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The Reliability of Sportfishing Demand and Value Estimates: Evidence from the Gulf of Mexico

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1. INTRODUCTION

Estimates of the value of recreational fishing are widely used in policy analysis. For example, NOAA Fisheries calculates the change in economic value anticipated with proposed changes in saltwater fishing regulations (National Marine Fisheries Service, 2007). Studies to generate new estimates of economic value are costly and time consuming. It is, therefore, important to understand the reliability of value estimates over time in order to know when a study needs to be replicated to remain relevant for policy analysis.

There are established methods to estimate the value of nonmarket goods like recreational fishing trips, but the true value of nonmarket goods are not observable.[1] Therefore, existing valuation methods, such as the travel cost method and stated preference analysis, estimate true values with error. Bishop and Boyle (2019) suggest that the error can be separated into sampling error and measurement error where the former deals with the variance of estimates and the latter represents the bias inherent in the methods. Research that compares nonmarket values estimated using the same methodology measured at different time periods is an attempt to understand the variance or *reliability* of estimates.

Our work evaluates the reliability of recreational fishing demand model parameters and related welfare measures estimated using a contingent behavior methodology from samples of the same population collected in two different years.[2] In the only other study we found that examines temporal reliability with contingent behavior, Xie and Adamowicz (2022) use data from three years to estimate the same demand model specification for deer hunting trips in Canada. They find that the majority of the demand model parameters and welfare estimate for site closures are temporally reliable across the three years. Interestingly, the hypothetical site closure welfare estimates for the subset who took trips to the the site to be closed were relatively more reliable.

There are many other studies that have evaluated the temporal reliability of recreational values estimated using trip demand models.[3] In a series of studies using a 2-year

[1]We are referring to *private* recreational fishing trips. There is an active market for *for-hire* fishing trips whereby customers can pay to charter a recreational fishing vessel and captain or purchase a spot on a boat to recreationally fish with others.

[2]In the framework of Bishop and Boyle (2019) we explore the variance or "reliability" of our estimates, conditional on the validity or "bias" of the research methods which we fix across the survey replications.

[3]We focus on the trip demand applications that use either travel cost and/or contingent behavior data. There is another strand of literature that examines the temporal reliability of recreation value estimates using contingent valuation or choice experiments (e.g., Whitehead and Aiken, 2007; O'Donnell, 2016)

panel of travel cost data on recreational trips to lakes in Iowa, researchers find welfare measures for site closures are reliable over a five year period, but welfare measures for water quality are not (Ji et al., 2020; Yi and Herriges, 2017). These studies use both test-retest and repeated sample strategies, like the approach in the present work, to evaluate temporal reliability.

The results are mixed over longer time horizons. In another example of the repeated sample approach, Rolfe and Dyack (2019) compare the travel cost demand and value estimates from two time periods about seven years apart in Australia. They reject the null hypothesis of equality of estimates for between years.[4] Zandersen et al. (2007) also rejects the equality of coefficient and value estimates from site-choice travel cost models of forest recreation in Denmark conducted twenty years apart. The results of these two studies stand in contrast to He and Poe (2021) who report three inflation-adjusted estimates of willingness-to-pay for a fishing trip from site-choice travel cost demand models that are remarkably similar over a thirty year period in New York.

Our work contributes to the literature in two ways. First, we provide the second study of the reliability of recreational demand and value using only contingent behavior data. As noted, the previous study found that the parameters and value estimates to be reliable over a three year period. Second, we present the first evaluation of reliability in the context of marine recreational fishing demand. Marine recreational fishing is an important activity that contributed to more than $50 billion in value-added economic activity in the United States during 2020 (National Marine Fisheries Service, 2023).

2. METHODS

The Florida Boating and Fishing Survey (FBFS) was conducted in early 2020 and 2022 to obtain information about Florida anglers' fishing activity in the Gulf of Mexico (GOM) during November and December of 2019 and 2021.[5] The target population for the FBFS was any person who might have fished offshore in the GOM during November and December. We were especially interested in anglers fishing for Gag Grouper (*Mycteroperca microlepis*).[6]

[4] They also compare recreational value estimates using contingent valuation surveys from the same two time periods to assess the convergent validity between the two methods. Their tests reject the null of convergence between the travel cost and contingent valuation estimates within years and the contingent valuation estimates changed less than the travel cost model estimates over the seven year period.

[5] In most of the discussion and tables we will refer to the samples based on the year the data was collected (i.e., 2020 and 2022) rather than the years that the data refers to (i.e., 2019 and 2021)

[6] The purpose of the FBFS was specifically to measure *changes* in recreational fishing effort, not to generate estimates of the absolute level of recreational fishing effort. In this way, the FBFS is distinct

Gag Grouper is one of the most popular reef fish targeted by anglers fishing in the GOM. Around 7% of all trips by private boat anglers fishing from the west coast of Florida (WFL) in 2019 targeted Gag Grouper during it's open season. In Federal waters, the share of private boat angler trips fishing for Gag Grouper is even higher at around 22%.[7]

The recreational harvest of Gag Grouper in the GOM is managed with fixed seasons and bag limits. The bag limit has been two fish per angler since 2009, but the seasons varied considerably until 2016 when the season in federal waters was set to open in June and continue through the end of the year. The minimum size limit was also set in 2016 to 24 inches.[8] These regulations and related regulations in the commercial sector were implemented to protect the Gag Grouper stock which was in decline during the early 2000's.

2.1. Survey Questions

The FBFS was designed to improve prediction of changes in angler effort and economic value anticipated with changes in Gag Grouper bag limits and seasons. The same instrument was used in the two years of the survey. There were two main sections of the survey following a question confirming boat ownership and questions regarding the type of boat usage during November and December. For the respondents that used their boat for fishing, the first section asks a series of questions related to fishing activity during November and December. Specifically, respondents were asked to report the number of trips taken in November and December and the total cost paid by all anglers on a typical trip. We also asked for the duration of and the number of anglers on board a typical trip.

The second section of the survey contained two types of contingent behavior (CB) questions that asked respondents to report the number of trips they would have taken in November and December if fishing costs or Gag Grouper regulations were different. This is a type of *reassessed contingent behavior* trip question format that asks anglers to reassess how many trips they would have taken if hypothetical trip costs or Gag

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from and not affiliated with other angler surveys in the Gulf of Mexico such as the Fishing Effort Survey of the Marine Recreational Information Program (MRIP) and the Florida State Reef Fish Survey (FS-RFS). The results of our survey are not strictly comparable to the MRIP or FSRFS results because our study used a narrower sampling frame, invited anglers via email and mail, had respondents complete the survey on the primarily on internet, and asked effort-related questions in different ways.

[7] On the west coast of Florida, Federal waters begin at 9 nautical miles from the shore. These estimates are based on the MRIP estimates for June through December of 2019.

[8] The minimum size limit was set to 20 inches in 1990 and 22 inches in 2000. In addition, there is a combined bag limit for a set of shallow-water grouper species, including gag, that is currently 5 fish.

Grouper regulations had been in place (Simoes et al., 2013). The full set of CB question scenarios are summarized in Table 1 where the first row represents actual conditions in November and December, the second two rows represent the cost (price) scenarios, and the last three rows represent the Gag Grouper bag limit scenarios. There are two sources of variation in the scenarios when collected for a set of anglers: (i) across anglers, and (ii) across scenarios within one angler.

The first CB question in the survey (row 2 of Table 1) asks for the number of trips that would have been taken if the cost would have been double the cost of a typical trip and the second CB question (row 3) asks for the number of trips if the cost were half that of a typical trip.

The other three CB questions (rows 4 through 6) ask for the number of trips that would have been taken if the bag limit were three fish, one fish, or zero fish (closed season). These questions were only shown to those who reported fishing for Gag Grouper during November or December and stated that they might have taken a different number of trips if Gag Grouper regulations had been different. Note that the hypothetical regulation questions ask the angler to consider changes in the number of *all* trips, not just those trips that targeted Gag Grouper.[9] For the analysis, we set the trips in the Gag Grouper regulation scenarios to the actual trips for those who stated that they would not have changed their trips under different Gag Grouper regulations.

2.2. Survey Sampling

There is no specific list of Florida anglers fishing in the GOM for Gag Grouper. Therefore, we focused on anglers fishing from the west coast of Florida because nearly all of the recreational harvest of Gag Grouper originates from this area. We further narrowed our interest to boat-based anglers because Gag Grouper are primarily located around offshore reefs, which can only be reached by boat. Our sampling strategy was slightly different in the two years of the survey.

2.2.1. 2020 Survey

For the 2020 survey we constructed a sample frame from two lists. The first is the list of registered Florida boat owners (FBO) and the second is the list of licensed saltwater

[9] Gag Grouper is part of a bottom fish complex that includes many substitute species. We assume that the respondent considers these alternative targets when reporting the number of trips that they would take under the hypothetical Gag Grouper regulation scenarios. We return to this point in the Discussion section.

anglers in Florida (FLSA).[10] The FBO list contains boat-based anglers missing from the saltwater license list due to exemptions, especially adults 65 and over which make up nearly 20% of the Florida population and by some accounts around 15% of the angling population (U. S. Fish and Wildlife Service, 2018).

The 2020 study sampled from 45 Florida counties that are most likely to be associated with GOM private boat fishing. In this case, a county is "associated" with GOM if, based on the MRIP data, at least 50% of the average annual estimated fishing trips during November and December from the county were to the GOM from WFL. We also define trips during this period as associated with Gag Grouper if the angler interviewed by the MRIP either targeted (primary or secondary) or caught (kept or released dead or alive) Gag Grouper in the GOM from WFL. These 45 counties account for 96% of all GOM trips and 99% of all Gag Grouper trips in the GOM. Note that this sample frame will not cover the entire population of anglers that fish in the GOM from WFL because approximately 14% of anglers fishing in the GOM from WFL from a private boat reside outside Florida.

The 2020 FBFS was a mixed-mode survey with two general sampling strategies. The first was an email and web survey strategy that made all contacts (invitations, reminders, etc.) via email. In this strategy, contacts from the FBO sample were instructed to click a link in the email to take the survey online. The second sampling approach was a mail-push strategy that made all contacts via the mail and included a $2 incentive with the survey invitation letter. In the mail-push strategy, contacts from the FBO sample were mailed a letter with instructions to use a URL and a unique identification code to complete the survey online. The mail-push strategy also sent a paper version of the survey to those who did not respond after a reminder postcard (Messer and Dillman, 2011).

According to the FBO database there were around 75,000 vessels registered in the 45 counties of interest during the study periods. We further narrowed the FBO frame to include only the registrations that were for a fiberglass hull power boat (inboard, outboard, or stern drive engine) at least 20 feet in length and designated for pleasure use. These vessels would be most likely to be able to fish in the GOM. We sampled around 7,000 vessel registrations from the FBO to obtain our target sample size (400) based on assumed response rates (~15% for email-only and ~35% for mail-push) and Gag Grouper angler prevalence (~30%). These assumptions were based on a pilot study that surveyed two Florida counties in early 2019 regarding fishing in November and

[10]The FBO list was obtained from BoatOwners Database maintained by Info-Link Technologies Inc. and the FLSA list was obtained from the Office of Science and Technology at NOAA Fisheries.

December of 2018. Note that sampling was adjusted slightly such that approximately 25 percent of the records *did not* have a match in the FLSA list to ensure that we had sufficient coverage of the population that can saltwater fish in Florida without a license.

2.2.2. 2022 Survey

We used a slightly different sampling strategy for the 2022 survey. Due to budget constraints we were unable to use the mail-push sampling strategy or incentives. The 2022 survey was an email-only survey that made all contacts (invitations, reminders, etc.) via email. However, we were able to sample boat owners who had the FSRF license, which is required by the State of Florida to fish for reef fish, even for those who are over 65 and would not otherwise require a Florida saltwater fishing license. The FSRF license designation allowed us to more directly target the reef fish angling population of interest.[11]

The State of Florida categorizes each record in the FSRF database based on county of residence and boat ownership. We sampled around 7,000 boat owners with emails from the six strata roughly corresponding to the counties sampled in the 2020 survey. The starting sample size was the same as in 2020, recognizing that we would end up with fewer target respondents because the email-only response rate is lower than the response rate achieved in 2020 using the mail-push strategy with an incentive.

Table 1: Trip Scenarios

Scenario	Price (p)	Trips (d)	Bag (r)
Price Changes			
Base (Actual)	p_0	d_0	2
Double Price	$p_1 = p_0 \cdot 2.0$	d_1	2
Half Price	$p_2 = p_0 \cdot 0.5$	d_2	2
Bag Limit Changes			
Bag 3	p_0	d_3	3
Bag 1	p_0	d_4	1
Bag 0 (closed)	p_0	d_5	0

[11] We did not use the FSRF license frame in the 2020 survey because the design of the associated FSRF (then called the "Gulf Reef Fish") survey had not yet been certified by NOAA Fisheries when we were creating our sampling strategy.

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2.3. Trip Demand Model

Following Alberini et al. (2007) we use a single-site travel cost model of recreational fishing in the GOM under alternative trip cost and fishing regulation scenarios shown in Table 1. We assume that an angler i chooses the number of fishing trips, d_{ij}, and a numeraire good, X_{ij}, under scenario j that maximizes utility subject to a budget constraint and fishing quality, q_{ij}, per trip or $\underset{X_{ij},d_{ij}}{max}\ U(X_{ij}, d_{ij})\ s.t.\ y_i = X_{ij} + d_{ij} \cdot p_{ij}$ and $q_{ij} = f(s, k_i, r_{ij})$ where p_{ij} is the cost per fishing trip in scenario j for angler i, y_i is angler income, and the price of the numeraire good is set to one. We further assume that fishing quality is a function of the fish stock, s, angler skill, k_i, and fishing regulations, r_{ij}. Note that angler income and skill do not vary by scenario and that fish stock does not vary by angler or scenario. Furthermore, we assume that fishing trips and fishing quality are weak complements such that $\partial U/\partial h = 0$ if $d = 0$, i.e., the individual does not care about the quality of fishing if he or she does not fish.

The solution to the angler problem yields the demand function for trips, $d_{ij} = d(s, y_i, k_i, p_{ij}, r_{ij})$. In our empirical work, we assume that the trip demand data follows a Poisson distribution and estimate the following fixed effect trip demand model:

$$d_{ij} = exp(\alpha_i + \gamma p_{ij} + \delta r_{ij} + \lambda r_{ij}^2 + \theta h_{ij} + \phi h_{ij} p_{ij} + \eta g_{ij} p_{ij}) \tag{1}$$

where p_{ij} is the trip cost with associated parameter γ, r_{ij} is the bag limit with parameters δ and λ, and α_i is an angler-specific fixed effect.[12] We include an indicator, h_{ij}, for the hypothetical scenarios and interact the indicator with the trip cost variable.[13] The parameters on the hypothetical indicator, θ and ϕ, are meant to capture the differences in the unmodeled factors that affect trips reported in the hypothetical scenarios (Englin and Cameron, 1996; Haab et al., 2012). For example, the hypothetical indicator could measure errors on the part of the respondent. The internet survey reminded the respondent how many trips they took in the base case before each hypothetical scenario question. However, respondents could have made an error (e.g., recording or recall) such that the expected trips over the hypothetical scenarios at the baseline cost and bag limit does not equal the actual trips. The parameters associated with the dummy variable designating the hypothetical scenarios should capture this error. We also include

[12] Factors, such as income, fishing skill and fish stock, that do not vary by scenario cannot be identified separate from the fixed effect. In the Appendix of Carter et al. (2022) we use an alternative procedure to estimate the income parameter for this model with the 2021 survey data and show that it is relatively small so that there is very little difference between the results with and without income effects.

[13] We cannot interact the hypothetical indicator with the bag limit variables because the bag limit is fixed at two for all anglers in the base case.

a variable, g_{ij}, to indicate the observations collected with the paper survey instrument (only in 2020) and interacted this with trip cost variable because the trip cost scenarios were presented slightly differently on the paper versus the internet versions of the survey. Specifically, we used piping on the internet survey to present respondents with trip cost alternatives that were double or half their actual costs whereas the paper survey used the language "double" or "half" the actual trip costs. We interact the paper survey indicator variable with the trip cost variable to address any potential response differences that might be associated with the way the trip cost questions were asked.

With the poisson fixed effects estimator, the unobserved factors represented by the fixed effects can be correlated with p, r, or h without biasing the corresponding parameters. This is important because the angler response to changes in trip costs and bag limits is likely to be related to angler characteristics or fish stock conditions not included in the model.[14]

There are several other important measures that we calculate to compare between the two survey rounds. The first type of measure is a semi-elasticity which measures the percent change in trips expected with a unit change in trip cost or bag limit, all else equal. The average trip cost semi-elasticity is simply the parameter γ on this variable. The average semi-elasticity for the bag limit in scenario j is slightly more complicated because there is a square term: $\epsilon_j = \delta + 2\lambda r_j$.

The other measures we compare between years are the value of a fishing trip and the change in value expected with a change in trip cost or the Gag Grouper bag limit (Haab and McConnell, 2002). The negative of the inverse of the trip cost parameter gives the expected value of a fishing trip, i.e., $CS = -1/\gamma$.[15] Similarly, the change in value per trip associated with a change in the bag limit is expressed as $MWTP_j = -\epsilon_j/\gamma$ which measures the marginal willingness-to-pay (MWTP) for each bag limit increment.

[14]The fixed effect poisson estimator has been frequently used in contingent behavior studies (e.g., Whitehead et al., 2011; Englin and Cameron, 1996) because it is fully robust even if trips do not follow a poisson distribution or trips reported by the same angler are correlated (Wooldridge, 2010). An alternative assumption would be a random-effects specification whereby α_i is unobserved, but *assumed to be* uncorrelated with trip cost and the bag limit (e.g., Alberini et al., 2007; Rosenberger and Loomis, 1999; Whitehead et al., 2000).

[15]The value per trip, including the effects of the hypothetical scenarios, would include the parameter on the interaction of the hypothetical indicator and trip cost, i.e., $CS = -1/(\gamma + \phi)$. Similarly, the value per trip, including the effect of the paper survey is $CS = -1/(\gamma + \eta)$. We focus on the CS estimate without the effects of the hypothetical scenarios or the paper survey.

2.4. Reliability Analysis

We consider several ways to formally compare the results across the two data collections. First, we use standard t-tests to compare the means of the key variables. Second, to compare the trip demand model parameters $(\gamma, \delta, \lambda, \phi)$, elasticities, ϵ, the value per trip CS, and the MWTP for bag limit changes per trip estimates, $\mathbf{MWTP}$, we use the results of a cluster bootstrap procedure (Cameron and Miller, 2015; Cheng et al., 2013).[16] To implement the bootstrap for the results of interest, denoted $\beta_t = (\gamma_t, \delta_t, \lambda_t, \phi_t, \epsilon_t, CS_t, \mathbf{MWTP}_t)$ for $t = 2020, 2022$, we proceeded as follows:

1. Sample anglers (respondents) with replacement N times from the original sample of anglers.
2. For the sampled N anglers, retain all the trips taken to form the first bootstrap sample.
3. Obtain estimates of β_t from the first sample.
4. Repeat steps 1, 2, and 3 B times to obtain B bootstrap estimates of β_t.

Note that the re-sampling is done over anglers, rather than over scenarios. In this way, some anglers may not appear in bootstrap samples at all while other anglers will appear multiple times. The results of the bootstrap simulation gives vectors of length B for each element in β_t for each data collection year t. We then evaluate the overlap of the two bootstrap distributions for each result of interest using plots and an overlap index (Pastore, 2018). In addition, we use the method of convolutions to test the null hypothesis of estimate equality (Poe et al., 2005; Aizaki, 2015). Specifically, we apply the method of convolutions to corresponding vectors in β for each year. For example, to evaluate the null of equality of the value per trip estimates for 2020 and 2022 we apply the method of convolutions on the vectors CS_{2020} and CS_{2022}.

3. RESULTS

The final disposition of the two samples is shown in Table 2. The response and completion rates shown in the table are consistent with other angler surveys employing a similar sampling strategy (Wallen et al., 2016). Note, however, that we were able to obtain around five percentage points more response with the mixed-mode survey in 2020.

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[16]Note that we collect the bag limit semi-elasticity and MWTP estimates for the different bag limit starting values into boldfaced vectors denoted $\boldsymbol{\epsilon} = (\epsilon_0, \epsilon_1, \epsilon_2, \epsilon_3)$ and $\mathbf{MWTP} = (MWTP_0, MWTP_1, MWTP_2, MWTP_3)$.

A series of maps showing the distribution of the sample (population) and returns across Florida counties for the two data collections is shown in Figure 1. A cursory examination of the shading suggests that the proportion of the sample and returns for each county is similar among the four maps.

Based on Table 2, around two-thirds of the completed surveys used their boat during November or December and roughly half used their boat to fish in the GOM.[17] More importantly, for our purposes, around a quarter of the completed surveys stated that they "fished for Gag Grouper" in the GOM during the same period.

3.1. Summary Statistics

The summary statistics for the two data collections are shown Table 3 where the last four columns show the p-values for the null hypothesis that means are equal between each sample and overall.[18] On average, anglers took around 5 or 6 trips during November and December. The typical trip cost just over $200, included three people, and went for around 7 hours, on average. Statistically, the duration (hours) of the typical trip was not the same among the two data collections (at the 0.05 significance level). However, the absolute difference in mean duration among the data collections was relatively small. We are not able to reject the null hypothesis of equality for the average income reported in the two data collections. This is not surprising, though, because there is extra noise in this variable, which was introduced when we converted the original categorical income variable to a continuous measure with the midpoint of each category. Interestingly, the difference in the average trip cost is consistent with the roughly eight percent increase in the general price level between December 2019 and December 2021 as measured by the CPI.

The last five rows of Table 3 give the summary statistics for the five hypothetical trips scenarios shown in Table 1, i.e., trips d_1 through d_5. In general, the reported trips are decreasing in trip cost and increasing in the Gag Grouper bag limit. We cannot reject the null hypothesis of equality of the hypothetical trips between the data collections for any of the trip cost change scenarios.

[17] We removed 20 fishers, including 9 gag fishers, who indicated that their typical trip was more than 12 hours. Trips over 12 hours a are fundamentally different type of fishing.

[18] The estimates throughout this manuscript that use the 2020 data collection are slightly different than the estimates from the same data collection published in Carter et al. (2022) because the present analysis includes roughly 30 more observations based on updated data processing methods. A copy of the Carter et al. (2022) paper with the updated data is available upon request.

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Table 2: Summary of Sampling Results for by Year

	2020	2022
Delivered	7,075	6,549
Started	1,586	1,064
Completed	1,443	958
Boaters	986	578
Fishers	739	469
Gag Fishers	379	236
Shares		
Started / Delivered	0.224	0.162
Completed / Delivered	0.204	0.146
Boaters / Completed	0.683	0.603
Fishers / Completed	0.512	0.49
Gag Fishers / Completed	0.263	0.246

Table 3: Means and significance tests for the key variables among Gag Fishers by Year

Variables	2019	2021	P-Value
Trips	6.06 (5.81)	5.58 (4.58)	0.254
Trip Cost	213 (186)	233 (250)	0.290
People	3.03 (1.09)	2.98 (1.55)	0.681
Hours	6.99 (1.99)	6.61 (1.85)	0.014
Income ($0000)	15.0 (9.05)	13.9 (8.43)	0.110
Hypothetical Trips			
Double Cost	3.26 (3.84)	2.81 (3.64)	0.143
Half Cost	8.59 (7.82)	7.87 (6.14)	0.205
3 bag	6.16 (6.22)	5.66 (4.72)	0.253
1 bag	4.58 (4.52)	4.61 (4.52)	0.946
0 bag	4.16 (5.09)	4.06 (4.71)	0.793

Note: Standard errors in parentheses.

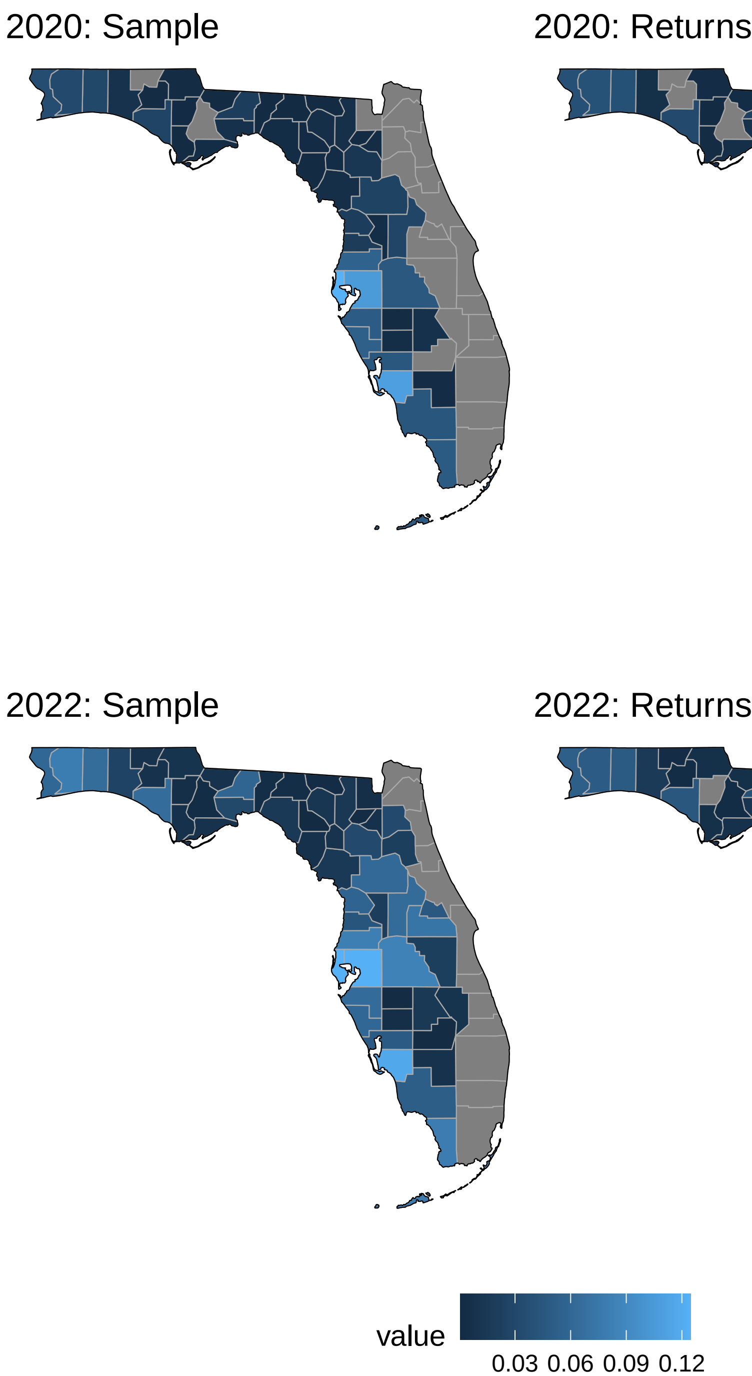

Figure 1: Map Showing the Share of Records from each Florida County for the Sample (Population) and the Survey Returns

3.2. Trip Demand

In Figure 2 we illustrate the similarity in trip demand among the two data collections by plotting the piecewise linear trip demand relationships based on the mean trips reported in the actual, cost doubling and cost halving scenarios. For reference, the horizontal and vertical lines in the figure indicate the mean reported actual trips taken during November and December of 2019 (based on the 2020 data collection). Consistent with the results in Table 3, the curves are relatively close together.

The estimated parameters of the trip demand regressions are shown in Table 4. We use cluster-robust standard errors to adjust for the fact that the multiple observations from the same individual are likely to be correlated. These adjusted standard errors account for both overdispersion and correlation over choices for a given angler (Bergé, 2018).

The trip cost parameters, γ, are close within three decimal points for both data collections. These parameters represent the percent change in trips with a unit change in trip cost for the average angler who targeted Gag Grouper. The negative of the reciprocal of the travel cost parameter measures the CS per trip for the average angler as shown in Table 4. The first CS estimate (actual) is based only on the trip cost parameter, γ, whereas the second CS estimate (hypothetical) adds the effect of the trip cost interaction with the hypothetical scenario indicator. The second CS estimate captures the effect of the hypothetical scenarios, which, as noted above, contain relatively more options that suggest trip decreases, rather than trip increases. Therefore, the CS per trip measures including the effects of the hypothetical choices are relatively lower.

The trip response of anglers to bag limit changes is formally measured in Table 4 as bag limit semi-elasticities. We use the semi-elasticity expressions for the bag limit change presented earlier to calculate the bag limit semi-elasticity starting from zero, one, two, and three fish. Generally, the percent change in trips with a unit change in the bag limit decreases with each bag limit increment with the first increment increasing trips by around 20 percent.

The last set of measures shown in Table 4 are the estimates of the marginal willingness-to-pay (MWTP) or CS_j for a change in the bag limit. Similar to the semi-elasticities, the MWTP is decreasing in the bag limit starting with around \$40 for the first fish.

Table 4: Poisson Fixed Effect Trip Demand Regression and Calculated Measures

	Parameter	2020	2022
Trip Demand Model Parameters			
Trip Cost per Angler (1/10)	γ	-0.006^{***}	-0.005^{***}
		(0.001)	(0.001)
Bag Limit	θ	0.260^{***}	0.187^{***}
		(0.043)	(0.045)
(Bag Limit)^2	δ	-0.036^{***}	-0.024^{*}
		(0.011)	(0.011)
Hypothetical	λ	-0.003	0.048
		(0.034)	(0.034)
Trip Cost (1/10)*Hypothetical	ϕ	-0.000	-0.001^{***}
		(0.000)	(0.000)
Trip Cost (1/10)*Paper	η	0.006^{***}	
		(0.001)	
Value per Trip			
CS per trip (actual)	$-1/\gamma$	171.059^{***}	209.576^{***}
		(19.219)	(35.761)
CS per trip (hypothetical)	$-1/(\gamma+\phi)$	158.635^{***}	168.174^{***}
		(16.456)	(23.740)
Bag Limit Semi-Elasticities			
Semi-Elast: 0 bag	$\delta + 2\lambda 0$	0.260^{***}	0.187^{***}
		(0.043)	(0.045)
Semi-Elast: 1 bag	$\delta + 2\lambda 1$	0.187^{***}	0.140^{***}
		(0.024)	(0.025)
Semi-Elast: 2 bag	$\delta + 2\lambda 2$	0.114^{***}	0.093^{***}
		(0.016)	(0.017)
Bag Limit MWTP			
MWTP: 0 bag	$(\delta + 2\lambda 0)/\gamma$	44.493^{***}	39.292^{***}
		(8.892)	(10.829)
MWTP: 1 bag	$(\delta + 2\lambda 1)/\gamma$	32.025^{***}	29.411^{***}
		(5.424)	(6.961)
MWTP: 2 bag	$(\delta + 2\lambda 2)/\gamma$	19.557^{***}	19.529^{***}
		(3.383)	(5.081)
Log Likelihood		-4805.197	-2834.206
Num. obs.		2274	1416
BIC		12586	7417
AIC		10380	6150

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

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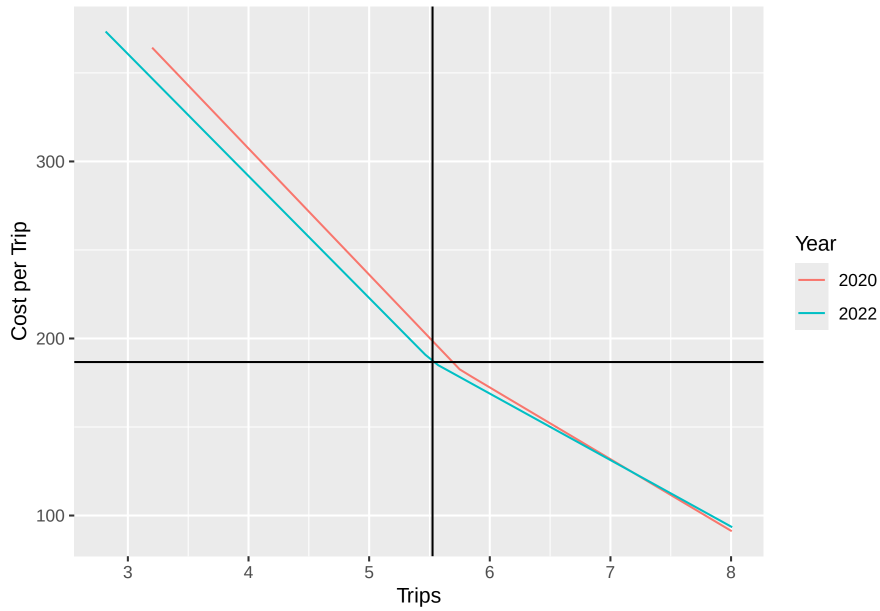

Figure 2: Piecewise-Linear Trip Demand based on the Cost Doubling and Cost Halving Contingent Behavior Questions

3.3. Reliability Analysis

The results of the bootstrap analysis are shown in Figure 3 and Table 5. Note that we have inflated the CS and MWTP dollar values from the 2020 study to be consistent with the dollar values in the 2022 study. Specifically, we multiplied the 2020 CS and MWTP results by 1.08 because, according to the BLS CPI Calculator, the general price level increased by 8% between December 2019 and December 2021 (the years of the data). Referring to Table 4, for example, expressing the 2019 dollar denominated CS per trip estimate for the 2020 sample in 2021 dollars consistent with the 2022 sample would increase the estimate from \$171 to \$185. For the purposes of Figure 3 and Table 5 we multiply 2020 the CS and MWTP bootstrap vectors by 1.08 before ploting or summarizing.

The plots in Figure 3 show the bootstrapped distributions by year for each parameter to visualize the extent of the overlap for each key parameter. For example, distributions for the trip cost parameter indicate considerable overlap, but the distributions for the first bag limit parameter are not as aligned. The overlap for each parameter is numerically evaluated in Table 5 where we give a formal measure of the percentage of overlap (Pastore, 2018) and the p-values for the null hypothesis that the means for each year are equal. Consistent with the overlap plots, the trip cost parameter has over 50 percent overlap. This high level of overlap is also apparent in the CS per trip which is simply the negative of the reciprocal of the trip cost parameter. Furthermore, we cannot reject the null hypothesis that the CS per trip is equal at a 0.05 significance level.

There is less agreement apparent in the plots and overlap measures for the bag limit parameters and the related semi-elasticities and MWTP measures. However, based on the p-values for the test of equality, none of the parameters and measures of interest are statistically different at the 0.05 significance level.

4. CONCLUSIONS

We collected data on recreational fishing trip behavior from similar sample frames of anglers in two different years. Summary statistics on key variables were very close between the two years, with only a few statistically significant differences in mean comparisons of ten different variables. The estimated parameters of the same recreational fishing trip demand model specification estimated using each data year were also very similar according to a bootstrap analysis that compared distribution plots and formal measures of overlap.

Our work specifically examined the temporal reliability of recreational fishing demand model parameters and related welfare measures estimated using contingent behavior data from samples of the same population collected at different times. In the framework of Bishop and Boyle (2019) we explored the variance (reliability) of our welfare estimates, conditional on the validity (bias) of the valuation method which we fix across the survey replications. Therefore, while our findings suggest that there is a relatively low variance in welfare measures over time, our method could be producing estimates that are "off target" relative to the true welfare values. The low temporal variance result is consistent with other research on welfare estimates that considered a time frame of five or fewer years (Xie and Adamowicz, 2022; Ji et al., 2020; Yi and Herriges, 2017).

The temporal reliability of survey data and estimates likely varies on a case-by-case basis and the methods employed by this paper give researchers a straightforward means of evaluating the need for fresh data, especially for marine recreational fishing. Our methods can be used to compare the sampling and valuation results for other areas and species. There are currently efforts underway to replicate our 2022 study during different times of the year, under different baseline regulatory conditions (e.g., closed vs. open season), and with different species. All of these variations offer opportunities to examine the reliability of welfare estimates across different conditions to build an evidence base on how quickly valuation estimates lose reliability in each context,

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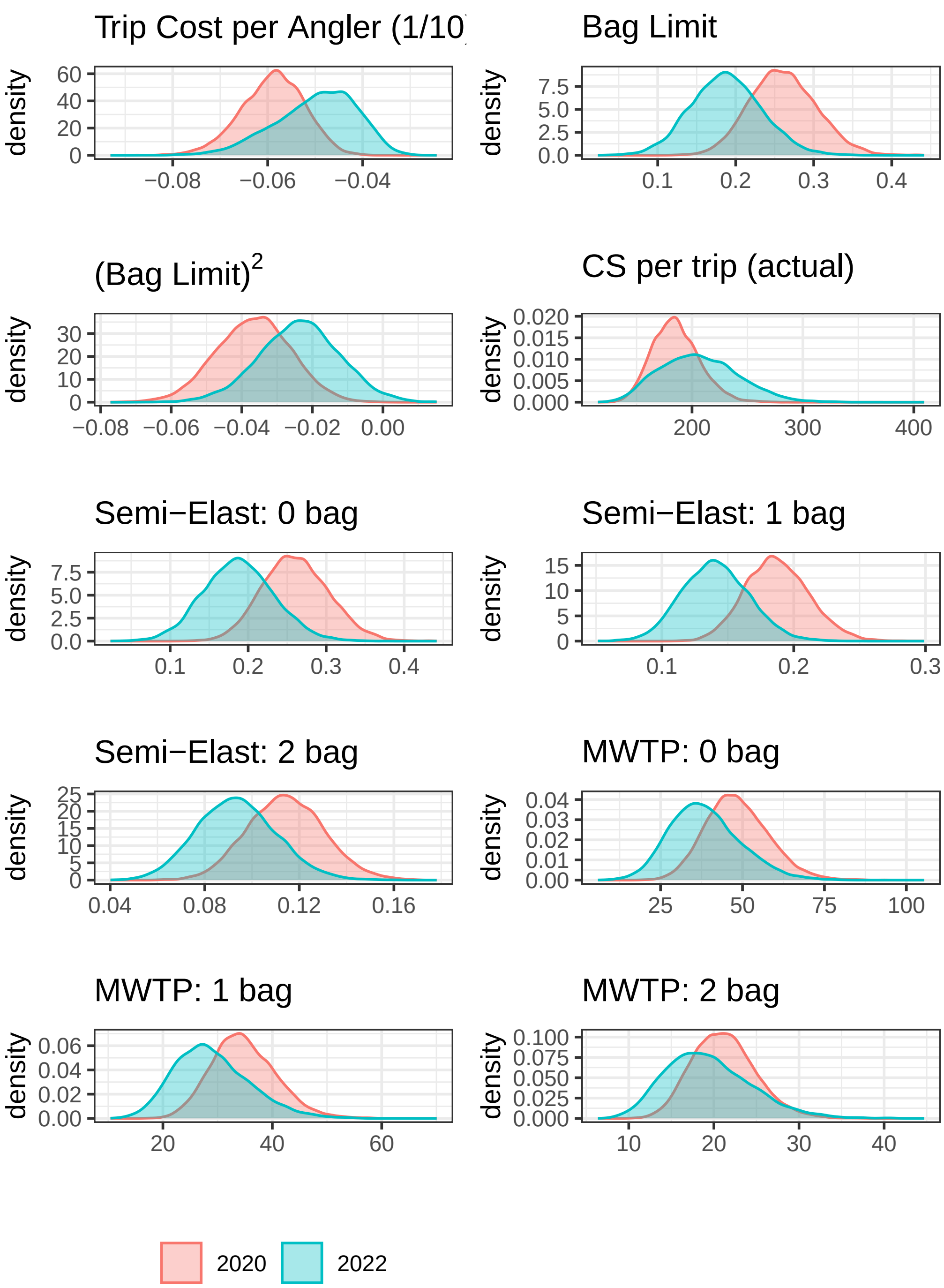

Figure 3: Overlap of Parameter Distributions of by Year

Table 5: Overlap and P-Values for the Null Hypothesis that Means are Equal for the 2 Rounds

Measure	Overlap	P-Value
Trip Demand Model Parameters		
Trip Cost per Angler (1/10)	0.51	0.804
Hypothetical	0.49	0.831
Bag Limit	0.41	0.119
$(\text{Bag Limit})^2$	0.55	0.799
Trip Cost (1/10)*Hypothetical	0.39	0.118
CS per trip		
CS per trip (actual)	0.67	0.688
CS per trip (hypothetical)	0.84	0.438
Bag Limit Semi-Elasticities		
Semi-Elast: 0 bag	0.41	0.119
Semi-Elast: 1 bag	0.35	0.09
Semi-Elast: 2 bag	0.53	0.185
Bag Limit MWTP		
MWTP: 0 bag	0.61	0.243
MWTP: 1 bag	0.62	0.254
MWTP: 2 bag	0.76	0.371

Note: The parameter on the cost-paper interaction is not shown because it only appears in the 2020 model.

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thereby informing optimal time-frames and geographic scopes for commissioning new studies versus relying on existing estimates.

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