2015; Holzger and McConnell 2014). Given that recreational anglers do not purchase quota, whereas commercial fishermen in the Gulf of Mexico do, however, this would compromise our analysis.

million pounds of king mackerel could expand to 97%, and the allocation of 8.3 million pounds of red grouper could increase from 31% to 95%. Note that the joint estimation of recreational values leads to lower WTP estimates relative to the WTP estimates from models that solely use SP data. The latter values would suggest that 100% of the quota should be allocated to the recreational sector. This result shows the impact that joint estimation in the recreational sector can have on allocation analysis in the U.S. The impact of ANA would be lower recreational quota relative to the estimates above.

One difficulty that can arise in synthesizing RP and SP data are differences in scope or structure of the data. We run into this issue in our application, as the choice experiment is focused upon private boat mode for fishing. In linking the RP and SP data, this limitation shrinks our dataset by approximately 75%. While SP studies must be explicit in their description of contingent scenarios, care should be taken to maximize the potential for combining SP with existing RP data.

Conclusions

In this paper we combine the MRIP RP data with the 2003/4 SP data that varies catch rates for private boat anglers. The SP choice models use data from previous work (Gentner 2004; Wallmo and Gentner 2008; Carter and Liese 2012), but tailored to allow combination of RP and SP data to capitalize on the strengths of each dataset. In particular, catch information in the RP are often thin, and use of SP scenarios for changes in catch can improve variation while minimizing multicollinearity. The SP data, however, can suffer from hypothetical bias, which often manifests as downward bias in the cost coefficient. Constraining cost coefficients or introducing parameters to control for attribute non-attendance (ANA) on the cost variable are ways to deal with this problem.

In general, we have demonstrated the gains from joint estimation. An independently estimated RP data model does not produce statistically significant willingness to pay estimates for kept or catch-and-release fish. An independently estimated SP data model produces statistically significant estimates of willingness to pay but the magnitude may be a result of a hypothetical exercise that is not disciplined by constraints faced by anglers. Combining and jointly estimating the models produces statistically significant willingness to pay estimates, which are lower than those presented in the SP only models. A model with ANA on the cost coefficient reduces the differences in RP and SP data. One interpretation of this result is that the SP data may suffer from hypothetical bias, which can be mitigated by joint estimation with the RP data and ANA. Our results suggest that ANA mitigates the problem of hypothetical bias but it does not eliminate it, assuming the revealed preference cost coefficient is measured without error and estimated without bias.

Utilizing our valuation estimates to assess fishery quota reallocations, we find evidence of substantial welfare gains associated with increasing recreational allocations. To be clear, this finding is the primary management contribution of this research. An over-reliance on SP data to estimate marginal catch values could lead to an overallocation of quota to the recreational sector. We emphasize that this allocation analysis is illustrative and not intended to inform current policy because numerous data constraints have limited the scope of our analysis. For example, the SP choice experiment constrains the recreational values to be estimated with both variable and fixed costs of operating an automobile. Using only variable costs would lead to lower values and a smaller allocation to the recreational sector. Also, the trip cost variable does not include the opportunity cost of time, which would increase the willingness to pay for catch. Considering the RP data, we estimate a simple model with information from an intercepted trip and no data on the participation decision. Future research should be conducted with RP and SP data from a study that does not suffer from these limitations.

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Table 1. Recreation Demand Data Summary

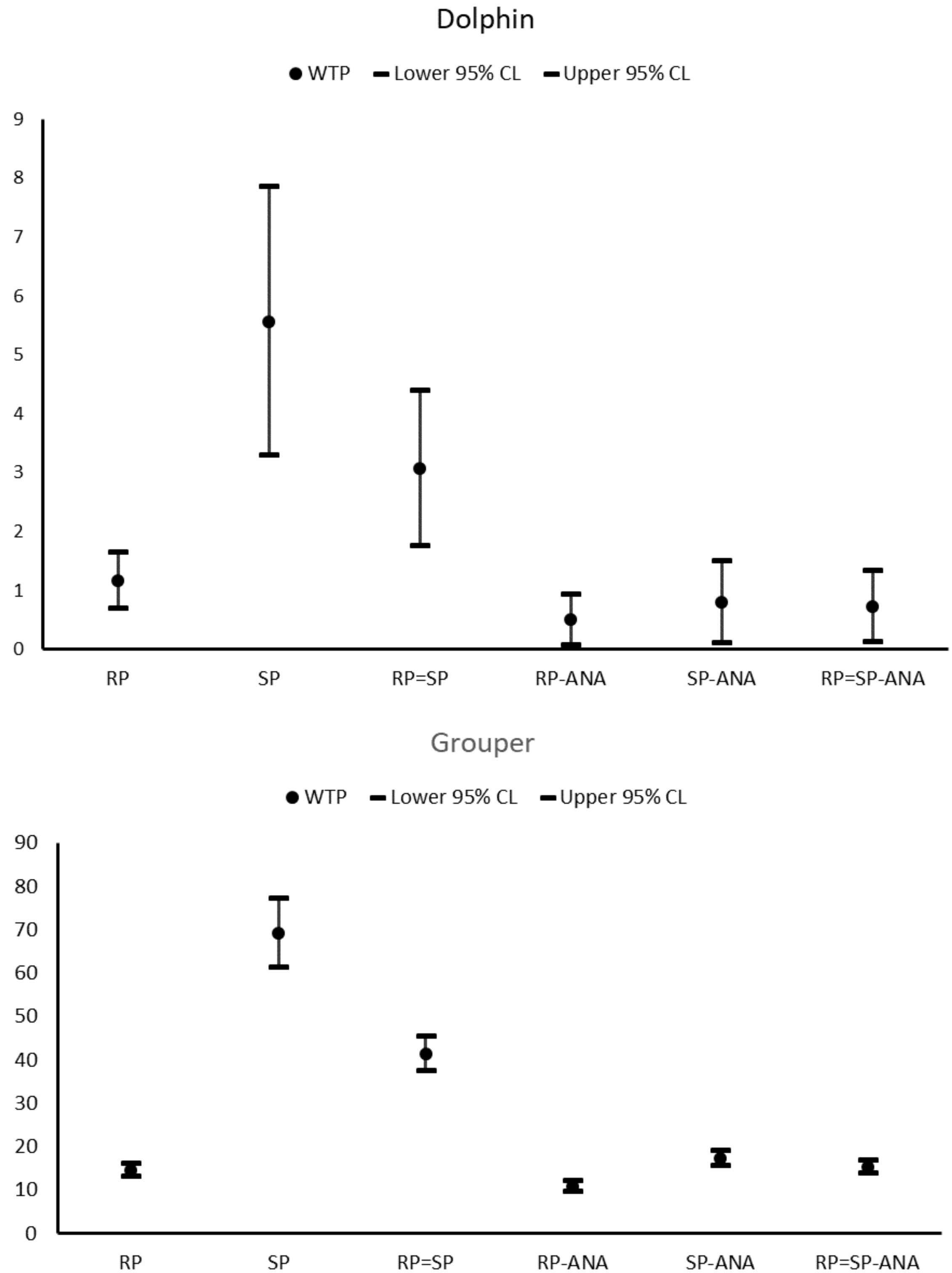
	Revealed Preference				Stated Preference			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Cost	106.10	42.92	10.91	186.15	89.91	35.84	45	140
Dolphin keep	0.04	0.08	0	1.64	1.07	2.39	0	10
Grouper keep	0.05	0.25	0	2.74	0.47	1.07	0	6
Red Snapper keep	0.02	0.09	0	1.11	0.45	0.95	0	5
King Mackerel keep	0.02	0.11	0	3.00	0.47	0.95	0	5
Dolphin release	0.00	0.01	0	0.17	0.64	1.79	0	9
Grouper release	0.18	0.29	0	3.08	0.59	1.40	0	5
Red Snapper release	0.01	0.01	0	0.12	0.39	0.99	0	4
King Mackerel release	0.07	0.21	0	1.77	0.43	1.03	0	4
Ln(number of sites)	3.07	0.90	0	5.17				
Other Catch					3.33	2.05	1	6
Cross-section	1928				1928			
Time-series	1				8			
Cases	1928				15,424			
Trip alternatives per angler	11.89				2			

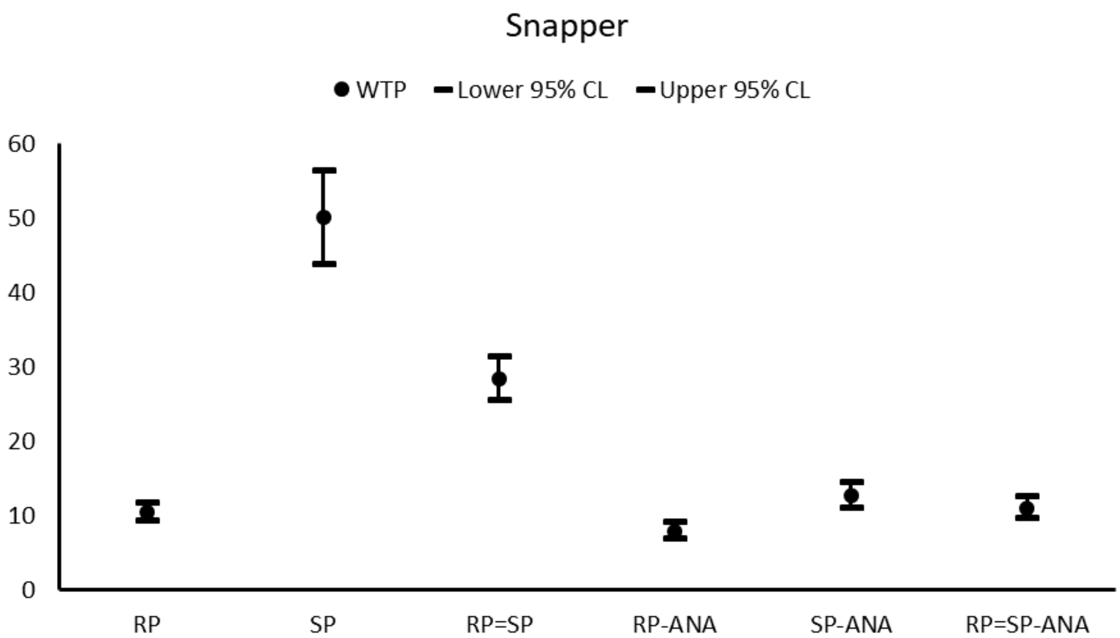
Table 2. Generalized Multinomial Logit Recreation Demand Models						
	Model 1			Model 2		
	Mean Coeff.	SE	t-stat	Mean Coeff.	SE	t-stat
Dolphin keep	0.090	0.015	5.85	0.107	0.017	6.20
Grouper keep	0.991	0.051	19.29	1.138	0.062	18.41
Red Snapper keep	0.715	0.042	16.88	0.800	0.047	17.19
King Mackerel keep	1.116	0.061	18.31	1.250	0.068	18.35
Dolphin release	0.091	0.014	6.69	0.091	0.016	5.71
Grouper release	0.188	0.022	8.42	0.199	0.025	7.85
Red Snapper release	0.184	0.025	7.28	0.206	0.029	7.08
King Mackerel release	0.420	0.033	12.60	0.492	0.038	12.85
Cost [RP]	-0.064	0.002	-40.840			
Cost [SP]	-0.014	0.001	-23.98			
Cost [RP=SP]				-0.028	0.001	-48.65
Other Catch	0.126	0.009	13.85	0.150	0.010	14.69
Stay at Home	-1.182	0.072	-16.48	-2.350	0.076	-31.10
ln(number of sites)	1.179	0.047	25.25	0.971	0.037	25.97
	Coeff. SD	SE	t-stat	Coeff. SD	SE	t-stat
Dolphin keep	0.421	0.023	18.09	0.532	0.027	19.47
Grouper keep	0.770	0.057	13.45	0.946	0.065	14.52
Red Snapper keep	0.788	0.049	16.20	0.880	0.053	16.50
King Mackerel keep	1.183	0.060	19.76	1.432	0.070	20.36
Dolphin release	0.183	0.034	5.32	0.285	0.033	8.68
Grouper release	0.340	0.037	9.11	0.455	0.037	12.26
Red Snapper release	0.342	0.053	6.49	0.526	0.053	9.98
King Mackerel release	0.429	0.057	7.57	0.607	0.074	8.24
θ [SP]	0.497	0.012	41.49	0.495	0.011	43.59
σ_i	0.991	0.887	1.12	0.991	0.884	1.12
Log likelihood function	-14,692.58			-15,424.04		
Restricted log likelihood	-51,091.91			-51,091.91		
χ^2[22 df]	72,799			71,336		
McFadden Pseudo R^2	0.71			0.70		
AIC	29,429			30,890		
Sample Size	17,352			17,352		
Cross-section	1928			1928		
Time-series	9			9		

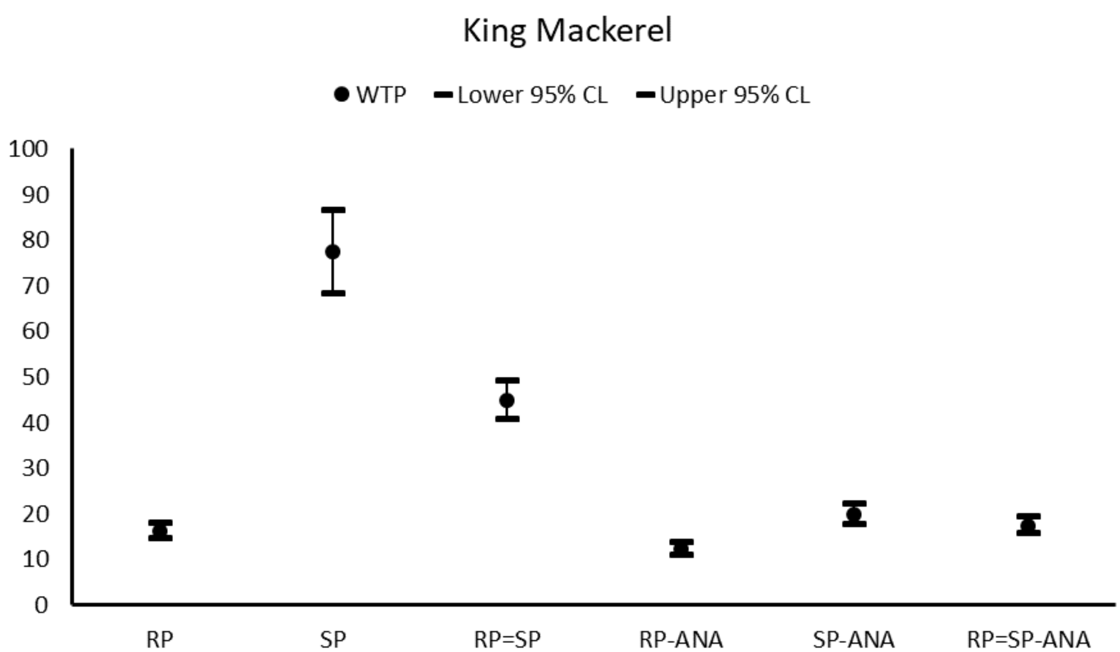
Table 3. Generalized Multinomial Logit Recreation Demand Models with ANA on Stated Preference Cost						
	Model 1			Model 2		
	Mean Coeff.	SE	t-stat	Mean Coeff.	SE	t-stat
Dolphin keep	0.032	0.014	2.27	0.035	0.015	2.36
Grouper keep	0.683	0.035	19.55	0.739	0.037	20.15
Red Snapper keep	0.505	0.033	15.10	0.537	0.035	15.28
King Mackerel keep	0.785	0.044	17.98	0.845	0.046	18.45
Dolphin release	0.034	0.014	2.48	0.033	0.015	2.17
Grouper release	0.138	0.018	7.54	0.149	0.019	7.69
Red Snapper release	0.117	0.021	5.52	0.129	0.024	5.46
King Mackerel release	0.306	0.025	12.44	0.337	0.027	12.58
Cost [RP]	-0.063	0.002	-40.63			
Cost [SP-ANA]	-0.040	0.001	-43.34			
Cost [RP=SP-ANA]				-0.048	0.001	-59.58
Other Catch	0.112	0.009	13.08	0.119	0.009	13.23
Stay at Home	-1.305	0.065	-20.00	-1.515	0.068	-22.33
ln(number of sites)	1.183	0.046	25.43	1.080	0.042	25.74
	Coeff. SD	SE	t-stat	Coeff. SD	SE	t-stat
Dolphin keep	0.333	0.021	15.59	0.362	0.022	16.45
Grouper keep	0.533	0.048	11.15	0.625	0.048	13.13
Red Snapper keep	0.701	0.043	16.44	0.764	0.043	17.93
King Mackerel keep	0.993	0.050	19.67	1.065	0.053	20.04
Dolphin release	0.201	0.032	6.30	0.243	0.030	7.98
Grouper release	0.269	0.032	8.32	0.309	0.031	9.95
Red Snapper release	0.212	0.063	3.36	0.331	0.048	6.85
King Mackerel release	0.326	0.052	6.25	0.420	0.049	8.50
θ [SP]	-0.248	0.025	-10.07	-0.431	0.029	-15.02
σ_i	0.997	0.415	2.41	0.998	0.356	2.80
Log likelihood function	-13,668.03			-13,753.76		
Restricted log likelihood	-51,091.91			-51091.91		
χ^2[22 df]	74,847.76			74,676.30		
McFadden Pseudo R^2	0.73			0.73		
AIC	27,380			27,549		
Sample Size	17,352			17,352		
Cross-section	1928			1928		
Time-series	9			9		

Table 4. Willingness to Pay Estimates									
	Model 1						Model 2		
	Revealed Preference			Stated Preference			Revealed-Stated Preference		
	WTP	95% C.I.		WTP	95% C.I.		WTP	95% C.I.	
Dolphin keep	1.41	0.94	1.89	6.70	4.41	8.99	3.88	2.65	5.10
Grouper keep	15.48	13.77	17.20	73.37	64.56	82.19	41.33	36.96	45.69
Red Snapper keep	11.17	9.78	12.55	52.91	45.86	59.97	29.05	25.73	32.36
King Mackerel keep	17.42	15.41	19.44	82.56	72.22	92.91	45.38	40.53	50.24
Dolphin release	1.43	1.01	1.85	6.77	4.73	8.81	3.30	2.17	4.43
Grouper release	2.94	2.24	3.64	13.93	10.55	17.31	7.23	5.41	9.05
Red Snapper release	2.87	2.08	3.65	13.58	9.81	17.36	7.49	5.42	9.57
King Mackerel release	6.55	5.49	7.61	31.05	25.85	36.24	17.88	15.16	20.60
	With ANA on the SP Cost Coefficient								
Dolphin keep	0.50	0.07	0.93	0.80	0.35	2.27	0.73	0.12	1.33
Grouper keep	10.76	9.57	11.95	17.23	0.92	18.77	15.31	13.82	16.79
Red Snapper keep	7.96	6.86	9.05	12.74	0.86	14.78	11.11	9.69	12.53
King Mackerel keep	12.38	10.91	13.85	19.82	1.14	17.35	17.48	15.62	19.34
Dolphin release	0.54	0.11	0.97	0.87	0.35	2.48	0.68	0.65	1.29
Grouper release	2.17	1.60	2.74	3.47	3.47	7.51	3.08	2.29	3.86
Red Snapper release	1.85	1.18	2.51	2.96	2.96	5.51	2.66	1.71	3.62
King Mackerel release	4.83	4.03	5.62	7.73	0.63	12.28	6.98	5.90	8.07

Figure 1. Willingness to Pay Estimates for Catch and Keep




Snapper
WTP
Lower 95% CL
Upper 95% CL
60
50
40
30
20
10
0
RP
SP
RP=SP
RP-ANA
SP-ANA
RP=SP-ANA


King Mackerel
WTP
Lower 95% CL
Upper 95% CL
100
90
80
70
60
50
40
30
20
10
0
RP
SP
RP=SP
RP-ANA
SP-ANA
RP=SP-ANA

Appendix. Conditional Logit and ECLC models

Table A1. Recreation Demand Logit Models

	Conditional Logit						Equality Constrained Latent Class		
	Revealed Preference			Stated Preference			Stated Preference		
	Coeff.	SE	t-stat	Coeff.	SE	t-stat	Coeff.	SE	t-stat
Dolphin keep	0.953	0.473	2.02	0.038	0.007	5.57	0.0375	0.0064	5.89
Grouper keep	0.280	0.708	0.40	0.358	0.016	21.82	0.3724	0.0154	24.12
Red Snapper keep	1.103	0.175	6.32	0.297	0.018	16.53	0.3017	0.0169	17.84
King Mackerel keep	0.163	0.390	0.42	0.397	0.020	20.07	0.4112	0.0183	22.48
Dolphin release	-2.883	3.236	-0.89	0.019	0.008	2.50	0.0206	0.0079	2.62
Grouper release	-0.327	0.198	-1.65	0.103	0.012	8.92	0.1002	0.0111	9.04
Red Snapper release	0.434	0.267	1.63	0.067	0.014	4.68	0.0696	0.0148	4.70
King Mackerel release	-4.354	2.824	-1.54	0.225	0.014	15.90	0.2283	0.0145	15.71
Cost	-0.063	0.002	-40.63	-0.008	0.000	-19.81	-0.0304	0.0007	-44.72
Ln(number of sites)	1.223	0.051	23.96						
Other catch				0.066	0.006	11.14	0.0693	0.0060	11.48
Stay at Home				-1.089	0.064	-16.92	-1.3484	0.0693	-19.45
Probability ANA Class							0.7923	0.0168	47.20
Probability Attending Class							0.2077	0.0168	12.38
LL Function	-2010.67			-13,953.15			-13,274.92		
AIC	4041			27,928			26,573		
Cases (n)	1928			15,424			15,424		
Cross-section	1928			1928			1928		
Time-series	1			8			8		

Table A2. Willingness to Pay Estimates									
	Conditional Logit						ECLC		
	Revealed Preference			Stated Preference			Stated Preference		
	WTP	95% C.I.		WTP	95% C.I.		WTP	95% C.I.	
Dolphin keep	15.07	0.42	29.71	4.98	1.24	0.21	5.84	0.82	1.65
Grouper keep	4.42	-17.50	26.34	46.45	12.27	0.57	21.62	11.16	13.38
Red Snapper keep	17.43	12.04	22.82	38.56	9.94	0.59	16.74	8.78	11.11
King Mackerel keep	2.57	-9.50	14.64	51.51	13.55	0.66	20.48	12.25	14.85
Dolphin release	-45.56	-145.80	54.68	2.47	0.68	0.26	2.62	0.17	1.19
Grouper release	-5.17	-11.31	0.98	13.33	3.30	0.37	8.86	2.57	4.03
Red Snapper release	6.86	-1.40	15.13	8.70	2.29	0.49	4.67	1.33	3.25
King Mackerel release	-68.81	-156.02	18.40	29.19	7.52	0.51	14.83	6.53	8.52