The Value of Oyster Reef Restoration

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Abstract
We analyze public preferences for oyster reef restoration, focusing on the U.S. Gulf Coast, one of the leading oyster-producing regions in the U.S. We administer a contingent-valuation survey to 4,690 households across the region using a web survey instrument employing videos to convey key information and follow-up questions to mitigate hypothetical bias. We test for status quo and scope effects, and compare a restricted sample of "high-quality" responses that are internally consistent against the full sample. We provide estimates of both household and aggregate willingness to pay and place these in the context on ongoing oyster restoration efforts and commercial landings. Results indicate that public support for oyster restoration, in terms of willingness to pay, exceeds current restoration expenditures and is consistent with the current market value of oysters. We also find that preferences are driven strongly by those who eat oysters as well as those who are saltwater anglers.

Keywords: contingent valuation, ecosystem service, Gulf of Mexico, nonmarket valuation, oyster, reef, restoration, Qualtrics, shellfish, survey

JEL Codes: C83, H41, Q22, Q25, Q51, Q57

Introduction

Oysters are considered a "keystone" species because they play a disproportionately important role in the natural environment and provide a multitude of ecosystem services (Fodrie et al. 2017; Grabowski et al. 2012; Humphries and La Peyre 2015; Kellogg et al. 2014; Petrolia et al. 2020; Smyth, Geraldi, and Piehler 2013). Despite the substantial global decline, with an estimated loss of 85% of oyster reefs (Beck et al. 2011), oysters continue to be an economically important species (MacKenzie 1996). In 2022, the Eastern Oyster was ranked the eighth-highest species nationally in terms of total landings value (NOAA Fisheries 2024). Efforts are ongoing to restore oyster reefs. La Peyre et al. (2014) documented 259 artificial inshore oyster reefs created for restoration purposes in the northern Gulf of Mexico region. NOAA's Restoration Atlas lists 403 projects across the U.S. listing oyster reef as the main habitat. Of these, 219 report project costs, totaling $83 million (NOAA 2024b). The Deepwater Horizon Project Tracker, which lists all projects funded as a result of the Deepwater Horizon oil spill, lists 100 projects totaling $286 million where oysters are the project resource (Deepwater Horizon Project Tracker 2024).

Although large public expenditures are being made to restore and maintain oyster reefs, there is limited knowledge regarding public preferences and valuation of oyster reef restoration. Several studies have monetized oysters and oyster reefs, but they use replacement/avoided cost and/or benefit transfer methods (Anderson and Plummer 2017; Barrett et al. 2022; DePiper, Lipton, and Lipcius 2017; Grabowski et al. 2011; Kasperski and Wieland 2009; Knoche et al. 2020; Kroeger and Guannel 2014; Lai, Irwin, and Zhang 2020; Miller 2009; Mykoniatis and Ready 2016; Parker and Bricker 2020; Petrolia, Walton, and Cebrian 2022; Stephenson and Shabman 2017) instead of directly valuing the targeted resource or project. The only study that directly targets public preferences and values is Interis and Petrolia (2016), who monetized oyster reefs in the context of a household survey examining how ecosystem service values associated with coastal restoration vary across locations and habitat types. Their survey featured a choice experiment with two contingent scenarios, each proposing the restoration of 1,500 acres of oyster reef in Alabama and Louisiana, respectively. They estimated average household WTP for restoration to be $393 among 1,448 Alabama respondents and $702 among 865 Louisiana respondents.

This study updates and expands upon the work of Interis and Petrolia (2016). We focus on the entire U.S. Gulf Coast, a region that has historically accounted for approximately half of all U.S. oyster landings. We administer a contingent-valuation survey regarding proposed oyster reef restoration efforts to 4,690 households across the five Gulf states (Alabama, Florida, Louisiana, Mississippi, and Texas). We utilize videos in the survey, which have been shown to make surveys easier for respondents to follow (Penn and Hu 2021). We utilize vote confidence follow-up responses to mitigate hypothetical bias, and test for status-quo and scope effects. We also construct an alternative "high-quality" subsample based on indicators that respondents are attending to the survey and responding logically. We provide estimates of both household and aggregate willingness to pay and place these in the context on ongoing oyster restoration efforts and commercial landings.

This study provides the most comprehensive analysis of public preferences and WTP estimates for oyster reef restoration to date, focusing on the Gulf Coast. Our estimates show that the average WTP for an oyster reef restoration project as described in our survey ranges from $32 to $83 per household, depending on the status-quo level of oyster landings. We also find that preferences are driven strongly by saltwater anglers and those who eat oysters. Our analyses indicate that the aggregated level of public support exceeds the current oyster restoration expenditures, and that the average WTP per pound of additional commercial landings is consistent with the current market value of oysters.

Conceptual Framework

Following Hanemann (1984), McFadden (1974), and Haab and McConnell (2002), the change in utility associated with oyster reef restoration is assumed to be a function of project cost (bid), the magnitude of change in oyster landings (scope), the status-quo level of landings, certain relevant household characteristics such as whether they eat oysters or are saltwater anglers, and other household characteristics such as income, education, age, etc. This change is represented by the function $U_j = \boldsymbol{\alpha}'\boldsymbol{x_j} + \beta \ln{(t_j)} + e_j$, where $\boldsymbol{x_j}$ is a vector of all of the aforementioned covariates for respondent j, excluding the bid, and $\boldsymbol{\alpha}$ is a vector of the associated coefficients; t_j is the bid offered to respondent j and β is the associated coefficient; and e_j is the error term. Following Duffield and Patterson (1991) and Whitehead et al. (2023), we include bid and income information using their natural logs. Median WTP is defined as $WTP_{Med} = e^{(-\alpha'\bar{x}/\beta)}$.

Contingent valuation is a method of recovering information about willingness to pay from direct questioning of households, that is, via stated preferences (Mitchell and Carson 1989). The method is used widely, in a variety of contexts. Petrolia et al. (2021) estimate its use in the literature since at least the mid-1970s, with forty to eighty contingent valuation studies published each year, many of which are featured in U.S. regulatory impact analyses to monetize impacts on the environment, health, and recreation. The method has seen major developments and controversies over time (Arrow et al. 1993; Carson 2012; Desvousges, Mathews, and Train 2015; Diamond and Hausman 1994; Haab et al. 2013, 2016; Hanemann 1994; Hausman 2012; Kling, Phaneuf, and Zhao 2012; Portney 1994), but remains an indispensable tool for economists working on valuation (Haab and McConnell 2002, Johnston et al. 2017).

Experimental Design

We began designing a contingent valuation survey in November 2021, and this process continued up until the full Qualtrics fielding in October 2022. After identifying the main objectives of the survey, we reviewed historical oyster landings data and consulted with oyster biologists and resource managers regarding the feasibility and credibility of the hypothetical improvements in reef restoration and landings being considered for the contingent scenarios. Because of the large differences in scope of oyster habitat across the Gulf States, it was determined that separate versions of the questionnaire would be needed, with a unique contingent scenario for each Gulf state.

Historically, Louisiana has been one of the dominant players in U.S. oyster production, and in recent years, Texas has been among the top producing states as well. Although historically Florida has been a major player in oyster production, levels in recent years have been more modest, and similar to those of Alabama. Mississippi has had the lowest production levels historically and has been particularly low in recent years. Appendix Figure B1 displays historical oyster landings in each Gulf state, 1950-2022 (NOAA Fisheries 2024).

Focus Groups and Pre-testing

We drafted some test material and questions for use in our first focus group, which took place on March 21, 2022, in Mobile, Alabama, and consisted of fifteen local residents. The focus group was facilitated by a professional moderator. We assessed the public's general knowledge of oysters, oyster reef restoration, we tested some photographs of oysters for use in the survey, we tested our survey videos, and we ascertained opinions on wording of key components. We then made further modifications and tested the next iteration in a second focus group that took place on April 21, 2022, in Gulfport, Mississippi. It also consisted of fifteen local residents, and the group was facilitated by the same professional moderator.

Additional edits were made, and a draft questionnaire was ready for pre-testing, running from September 30, 2022 to October 10, 2022 using a "snowball" convenience sample. Further edits were made, and a Qualtrics "soft launch" was fielded using Qualtrics panelists on October 10, 2022, resulting in 48-51 observations per state survey. After data and questionnaires were inspected, the full Qualtrics fielding occurred beginning October 12, 2022, with the last observation collected on October 18, 2022. The Qualtrics sample is discussed in more detail later.

Background Provided to Respondents

Respondents were shown a one-minute video introducing the survey. The first forty seconds stated that the survey is about oysters and oyster reefs, and that opinions are sought about reviving the oyster fishery. To establish consequentiality, they were told that their responses were important and would be shared with policymakers, resource managers, and other stakeholders, and that the survey would likely affect policies and taxes in the future. They were also told that a large number of residents in the state would be taking the survey, and that the survey was funded by NOAA and carried out by Mississippi State University. The last twenty seconds stated in very general terms that oysters provide benefits including food, habitat for other fish, water-quality improvements, shoreline protection (in some cases), and support the local economy and provide jobs. Respondents were then asked some ice-breaker questions including whether they eat oysters and if so, how often, and whether they hold a saltwater fishing license and if so, how often they go saltwater fishing.

Respondents were then shown a forty-second video describing the problem of decline in the number of oysters over time. Each video, which was state-specific, described how the decline was due primarily to the loss of oyster habitat and changes in water conditions (low oxygen and too low or too high salinity) caused by storms, droughts, floods, and other environmental factors. This was followed by an animated bar chart of the state's annual average oyster harvest by decade since the 1950s. Respondents were then asked whether they felt like they understood the problem (Yes, No, Not sure) and how much they cared about the issue (a lot, somewhat, don't care at all). Next, they were asked what benefits from oysters and oyster reefs are most important to them and asked to rank them using a drag-and-drop feature of the benefits mentioned previously in the video (food, better fishing, better water quality, shoreline protection, better fish habitat, jobs).

Contingent Scenario

There are inherent differences in the scale of oyster production across the five states, and the proposed increases used in the contingent scenarios had to be consistent with the status quo, believable, and meaningful to respondents. Thus, the proposed increases for states with low status-quo harvests were necessarily lower than those for states with high status-quo harvests.

Louisiana and Texas have both the highest status-quo levels of landings and the largest proposed increases: one million pounds (low scenario) and two million pounds (high scenario). Proposed increases for Alabama, Florida, and Mississippi were set at 250,000 (low scenario) and

1 million pounds (high scenario). The design allowed for the isolation of both status-quo / state effects and scope effects. Within states, status-quo levels are fixed, but there are two proposed increases; thus, within each state, we can test for scope effects. Across states, status-quo levels vary but proposed increases are fixed for particular subsets of observations. For example, Alabama, Florida, and Mississippi have a 250,000-pound increase in common. Thus, scope is fixed among these observations, and any differences can be attributed to status-quo / state effects. The same holds for Louisiana and Texas, who share the two-million-pound increase, and all five states share the one-million-pound increase.

Commercial landings were used as the project outcome metric for two reasons: 1) it is a metric recognized by both the scientific community and the public, and 2) it is the only consistently reported oyster metric across both time and space. Recognizing the weaknesses, we assume a direct relationship between oyster habitat restoration (what is being proposed) and oyster landings (the metric of project success). Although such a relationship may not be perfect, it is the best approach for our purpose.

Respondents were shown a 1.25-minute video about the proposed oyster restoration project, described as follows (Texas example shown):

> *Suppose there was a project that would get more oysters growing again in Texas's waters. This project would rely on strategies identified by scientists and resource managers, including: rebuilding old oyster reefs and building new ones, oyster farming, and using new technologies to identify the best locations to build reefs.*

They were then told about the expected impact of the project, described as follows, while showing an animated bar chart (Figure 1, Louisiana example shown). Respondents were then asked whether they felt like they understood how the project would address the problem (Yes, No, Not sure).

Payment Vehicle

The payment vehicle was described to respondents as follows (Alabama example shown):

> *This project would require additional state funding. Funds would likely come from multiple sources, but at least part of the funds would come from taxpaying households like yours. Suppose that each taxpaying household in Alabama would need to make a one-time payment of $[X] to fund the project. The payment would be fixed at the same amount for every taxpaying household. The payment would be collected on your 2023 state income tax return.*

Because Florida and Texas do not have income taxes, their payment vehicles were slightly different (Florida example shown):

> *Suppose a special fund was set up just for this purpose, and a one-time fee of $[X] was collected from each Florida household, including yours. Each county would arrange to collect the fees from their households and deposit them into the special fund in 2023.*

Respondents were then asked if they feel like they understand how the project would be funded (Yes, No, Not sure). We then showed them a review/reminder page, stating (Mississippi example shown):

> *Suppose a vote were held today on whether Mississippi should carry out this project. We would like to know how you would vote.* [Consequentiality reminder:] *Remember that the results of this survey will be shared with Mississippi policy makers, resource*

managers, and other stakeholders. But before you vote, let's review what the project would do and what it would cost.

They were then shown the with- and without-project harvest impacts and timeline as shown previously and given the option to return to and review the background information.

The Vote

We used the referendum-style elicitation method, which was recommended by Arrow et al. (1993) and confirmed by Johnston et al. (2017) as the standard in cases of non-use values for public goods where majority vote is a plausible decision mechanism. Respondents were then asked to cast a vote, described as follows (Mississippi example shown):

Suppose that each taxpaying household in Mississippi would need to make a one-time payment of $[X] to fund the project. The payment would be fixed at the same amount for every taxpaying household. The payment would be collected on your 2023 state income tax return. Given the expected benefits and costs, would you vote FOR or AGAINST the project? (I would vote FOR the project, I would vote AGAINST the project)

After the vote question, we included a follow-up question asking those who voted for the project how sure they are about being willing to pay the offered bid on a scale of 1 (Not at all sure) to 10 (Very sure). Penn and Hu (2018; 2023) provide evidence that adjusting votes using follow-up confidence information can reduce or even eliminate hypothetical bias. Also, as a consistency check discussed in more detail later, we asked those who voted against the project to indicate the highest one-time payment at which they would vote for the project.

Other Supporting Questions

In addition to including the above text to establish consequentiality, we asked respondents to indicate how confident they were that this survey would influence what is actually done, on a scale of 1 (Not at all confident) to 10 (Very confident). We then asked a series of questions to collect demographic information. The full survey (Mississippi version) can be accessed here: *https://msstate.co1.qualtrics.com/jfe/form/SV_eVFd8YnoaAiQxue.*

Data

We contracted with Qualtrics to obtain a sample of responses to our survey. We requested a stratified sample, consisting of 1,000 completed responses from each Gulf state, though Qualtrics indicated that only 750 were feasible from Mississippi. Figure 2 displays the geographic distribution of respondents, categorized as "coastal" and "non-coastal" according to NOAA's definition (NOAA 2024a). Qualtrics uses a variety of sample recruiting methods, but ultimately their method is a form of non-probability "convenience" sampling, meaning that the sample may not be representative of the population of interest. To address this shortcoming in some way, we calculate sampling weights to provide alternative sets of results that may be considered more appropriate for inference to the population of interest. These weights are discussed later.

Sample Quality Control

We programmed the survey in the Qualtrics platform to randomly assign each respondent to a treatment-scale-bid combination within the questionnaire version particular to their state of residence. Table 1 reports the target breakdown of the sample by treatment and scale. We implemented a series of quality-control measures, summarized in Appendix A. Overall, we classified 159 observations as potentially problematic and excluded them, leaving 5,952 observations. Of those, we classified 1,262 observations as incomplete, leaving 4,690 complete observations. When then further classified observations according to some additional criteria to identify what we call our "high-quality" sample. The remainder of this section provides an overview of these criteria and data.

An implicit assumption about the responses to a survey is that respondents understand what they are being asked about. We included three questions in the survey asking respondents whether they 1) understood the problem, 2) understood the proposed project that would address the problem, and 3) understood how the project would be funded. Respondents were given the option to respond "Yes", "No", or "Not sure". We identified 413 respondents who responded "No" to at least one of these questions. Another key assumption is that respondents perceive the survey as consequential, that is, they perceive that the survey will have some real impact on the likelihood of the proposed project being implemented and/or of them being made to pay for it. Respondents have an incentive to answer truthfully to a consequential survey, but there is not necessarily any incentive to answer truthfully to an inconsequential one. We asked respondents how confident they were that this survey would influence what is actually done and identified an additional 280 respondents who responded with the lowest possible confidence on a scale from one to ten: "1 (Not at all confident)". Finally, we inspected responses for consistency of preferences. Early in the survey, we asked respondents how much they cared about the issue of oysters in their state. We identified an additional 74 respondents who either: 1) indicated that they didn't care at all about the issue but still indicated a positive willingness to pay for the project, or 2) voted against the project at the offered bid, but when asked in a follow-up how much money they *would* be willing to pay, indicated an amount greater than the original bid. All told, we identified 767 respondents that we classify as “low-quality completes”, leaving 3,923 that we classify as “high-quality” completes. We present results for both the full sample of complete observations, which we call the “full sample” (N = 4,690) and this more limited subsample, which we call our “high-quality sample” (N = 3,923).

Sampling Weights

Sampling weights can improve inference in non-probability samples by approximating the probability of being sampled. The approach works by weighting observations to compensate for differences between the population and sample (Penn, Petrolia, and Fannin 2023). We start with population data taken from the U.S. Census for the five Gulf states, specifically population totals regarding total population 18 and older, sex, age categories, educational attainment, and race. All data except race are taken from the 2022 American Community Survey 1-Year Estimates (U.S. Census Bureau 2022); race data are taken from the 2020 Census Demographic and Housing Characteristics File (U.S. Census Bureau 2020). Appendix Table B1 contains the original population totals taken from the Census files. The Total column to the far right contains the final group totals used for weighting. Race data included the under-18 population, so it was necessary to scale these down proportionally to match the 18+ population. Sampling weights were constructed using Stata’s “svycal” routine, which generates calibration-adjusted weights (StataCorp 2023). We constructed weights using a multiplicative distance measure method (i.e., raking) based on the metrics in Table B1. Appendix Table B2 reports the population and sample shares and the mean weight value for each demographic subgroup. We construct different weights for the full sample and the “high-quality” subsample.

Econometric Model

We use a probit to model the estimate the effects of covariates on the probability of a Yes vote to the proposed restoration and increase in oyster landings. The dependent variable is a binary indicator = 1 where a Yes vote is observed, and = 0 otherwise. The log-likelihood of the probit model is $LL = \sum_{Yes} w_j \ln\{\Phi(\boldsymbol{\alpha}'\boldsymbol{x_j} + \beta\ln(t_j))\} + \sum_{No} w_j \ln\{1 - \Phi(\boldsymbol{\alpha}'\boldsymbol{x_j} + \beta\ln(t_j))\}$, where w_j are weights and Φ is the cumulative normal. Table 2 reports the variables included in the regression and their definitions. Vote data used are based on the vote confidence threshold of six, thus, any No votes with vote confidence less than six were re-coded to No. In other words, we require all Yes votes to be associated with a stated level of confidence on the upper half of the scale. The literature is mixed in terms of the best threshold to use (Penn and Hu 2018; 2023). Loomis and Ekstrand (1998) and Whitehead and Cherry (2007) use a threshold of seven, while Champ and Bishop (2001) and Petrolia et al. (2019) use a threshold of eight. We provide results based on the original unadjusted vote data in Appendix Table B3.

Model specification testing is done regarding state / status-quo and scope effects. By "status-quo effects" we mean effects attributable to differences in the status-quo landings levels across states (with scope levels fixed). By "scope effects", we mean effects attributable to differences in the proposed increases in landings both within and across states (with status-quo levels fixed). For status-quo effects, a probit model containing state dummies is estimated over observations from states with the same scope level. The null hypothesis is that the coefficient for one state is not significantly different from that of another state within the same scope group. For scope effects, a probit model containing a scope dummy was estimated over observations for each state. The null hypothesis is that the coefficient for the scope dummy is not significantly different. We use post-estimation Wald tests, that is, χ^2 tests of parameter equivalence, to test each null. Based on these findings, we then conduct additional tests with pooled scope effects. First, we conduct a Chow test (χ^2 likelihood ratio test of nested models), whose null hypothesis is that a model with state dummies and pooled scope is not significantly different from a model with state-scope dummies. We then conducted Wald tests of coefficient equivalence across states for the pooled model (all scope levels) with state dummies.

Results

Votes

Figure 3 displays the distribution of vote proportions by bid and vote confidence threshold. Overall and as expected, the share of Yes votes declines with bid. After the vote question, we included a follow-up question asking those who voted Yes how sure they are about being willing to pay the offered bid on a scale of 1 (Not at all sure) to 10 (Very sure). We re-classified any Yes vote with a confidence response less than a particular threshold as a No vote. Figure 3 also displays how a gradient of confidence adjustments affects the proportion of Yes votes at each offered bid. At the lowest offered bid of \$25 (one-time tax), the proportion of Yes votes was adjusted down from 80% at one extreme (under the original data) to 28% at the other extreme (under the strictest threshold of 10). At the maximum bid of \$500, it was adjusted down from 57% to 7%. Overall, the total proportion of Yes votes across all bids was adjusted down from 70% to 31%.

Figure 4 reports the proportion of votes by state and scope, using the original unadjusted votes and adjusted using a threshold = 6. Differences across states and scope scenarios are small, with proportions ranging between 0.69 and 0.74 under the original vote data. Using the vote threshold reduces vote proportions to below 0.50, ranging from 0.39 to 0.48.

Econometric Results

Table 3 provides a summary of model specification test results; see Table B4 in Appendix B for details. For status-quo effects, we found no significant differences for the 25,000 pounds-scope group and the two-million pounds-scope group. However, we found significant differences for the one-million pounds-scope group. Specifically, we found that Alabama (AL) is significantly different from Florida (FL) and Texas (TX), and that Mississippi (MS) and Louisiana (LA) are significantly different from Texas, with the magnitude of state dummies in the order shown in the table. For scope effects within each state, we found no significant differences. Based on these findings, we conducted additional tests with pooled scope effects. We could not reject the null hypothesis that a model with state dummies and pooled scope is not significantly different from a model with state-scope dummies, indicating that scope scenarios can be pooled within states. We then conducted Wald tests of coefficient equivalence across states for the pooled model (all scope levels) with state dummies. We found that Alabama is significantly different from Louisiana, Florida, and Texas; that Mississippi is significantly different from Florida and Texas; and that Florida and Louisiana are significantly different from Texas.

Results indicate strongly that there were no scope effects. However, while not aligning perfectly, results indicate that states with lower status-quo levels of landings (Alabama and Mississippi) tend to have higher likelihood of Yes votes, while states with higher status-quo levels of landings (Louisiana, Texas) tend to have lower likelihood of Yes votes. Given this finding, we then compared the model with state dummies to an alternative model that includes a continuous status-quo level variable rather than state dummies. The status-quo variable was highly significant and negative, indicating that the probability of a Yes vote declines as the status-quo level of landings increases, i.e., as one moves from a state of relative scarcity to one of abundance. Although the model with state dummies has slightly better AIC and BIC scores, we prefer the model with the single continuous status-quo level variable, as it makes clear the relationship between status-quo landings levels and likelihood of Yes vote. Thus, we adopt this latter model for the main results but provide the results with state dummies in Appendix Table B5.

Table 4 reports the main regression results. We report four sets of results, based on sample (full versus "high-quality" subsample) and sampling weights (unweighted versus weighted). We find general consistency across models. Only the variables black and age, and the constant, differ significantly across models. Black is significant in both unweighted models while not significant in the weighted models. Age is significant in only the weighted "high-quality" subsample model. The constant term is significant in the full sample models only, though the sign is the same across the board. Overall, we do not find any significant differences between the full sample and "high-quality" subsample results, nor between the unweighted and weighted results.

As expected, ln(bid) is negative and significant, and ln(income) is positive and significant. Consistent with the results discussed earlier, ln(status-quo) is negative and significant, indicating that the likelihood of a Yes vote is higher in states with a lower status-quo level of oyster landings. We also find that those who eat oysters and those who hold a saltwater fishing license are significantly more likely to vote Yes. The coastal variable is not significant, likely because status-quo landings, income, eating oysters, and holding a saltwater license, better explain preferences. Among the demographic indicators, those with more formal education are more likely to vote Yes, whereas females and blacks are less likely to vote Yes.

Household Willingness to Pay

Table 5 contains the median maximum WTP (and 95% confidence intervals) as a function of status-quo landings level, based on the weighted full sample and a vote confidence threshold of six. Standard errors are estimated using the Delta Method (Cameron 1991; Bliemer and Rose 2013). We believe that the weighted results are more appropriate for inference and policy analysis. Because state-level welfare estimates are of particular importance in this study, results are provided both for the model with the continuous status-quo variable (from Table 4) and the model with individual state dummies (from Table B5).

Based on the model containing the continuous status-quo variable, WTP ranges from a high of \$83 per household (95% confidence interval \$30-136) at the lowest status-quo level (Mississippi), to a low of \$32 per household (95% confidence interval \$14-50) at the highest status-quo level (Louisiana). Although the 95% confidence intervals around these estimates overlap, pair-wise tests of the means ($z = \frac{(WTP_1 - WTP_2)}{\sqrt{V(WTP_1)+V(WTP_2)}} \sim \chi^2$) indicate that Mississippi's WTP differs significantly ($p < 0.10$) from Texas and Louisiana.

These estimates vary only slightly based on the model with individual state dummies, with Mississippi slightly lower in the state dummy model, and AL and LA slightly higher. WTP ranges from a low of \$31 per household (95% confidence interval \$11-50) for Texas to a high of \$85 per household (95% confidence interval \$28-142) for Alabama. Here, pairwise tests indicate that only Florida differs from Texas ($p < 0.10$), though all confidence intervals overlap. Figure 5 displays these same results visually and shows how well the continuous function tracks the state dummies. The solid and dashed lines represent WTP based on the model containing the continuous ln(status-quo) variable, while the bars and whiskers represent WTP based on the model containing individual state dummies.

As the regression results indicate, the likelihood of support for the proposed project was strongly associated with eating oysters and saltwater fishing. To elaborate on how these factors affect WTP, Figure 6 displays estimated median maximum WTP per household by affinity group. Estimated WTP is $20 per household that neither eats oysters nor has a saltwater angler. It increases to $44 for saltwater anglers, increases to $108 for oyster eaters that are not saltwater anglers, and reaches a maximum of $238 for those that are both oyster eaters and saltwater anglers.

As a robustness check, we present a variety of alternative WTP estimates. Figure 7 displays estimated median maximum WTP per household using the sample means as a function of vote confidence threshold, as well as estimates based on the Turnbull non-parametric method (Haab and McConnell 2002). At lower vote confidence thresholds, the probit models yield much higher welfare estimates, exceeding $1,000 per household. As the threshold approaches four, model estimates begin to converge around $200 per household. At higher thresholds, there is a moderate gap between probit and Turnbull models of about $60-$100. Overall, the "high-quality" subsample yields slightly higher WTP estimates than the full sample, and the weighted sample yields slightly higher WTP estimates than the unweighted sample. Additionally, in comparison to Figure 5, Appendix Figure B2 provides analogous results based on the weighted "high-quality" subsample. Regression results and Turnbull calculations of all 80 alternative estimates are available from the authors upon request.

Aggregate Willingness to Pay

What is the aggregate willingness to pay for oyster restoration? Table 6 summarizes the calculations. Assuming that each respondent represents its entire household, we need the number of households in each Gulf state, which we take from the U.S. Census (2024). Next, it is necessary to account for non-respondents. The concept of non-response does not apply to our non-probability Qualtrics sample, but if we interpret incompletes as respondents that were not interested or lost interest in the survey, then they can serve as a proxy for non-response, and the interpretation of lack of interest implies a WTP of zero. Appendix Table A1 reports 1,262 incompletes out of 5,952 respondents, implying a 21% non-completion rate. We multiply the number of households in each state by this value to arrive at the adjusted number of households, that is, those with positive WTP. We then multiply these values by the estimated WTP per household to arrive at aggregate WTP. Here we use the WTP estimates reported in Table 5 for the status-quo model. We estimate aggregate WTP of $835 million across the five states. But how to interpret this estimate? Is it a large number or a small number? We can compare these estimates to the existing level of expenditures on oyster restoration in the Gulf region. Total expenditures of oyster-related projects reported by NOAA and the Deepwater Horizon Project Tracker add up to $369 million. Thus our estimates indicate that the value of the benefits associated with oyster restoration is nearly three times as large as existing costs, implying that the public supports both existing restoration efforts as well as additional future efforts. Even if we base the estimate on the lower bounds of the 95% confidence intervals, aggregate WTP would be $462 million, still exceeding the $369 million figure.

To provide some additional context, we also express the estimates in terms of dollars per pound of increased landings per year. Here we use the mid-point of the proposed increase used in each state and assume a ten-year project life, which is what respondents were told. Under these assumptions, we find WTP to range between $7 and $23 per pound of increased landings per year. For comparison, the average implied dockside oyster price (total dollars divided by total pounds) across the five Gulf states over the past ten years (2013-2022) ranged between $4 and $10 per pound (NOAA Fisheries 2024). Considering that households generally pay retail for oysters, which can be two or three times the dockside price, the estimated WTP is in the same range as the market value of oysters.

Conclusion

We provide the most comprehensive analysis of public preferences and WTP estimates for oyster reef restoration to date, focusing on the Gulf Coast, one of the leading oyster-producing regions in the U.S. Our results indicate that there exists public support for oyster restoration and that the average level of support, in terms of willingness to pay, exceeds current restoration expenditures and is consistent with the current market value of oysters. Thus, our findings indicate that the benefits associated with oyster reef restoration exceed current expenditures plus additional restoration efforts in the future. We also find that preferences are driven strongly by those who eat oysters as well as those who are saltwater anglers.

While we are somewhat concerned about the lack of scope effects in the survey, such a lack does not invalidate a contingent-valuation survey (Whitehead 2016), because other factors can be at play, such as diminishing marginal utility, substitution effects, or behavioral anomalies. Our results provide strong evidence of diminishing marginal utility at play, as we find that the likelihood of a Yes vote decreases significantly as the status-quo landings level increases. Specifically, we find that Alabama and Mississippi, the two states with the lowest status-quo landings levels have the highest WTP, whereas Texas, which has the second-highest status-quo has the lowest. These findings are not perfect, however, as we find that Louisiana's WTP is higher than that of Texas, and Florida's WTP is less than Louisiana. The former can likely be explained by the fact that oysters have historically been much more important economically and culturally in Louisiana. Louisiana historically accounts for more than half of all Gulf oyster landings and about a third of U.S. oyster landings.

The only other estimates of WTP for oyster restoration in the literature are those of Interis and Petrolia (2016), who estimated WTP for restoration to be $393 per Alabama household and $702 per Louisiana household. Our estimates are substantially lower than theirs. There are a few reasons why our estimates are a departure from theirs. The main reason is that, although they do not report the specific proportions of Yes votes, they did not employ a vote confidence adjustment. As Figure 7 shows, had we used the original, unadjusted vote information, our estimated WTP based on the probit models would have exceeded $1000 per household, more consistent with, but still exceeding their Louisiana estimate. Our unadjusted WTP based on the non-parametric Turnbull model is about $350, which is more in line with their Alabama estimate. Second, their estimates were obtained via choice experiment, and the literature has demonstrated that the elicitation method can affect welfare estimates (Petrolia, Interis, and Hwang 2018; Petrolia, Interis, and Hwang 2014). Third, their survey was fielded in 2013, not long after the 2010 Deepwater Horizon oil spill, which could have also influenced preferences.

We wish to end by pointing out a couple of things. First, we wish to remind the reader that our estimates are based on a non-probability-based sample, although we use sample weighting to mitigate this weakness. Second, as oyster landings are affected by a variety of factors that contain high randomness (e.g., temperature, salinity levels, dissolved oxygen levels), the projected outcome could involve relatively large uncertainty, which is not addressed in the current analysis. The uncertainty in outcomes may also be a factor contributing to the lack of scope effect in this study, as large uncertainty may make the precise outcome levels less relevant.

In future work, we plan to investigate how uncertainties in projected outcomes affect WTP estimates and the scope effect.

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Table 1. Survey versions and contingent scenarios.

State	Format	Status-Quo (lbs)	Proposed Increase in Annual Commercial Landings, in pounds		Target Sample Size	
			Low Scenario	High Scenario	Low Scenario	High Scenario
Alabama	Certain	222,000	250,000	1,000,000	500	500
Louisiana	Certain	3,900,000	1,000,000	2,000,000	500	500
Florida	Certain	291,000	250,000	1,000,000	500	500
Mississippi	Certain	25,000	250,000	1,000,000	375	375
Texas	Certain	2,600,000	1,000,000	2,000,000	500	500

Table 2. Regression variable definitions and summary statistics.

Variable Name	Variable Description	Variable Means: Full Sample (N = 4,690) Unweighted Mean	Std. err.	Weighted Mean	Std. err.	"High-Quality" Subsample (N = 3,923) Unweighted Mean	Std. err.	Weighted Mean	Std. err.
vote	= 1 if voted in favor of proposed restoration with vote confidence ≥ 6, = 0 otherwise	0.439	0.007	0.427	0.012	0.497	0.008	0.485	0.014
bid	offered bid ($25, $50, $100, $250, $500)	185.528	2.570	184.743	4.283	180.799	2.785	177.058	4.525
status-quo	status-quo expected annual commercial landings, in pounds	1,509,236	23,036	1,563,985	29,625	1,535,020	25,245	1,563,985	33,207
income	income, using mid-point of reported income category	53,435	656	54,595	1,109	55,577	718	55,736	1,226
eats oysters	= 1 if eats oysters at least occasionally, = 0 otherwise	0.584	0.007	0.586	0.013	0.621	0.008	0.620	0.014
saltwater	= 1 if holds saltwater fishing license, = 0 otherwise	0.156	0.005	0.162	0.009	0.163	0.006	0.165	0.010
coastal	= 1 if lives in NOAA-defined coastal county, = 0 otherwise	0.504	0.007	0.579	0.012	0.509	0.008	0.575	0.014
no children	= 1 if no children living in HH, = 0 otherwise	0.604	0.007	0.662	0.012	0.596	0.008	0.656	0.013
education	some school =1, high school =2, some college =3, assoc. degree =4, bachelor's =5, grad/prof degree =6	1.977	0.011	1.902	0.022	2.023	0.012	1.902	0.024
female	= 1 if female, = 0 otherwise	0.719	0.007	0.510	0.013	0.719	0.007	0.510	0.014
black	= 1 if reported race as black, = 0 otherwise	0.222	0.006	0.164	0.008	0.199	0.006	0.164	0.009
other race	= 1 if race other than white or black, = 0 otherwise	0.030	0.003	0.079	0.009	0.030	0.003	0.079	0.009
age	age, in years	44.894	0.234	47.754	0.525	44.984	0.254	47.609	0.591
republican	= 1 if Republican, = 0 otherwise	0.413	0.007	0.359	0.012	0.420	0.008	0.358	0.013

Table 3. Status-quo and scope effect test results. Superscripts indicate statistically equivalent groups. See Table B4 in Appendix B for details.

Subsamples	Test Result
Status-Quo Effects (Scope Fixed)	
AL, FL, MS (scope = 25,000 lbs)	No Sig. Diff.
AL, FL, LA, MS, TX (scope = 1M lbs)	$MS^{a} > AL^{a,b} > LA^{a,b} > FL^{b,c} > TX^{c}$
LA, TX (scope = 2M lbs)	No Sig. Diff.
Scope Effects (Status-Quo Fixed)	
AL	No Sig. Diff.
FL	No Sig. Diff.
LA	No Sig. Diff.
MS	No Sig. Diff.
TX	No Sig. Diff.
Additional Tests	
All observations; state-scenario dummies vs. state dummies with pooled scope	No Sig. Diff. (Chow Test)
All observations; state dummies with pooled scope	$AL^{a} > MS^{a,b} > LA^{b,c} > FL^{c} > TX^{d}$

Table 4. Probit regression results of confidence-adjusted (≥ 6) vote.

	Full Sample (N = 4,690)						"High-Quality" Subsample (N = 3,923)					
	Unweighted			Weighted			Unweighted			Weighted		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
ln(bid)	-0.294	***	-0.018	-0.217	***	-0.031	-0.309	***	-0.02	-0.238	***	-0.033
ln(status-quo)	-0.039	***	-0.011	-0.041	**	-0.02	-0.043	***	-0.012	-0.047	**	-0.021
ln(income)	0.195	***	-0.024	0.213	***	-0.043	0.183	***	-0.026	0.191	***	-0.049
eats oysters	0.498	***	-0.041	0.432	***	-0.072	0.439	***	-0.044	0.371	***	-0.078
saltwater	0.233	***	-0.055	0.28	***	-0.091	0.221	***	-0.059	0.326	***	-0.1
coastal	0.01		-0.04	-0.029		-0.065	0.018		-0.043	-0.048		-0.072
no children	-0.016		-0.042	0.003		-0.077	-0.024		-0.046	-0.019		-0.087
education	0.127	***	-0.028	0.152	***	-0.047	0.089	***	-0.03	0.106	**	-0.049
female	-0.186	***	-0.044	-0.151	**	-0.069	-0.2	***	-0.048	-0.138	*	-0.075
black	-0.191	***	-0.051	-0.052		-0.081	-0.12	**	-0.056	0.017		-0.093
other race	-0.084		-0.112	-0.194		-0.152	-0.039		-0.123	-0.083		-0.162
age	-0.001		-0.001	0.001		-0.002	0.001		-0.001	0.005	*	-0.003
republican	-0.056		-0.042	0.013		-0.072	-0.068		-0.045	-0.006		-0.079
constant	-0.66	**	-0.29	-1.403	***	-0.492	-0.26		-0.318	-0.895		-0.555
LL	-2858.848						-2450.166					

Note: ***, **, and * are statistically significant at 1%, 5%, 10%, respectively.

Table 5. Median Maximum WTP per household by status-quo landings levels. 95% confidence intervals shown in parentheses.

Status-Quo Landings Level	State	Status-Quo Model		State Dummy Model	
25,000	MS	$83	($30,$136)	$69	($24,$113)
222,000	AL	$55	($34,$76)	$85	($28,$142)
291,000	FL	$53	($33,$72)	$51	($18,$84)
2,600,000	TX	$35	($17,$52)	$31	($11,$50)
3,900,000	LA	$32	($14,$50)	$56	($22,$89)

Table 6. Estimated Aggregate WTP.

	no. households	adj. no. HHs	median HH WTP	aggr. WTP	annual landings increase (lbs)	$ / lb / yr
AL	1,933,150	1,523,265	$55	$84,160,642	625,000	$13
FL	8,353,441	6,582,264	$53	$345,617,773	1,500,000	$23
LA	1,765,264	1,390,976	$32	$44,821,385	625,000	$7
MS	1,121,269	883,527	$83	$73,617,057	625,000	$12
TX	10,490,553	8,266,246	$35	$287,476,321	1,500,000	$19
Total	23,663,677	18,646,278		$835,693,178		

Figure 1. Contingent scenario information shown to respondents as a review prior to vote. Louisiana example shown.

<u>Without</u> the project, oyster harvest in Louisiana is expected to be around ***3.9 million pounds*** *per year during the next 10 years, as shown below.*

<u>With</u> the project, Louisiana's oyster harvest is expected to increase by ***1.0 million pounds****, for a total of* ***4.9 million pounds*** *per year.*

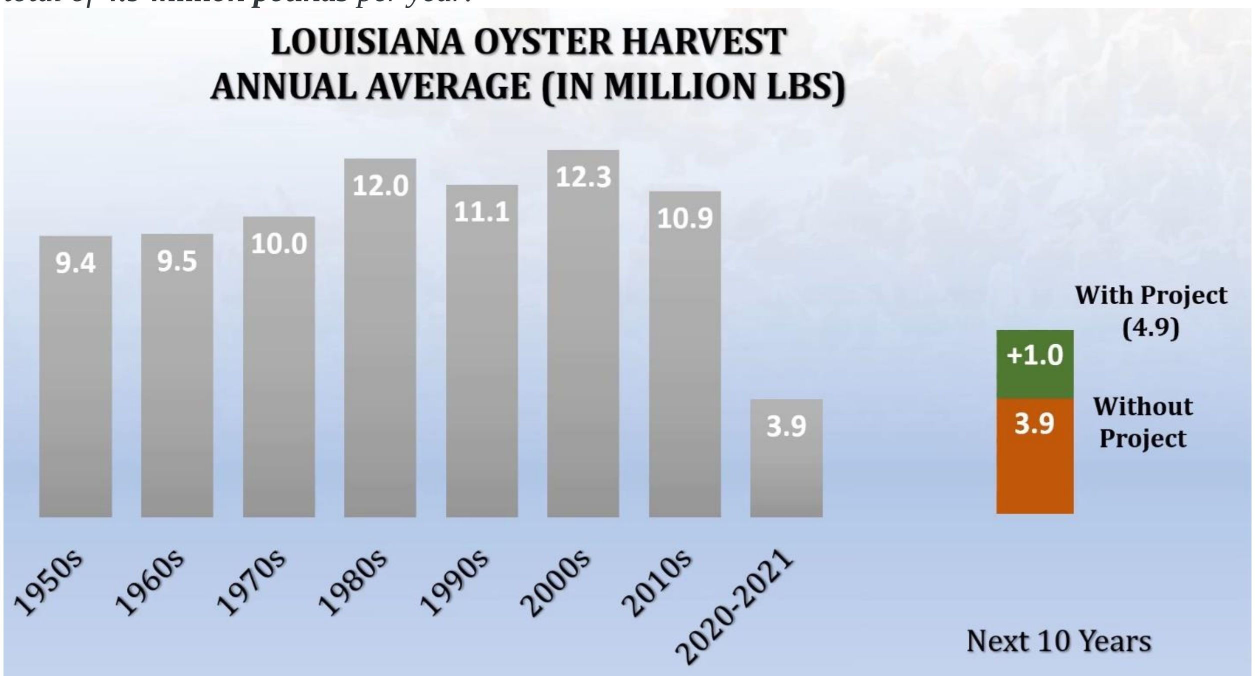


Figure 2. Geographic distribution of respondents. Blue observations are classified as "coastal" and red observations are classified as "non-coastal" according to NOAA's (2024a) definition.

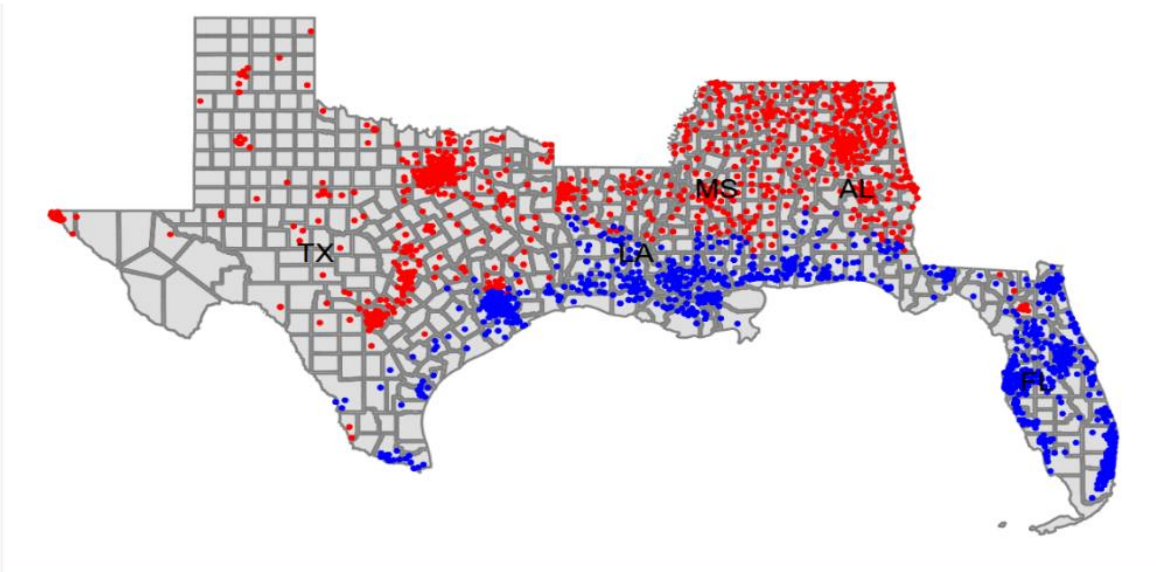


Figure 3. Proportion of Yes Votes by Offered Bid and Vote Confidence Threshold T.

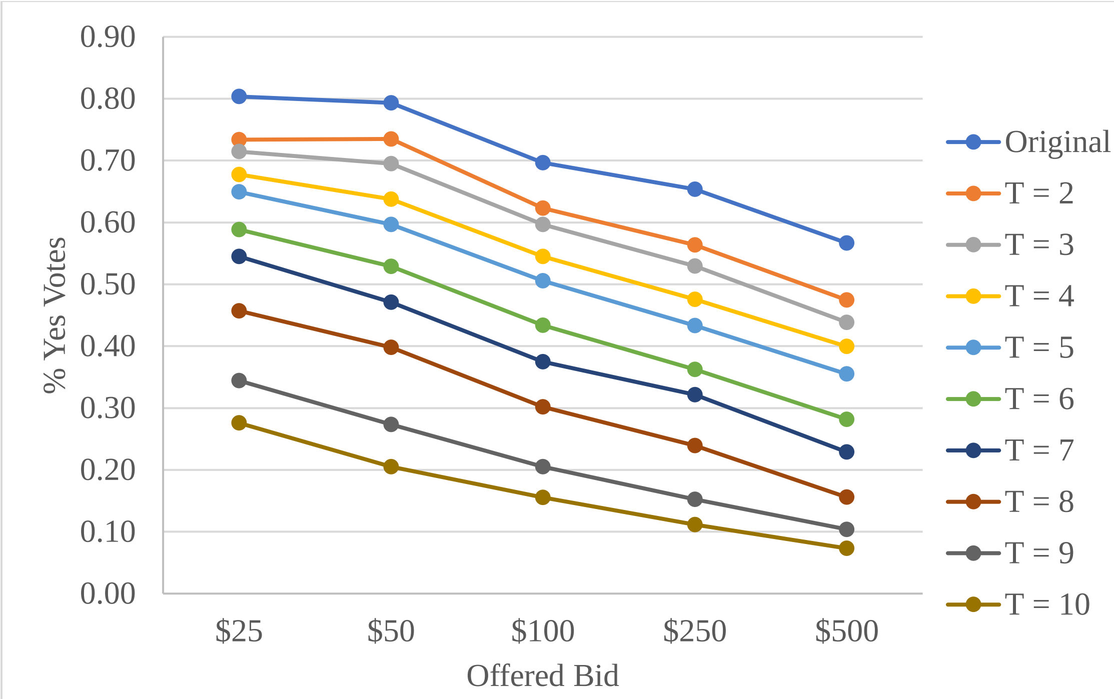


Figure 4. Proportion of Yes Votes by State and Scope Scenario.

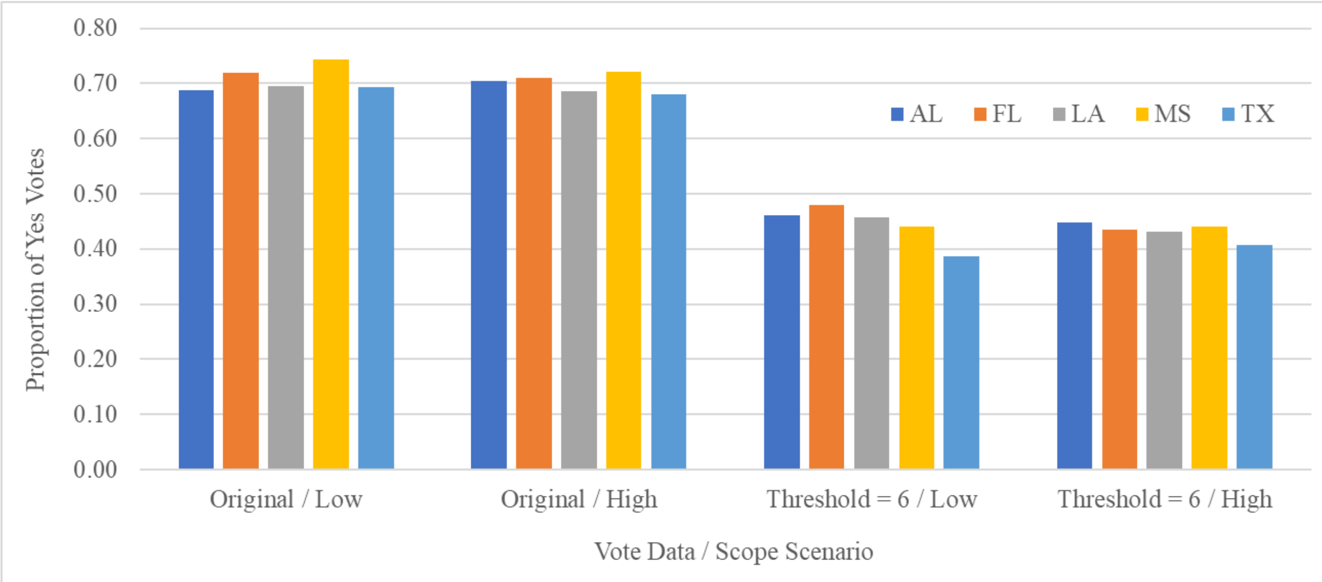


Figure 5. Median Maximum Willingness to Pay by model, based on full sample: (discrete state dummies (bars and whiskers) versus continuous status-quo variable (solid and dashed lines).

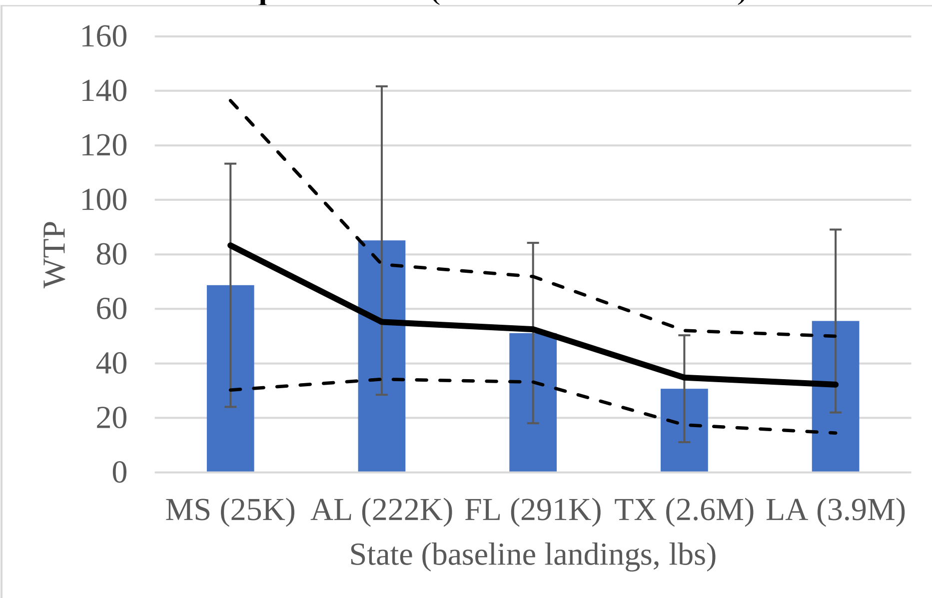


Figure 6. Median Maximum Willingness to Pay by Affinity Group (95% confidence interval shown with whiskers).

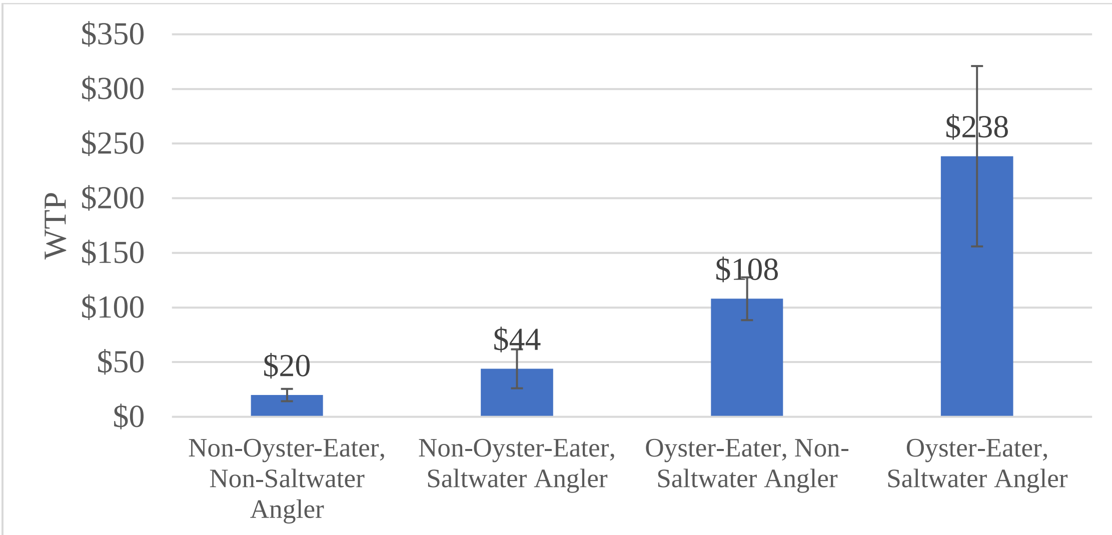
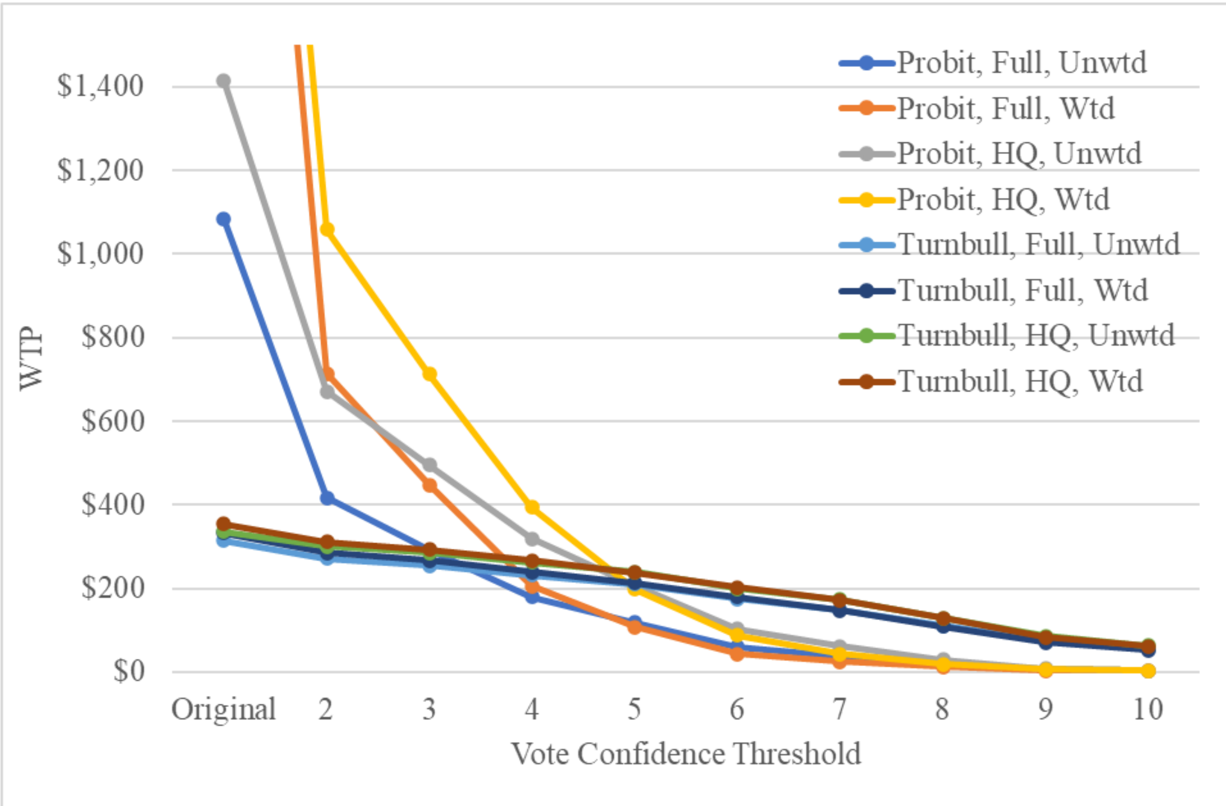


Figure 7. Median Maximum Willingness to Pay by Model (Probit, Turnbull), Sample (Full, High-Quality (HQ)), Sample Weighting (Unweighted, Weighted), and Vote Confidence Threshold



APPENDIX A

Qualtrics Sample Quality Control

Normally, Qualtrics filters out "bad" responses (incompletes, speeders, bots, etc.), but we requested they provide all responses to us. Qualtrics inserted an oath-style question into the beginning of the survey, asking respondents to commit to providing thoughtful and honest answers, with response options "I will provide my best answers.", "I will not provide my best answers.", and "I can't promise either way." Qualtrics also uses Google's free reCAPTCHA service, which helps identify "bots" and other malicious software. Qualtrics provided their own set of flag codes to aid in sorting through responses, which we call here "QCodes" including:

- QCode 1: good responses (N = 6,628)
- QCode 2: screened out responses: indicated residence in a state other than the assigned survey or did not pass the Qualtrics-inserted oath question (they responded something other than "I will provide my best answers.") (N = 575)
- QCode 3: responses over purchased quota that were terminated early (N = 260)
- QCode 4: responses that failed quality check: either a reCAPTCHA score ≤ 0.4 that indicates a bot or completed survey in less than half the median completion time. (N = 703)
- QCode 5: Other responses flagged for bad zip codes, bad open-ended responses (nonsense, vulgarity, etc.), or some other reason not identifiable by us (N = 153)
- QCode = Blank: Incompletes (N = 1,114)

Appendix Table A1 reports the breakdown of the full set of responses received through all of the various drops, down to the final sample. We first dropped observations that indicated a state of residence different from the assigned survey or did not provide a state of residence. We then drop observations that failed the Qualtrics oath. At this point, all QCode = 2 observations were dropped. We then dropped observations with a reCAPTCHA score ≤ 0.4.

We found the QCode = 5 to be somewhat unreliable. Although some observations with invalid zip codes (e.g., 11111), and vulgarity in the final open comments were detected, we also found many observations with no apparent problem. For example, one observation was of a resident from the correct state who had a valid zip code and wrote in the comment box "I really liked this one! Very informative". Additionally, some of the ones with vulgarity nevertheless appeared valid. Others used "text" abbreviations like "yw" ("you're welcome") or wrote simply "Thank you" or "No comment". Other comments were nonsense, but we are not convinced that this necessarily indicates an invalid response. Some respondents may have thought that they could not leave it blank. We decided to ignore QCode = 5. Overall, we classified 159 observations as potentially problematic and excluded them, leaving 5,952 observations.

We turned next to identifying incomplete observations. First, we dropped those who quit early enough that they were never assigned a bid and/or a scope treatment, then those who did not vote, then those who skipped key demographic questions. Qualtrics communicated to us that they flagged "speeders" as those completing the survey in less than half the median completion time, which they reported to us as approximately 210 seconds (actual time varied per survey version). However, we found observations flagged as "good", i.e., QCode = 1, who completed the survey in as few as 156 seconds, nearly a minute faster than the approximate Qualtrics cutoff. Additionally, the three videos shown to respondents in the survey take 180 seconds by themselves to play in full. We decided to apply the 210-second cutoff for speeders directly rather than relying on the QCode. This cutoff represents a minimum amount of time to watch the videos (180 seconds) plus another thirty seconds to answer questions. At this point, all QCode = 3 observations were dropped. We then dropped those reporting an invalid or no zip code. Note that the zip code question was asked at the end of the survey, separate from the state of residence question at the beginning. The result was that we classified 1,262 observations as incomplete, leaving 4,690 complete observations. All told, the net result was that we agreed with Qualtrics in most cases. We reclassified 2% of their "good" responses as invalid or incomplete. We retained 3% of those flagged as failing a quality check (QCode = 4), 65% of those flagged for other reasons (QCode = 5), and 1% of those flagged as incomplete (QCode = Blank).

Table A1. Sample quality control distribution of observations.

		Qualtrics Flag Code (QCode)					
	Overall	1	2	3	4	5	Blank
Starting Responses	6,111	4,666	137	132	554	128	494
	Illegitimate Responses						
Wrong state or no state provided	-54		-54				
Failed oath	-104		-83				-21
Recaptcha <= 0.4	-1				-1		
Total Illegitimate Responses	**159**	**0**	**137**	**0**	**1**	**0**	**21**
Total Remaining	**5,952**	**4,666**	**0**	**132**	**553**	**128**	**473**
	Incomplete Responses						
No bid/scope assignment	-249				-7		-242
No vote	-161	-3					-158
Skipped key demographics	-97	-31		-2	-5		-59
Speeders	-709	-39		-130	-528	-11	-1
Invalid or no zipcode reported	-46	-15				-31	
Total Incompletes	**1,262**	**88**	**0**	**132**	**540**	**42**	**460**
Total Remaining	**4,690**	**4,578**	**0**	**0**	**13**	**86**	**13**
	Further Quality Controls						
Didn't understand problem	-162	-153				-6	-3
Didn't understand project	-96	-92				-4	
Didn't understand payment	-155	-151			-1	-1	-2
Not consequential	-280	-270			-2	-6	-2
Inconsistent vote	-74	-73				-1	
Total Low-Quality Completes	**767**	**739**	**0**	**0**	**3**	**18**	**7**
Total Remaining	**3,923**	**3,839**	**0**	**0**	**10**	**68**	**6**

APPENDIX B

Table B1. Population statistics used as basis for sampling weights. Source: U.S. Census (2023).

	AL	FL	LA	MS	TX	Total
Total Population 18+	**3,963,268**	**17,949,929**	**3,531,381**	**2,263,972**	**22,589,909**	**50,298,459**
Age						
18 to 24 years	488,344	1,845,519	435,260	300,650	2,992,526	
25 to 29 years	315,165	1,330,720	278,806	168,422	2,124,620	**10,280,032**
30 to 34 years	336,987	1,453,041	313,260	183,094	2,204,737	
35 to 39 years	309,127	1,415,689	321,167	185,470	2,142,529	**8,865,101**
40 to 44 years	323,289	1,383,810	290,133	194,426	2,096,393	
45 to 49 years	296,897	1,309,763	255,190	174,342	1,860,639	**8,184,882**
50 to 54 years	320,783	1,424,400	277,963	178,876	1,827,226	
55 to 59 years	318,087	1,472,092	262,705	166,777	1,641,396	**7,890,305**
60 to 64 years	341,576	1,520,481	316,836	198,731	1,662,758	
65 to 69 years	304,634	1,379,690	260,400	169,742	1,375,570	**7,530,418**
70 to 74 years	241,555	1,224,324	211,605	139,942	1,085,585	
75 to 79 years	177,876	1,011,259	146,731	93,192	747,528	**5,079,597**
80 to 84 years	103,915	627,349	90,195	60,716	444,397	
85 years and over	85,033	551,792	71,130	49,592	384,005	**2,468,124**
Total	**3,963,268**	**17,949,929**	**3,531,381**	**2,263,972**	**22,589,909**	**50,298,459**
Sex						
Male 18+	1,893,900	8,751,831	1,705,107	1,082,712	11,218,794	**24,652,344**
Female 18+	2,069,368	9,198,098	1,826,274	1,181,260	11,371,115	**25,646,115**
Total	**3,963,268**	**17,949,929**	**3,531,381**	**2,263,972**	**22,589,909**	**50,298,459**

	AL	FL	LA	MS	TX	Total
Education						
Less than 9th grade (25+)	118,034	679,435	128,792	83,604	1,406,769	
Less than high school graduate (18-24)	58,089	229,379	60,146	45,268	425,179	
9th to 12th grade, no diploma (25+)	271,263	943,495	264,491	159,922	1,315,239	
High school graduate (incl. equiv.) (18-24)	176,620	638,736	160,986	107,203	1,068,636	
High school graduate (incl. equiv.) (25+)	1,057,155	4,363,609	1,006,184	604,163	4,733,230	**20,105,627**
Some college, no degree (25+)	716,144	2,955,638	635,109	419,570	3,970,970	
Some college or associate's degree (18-24)	208,994	754,968	176,961	125,406	1,142,295	
Associate's degree (25+)	311,537	1,643,815	221,439	209,877	1,519,767	**15,012,490**
Bachelor's degree (25+)	609,316	3,445,343	525,044	297,480	4,242,031	
Bachelor's degree or higher (18-24)	44,641	222,436	37,167	22,773	356,416	
Graduate or professional degree (25+)	391,475	2,073,075	315,062	188,706	2,409,377	**15,180,342**
Total	**3,963,268**	**17,949,929**	**3,531,381**	**2,263,972**	**22,589,909**	**50,298,459**
Race*						
Hispanic or Latino	264,047	5,697,240	322,549	105,220	11,441,717	**14,162,368**
Black or African American alone, Non-Hispanic	1,288,159	3,127,052	1,452,420	1,079,001	3,444,712	**8,253,486**
White alone, Non-Hispanic	3,171,351	11,100,503	2,596,702	1,639,077	11,584,597	**23,901,221**
Asian alone, Non-Hispanic	75,918	629,626	85,336	32,305	1,561,518	
American Indian and Alaska Native alone, Non-Hispanic	23,119	42,169	25,994	14,019	85,425	
Native Hawaiian and Other Pacific Islander alone, Non-Hispanic	2,612	11,521	1,706	1,037	27,857	
Some Other Race alone, Non-Hispanic	14,455	137,933	16,954	7,174	113,584	
Two or more races, Non-Hispanic	184,618	792,143	156,096	83,446	886,095	**3,981,384**
Total	**5,024,279**	**21,538,187**	**4,657,757**	**2,961,279**	**29,145,505**	**50,298,459**

* Race totals scaled down proportionally in Total column to match 18+ population.

Table B2. Mean population weight by demographic indicator group.

	Population Share	Full Sample Share	Full Sample Mean Weight	Quality Sample Share	Quality Sample Mean Weight
State					
AL	0.08	0.22	0.36	0.21	0.44
FL	0.36	0.19	1.92	0.19	2.26
LA	0.07	0.22	0.33	0.22	0.38
MS	0.05	0.16	0.28	0.16	0.34
TX	0.45	0.22	2.08	0.22	2.44
Age					
18 to 29 years	0.20	0.20	1.01	0.20	1.25
30 to 39 years	0.18	0.22	0.80	0.22	0.95
40 to 49 years	0.16	0.20	0.81	0.20	0.96
50 to 59 years	0.16	0.16	0.96	0.16	1.16
60 to 69 years	0.15	0.13	1.12	0.13	1.33
70 to 79 years	0.10	0.07	1.42	0.08	1.61
80 years and over	0.05	0.01	4.90	0.01	7.19
Sex					
Male 18+	0.49	0.28	1.75	0.28	2.08
Female 18+	0.51	0.72	0.71	0.72	0.85
Education					
High school graduate (incl. equiv.) or less	0.40	0.32	1.26	0.30	1.64
Some college or associate's degree	0.30	0.39	0.76	0.39	0.91
Bachelor's degree or higher	0.30	0.29	1.03	0.32	1.15
Race					
Hispanic or Latino	0.28	0.08	3.64	0.08	4.42
Black or African American alone, Non-Hispanic	0.16	0.22	0.74	0.20	0.99
White alone, Non-Hispanic	0.48	0.67	0.71	0.70	0.82
All other races, Non-Hispanic	0.08	0.03	2.61	0.03	3.20

Table B3. Probit regression results of original (confidence unadjusted) Vote.

	Full Sample (N = 4,690)							"High-Quality" Subsample (N = 3,923)					
	Unweighted			Weighted			Unweighted			Weighted		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
ln(bid)	-0.253	***	-0.019	-0.181	***	-0.032	-0.28	***	-0.021	-0.219	***	-0.035
ln(status-quo)	-0.036	***	-0.012	-0.028		-0.02	-0.037	***	-0.013	-0.021		-0.023
ln(income)	0.019		-0.024	0.018		-0.041	0.036		-0.028	0.031		-0.049
eats oysters	0.438	***	-0.041	0.362	***	-0.071	0.42	***	-0.047	0.321	***	-0.081
saltwater	0.272	***	-0.061	0.339	***	-0.101	0.254	***	-0.068	0.363	***	-0.115
coastal	0.021		-0.041	0.084		-0.066	0.024		-0.047	0.094		-0.075
no children	-0.051		-0.044	-0.122		-0.075	-0.031		-0.05	-0.087		-0.09
education	-0.07	**	-0.029	-0.042		-0.05	-0.136	***	-0.032	-0.095	*	-0.052
female	-0.158	***	-0.046	-0.184	**	-0.073	-0.177	***	-0.053	-0.172	**	-0.083
black	-0.059		-0.053	-0.002		-0.08	0.057		-0.063	0.144		-0.099
other race	0.148		-0.121	0.011		-0.177	0.185		-0.14	0.068		-0.189
age	-0.01	***	-0.001	-0.008	***	-0.002	-0.009	***	-0.002	-0.007	**	-0.003
republican	-0.094	**	-0.043	-0.017		-0.072	-0.087	*	-0.049	0.023		-0.079
constant	2.519	***	-0.302	2.01	***	-0.516	2.673	***	-0.346	2.059	***	-0.622
LL	-2629.618						-2033.824					

Note: ***, **, and * are statistically significant at 1%, 5%, 10%, respectively.

Table B4. Status-quo and scope effect test results.

Subsamples	Test Results
Status-Quo Effects (Scope Fixed)	
AL, FL, MS (scope = 25,000 lbs)	$H_0: \beta_{AL} = \beta_{FL}$, χ^2 = 0.67 (p = 0.41) $H_0: \beta_{AL} = \beta_{MS}$, χ^2 = 0.55 (p = 0.46) $H_0: \beta_{FL} = \beta_{MS}$, χ^2 = 0.08 (p = 0.78)
AL, FL, LA, MS, TX (scope = 1M lbs)	$H_0: \beta_{AL} = \beta_{FL}$, χ^2 = 2.70 (p = 0.10) $H_0: \beta_{AL} = \beta_{LA}$, χ^2 = 0.18 (p = 0.67) $H_0: \beta_{AL} = \beta_{MS}$, χ^2 = 0.13 (p = 0.72) $H_0: \beta_{AL} = \beta_{TX}$, χ^2 = 12.03 (p = 0.005) $H_0: \beta_{FL} = \beta_{LA}$, χ^2 = 2.22 (p = 0.14) $H_0: \beta_{FL} = \beta_{MS}$, χ^2 = 3.63 (p = 0.06) $H_0: \beta_{FL} = \beta_{TX}$, χ^2 = 1.53 (p = 0.22) $H_0: \beta_{LA} = \beta_{MS}$, χ^2 = 0.57 (p = 0.45) $H_0: \beta_{LA} = \beta_{TX}$, χ^2 = 7.74 (p = 0.005) $H_0: \beta_{MS} = \beta_{TX}$, χ^2 = 12.20 (p = 0.0005)
LA, TX (scope = 2M lbs)	$H_0: \beta_{LA} = \beta_{TX}$, χ^2 = 0.19 (p = 0.66)
Scope Effects (Status-Quo Fixed)	
AL	$H_0: \beta_{Scope} = 0$, χ^2 = 0.88 (p = 0.35)
FL	$H_0: \beta_{Scope} = 0$, χ^2 = 1.98 (p = 0.16)
LA	$H_0: \beta_{Scope} = 0$, χ^2 = 0.97 (p = 0.33)
MS	$H_0: \beta_{Scope} = 0$, χ^2 = 0.09 (p = 0.77)
TX	$H_0: \beta_{Scope} = 0$, χ^2 = 0.92 (p = 0.34)
Additional Tests	
All observations; state-scenario dummies vs. state dummies with pooled scope	H_0: state dummies with pooled scope model nested within state-scope dummies model, χ^2 = 5.06 (p = 0.41)
All observations; state dummies with pooled scope	$H_0: \beta_{AL} = \beta_{FL}$, χ^2 = 4.13 (p = 0.04) $H_0: \beta_{AL} = \beta_{LA}$, χ^2 = 3.45 (p = 0.06) $H_0: \beta_{AL} = \beta_{MS}$, χ^2 = 0.10 (p = 0.75) $H_0: \beta_{AL} = \beta_{TX}$, χ^2 = 22.82 (p = 0.0000) $H_0: \beta_{FL} = \beta_{LA}$, χ^2 = 0.18 (p = 0.68) $H_0: \beta_{FL} = \beta_{MS}$, χ^2 = 2.94 (p = 0.09) $H_0: \beta_{FL} = \beta_{TX}$, χ^2 = 3.77 (p = 0.05) $H_0: \beta_{LA} = \beta_{MS}$, χ^2 = 2.25 (p = 0.13) $H_0: \beta_{LA} = \beta_{TX}$, χ^2 = 6.32 (p = 0.01) $H_0: \beta_{MS} = \beta_{TX}$, χ^2 = 16.47 (p = 0.0000)

Table B5. Probit regression results using state dummies.

	Full Sample (N = 4,690)						"High-Quality" Subsample (N = 3,923)					
	Unweighted			Weighted			Unweighted			Weighted		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
ln(bid)	-0.295	***	0.018	-0.216	***	0.031	-0.311	***	0.02	-0.239	***	0.033
FL	-0.149	**	0.073	-0.11		0.113	-0.257	***	0.08	-0.27	**	0.119
LA	-0.123	*	0.066	-0.092		0.101	-0.193	***	0.072	-0.282	**	0.114
MS	-0.02		0.064	-0.046		0.089	-0.075		0.07	-0.118		0.092
TX	-0.285	***	0.06	-0.221	**	0.087	-0.356	***	0.065	-0.317	***	0.09
ln(income)	0.2	***	0.024	0.214	***	0.044	0.189	***	0.026	0.193	***	0.05
eats oysters	0.493	***	0.041	0.43	***	0.072	0.432	***	0.044	0.367	***	0.079
saltwater	0.236	***	0.055	0.28	***	0.091	0.222	***	0.059	0.32	***	0.1
coastal	0.012		0.05	-0.036		0.089	0.051		0.055	0.007		0.098
no children	-0.008		0.042	0.005		0.078	-0.014		0.046	-0.018		0.087
education	0.132	***	0.028	0.155	***	0.048	0.098	***	0.03	0.111	**	0.05
female	-0.191	***	0.044	-0.153	**	0.069	-0.208	***	0.048	-0.14	*	0.075
black	-0.206	***	0.051	-0.066		0.083	-0.137	**	0.057	0.001		0.095
other race	-0.083		0.113	-0.203		0.152	-0.044		0.124	-0.098		0.163
age	-0.001		0.001	0.001		0.002	0.001		0.001	0.005	*	0.003
republican	-0.073	*	0.042	0.006		0.074	-0.092	**	0.046	-0.016		0.081
constant	-1.116	***	0.261	-1.819	***	0.453	-0.733	**	0.286	-1.324	***	0.506
LL	-2851.462						-2439.328					

Note: ***, **, and * are statistically significant at 1%, 5%, 10%, respectively.

Figure B1. Historical commercial oyster landings by Gulf state. Source: NOAA Fisheries (2024).

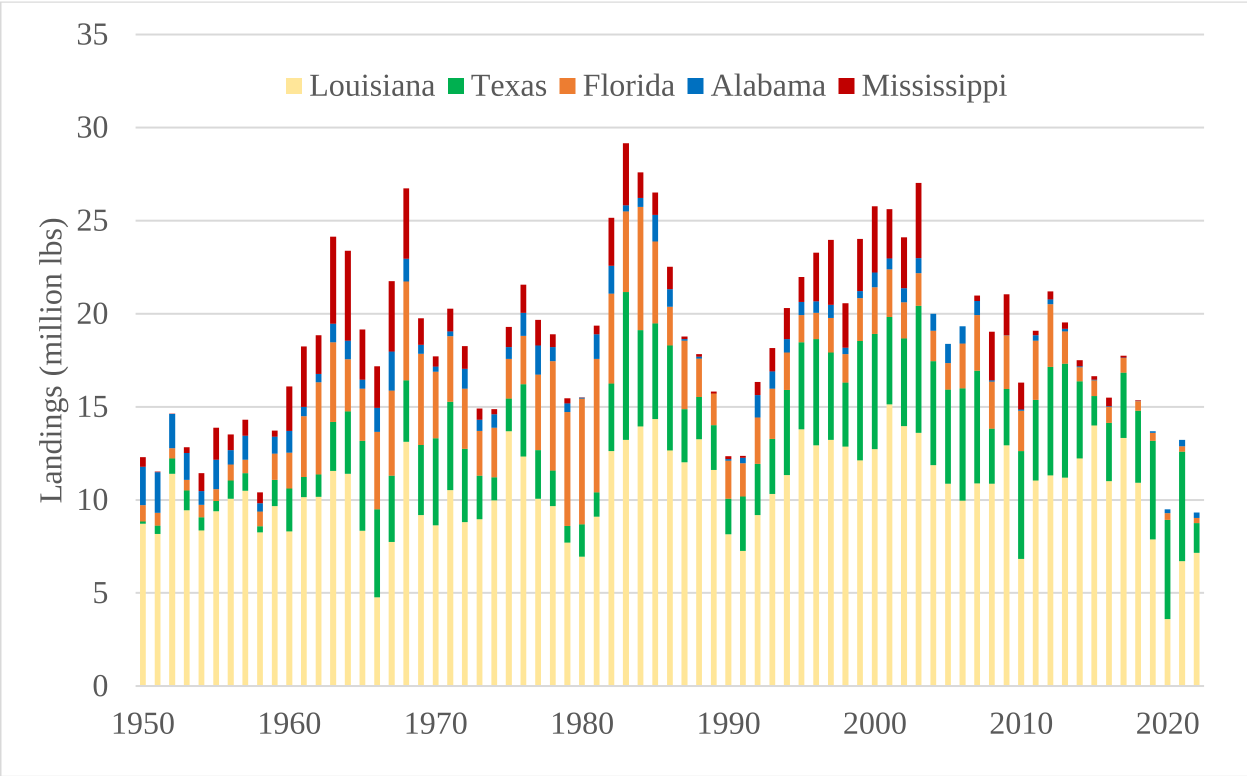


Figure B2. Median Maximum Willingness to Pay by model, based on "High-Quality" Subsample: (discrete state dummies (bars and whiskers) versus continuous status-quo variable (solid and dashed lines).