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DEPARTMENT OF
AGRICULTURAL ECONOMICS

Working Paper Number 19 – 3 | September 2019

Accounting for Attribute Non-Attendance in Three Previously-Published Choice Studies of Coastal Resources

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Acknowledgments

This research was supported by the National Institute of Food and Agriculture and the Mississippi Agricultural and Forestry Experiment Station via Multistate Project W-4133 “Costs and Benefits of Natural Resources on Public and Private Lands: Management, Economic Valuation, and Integrated Decision-Making” (Hatch Project MIS-033140).

Accounting for Attribute Non-Attendance in Three Previously-Published Choice Studies of Coastal and Marine Resources

Abstract

We revisit three recently-published papers that apply discrete-choice experiment methods to coastal and marine ecosystem goods and services, in light of attribute non-attendance (AN-A). We find that accounting for AN-A does not always improve model fit, but when it does, the improvement can be substantial. Estimated price and attribute coefficients change, but these changes do not follow a consistent pattern, either in direction or magnitude. Mean attribute increment value (i.e., willingness to pay, WTP) estimates change, but also with no discernible pattern. However, in several cases, generally in those cases where accounting for AN-A improves model fit, we observe substantial improvements in the confidence intervals on WTP, i.e., accounting for AN-A appears to produce much more precise WTP estimates. In short, we find that accounting for AN-A is not always warranted, but when it is, the key payoff appears to be more precise WTP estimates.

Keywords: attribute increment value, discrete-choice experiment, ecosystem service valuation, latent class, inferred attribute non-attendance, willingness to pay

JEL Codes: D12, Q5, Q22, Q25, Q51, Q57

Accounting for Attribute Non-Attendance in Three Previously-Published Choice Studies of Coastal Resources

Introduction

Stated preference discrete choice experiments (DCE) are used by researchers seeking to understand consumer preferences and values in environmental economics, transportation, health, and marketing. An active DCE research area relates to behaviors that break from the assumptions of fully compensatory behavior assumed in standard discrete choice models. This has led to research on ways of incorporating heuristics and cognitive processes in models of DCE response behavior. In particular, considerable attention in recent years has been on attribute non-attendance (AN-A), which is a type of choice behavior where individuals ignore one or more attributes in the DCE question.

We revisit three recently-published papers that apply DCE methods to coastal and marine ecosystem goods and services, in light of AN-A. These papers include a study of household preferences for a proposed restoration of coastal wetlands (Petrolia, Interis, and Hwang 2014); a study of household preferences for a proposed restoration of three habitats in two locations that provide four ecosystem services (Interis and Petrolia 2016); and a study of consumer preferences for oysters on the half-shell (Petrolia, Walton, and Yehouenou 2017).

This paper endeavors to answer three main questions regarding AN-A for each of these three studies: 1) Does accounting for AN-A improve model fit relative to the originally-published models? 2) Do estimated price and attribute coefficients change and do these changes follow a consistent pattern? And, 3) do estimated means and confidence intervals of attribute increment values (i.e., willingness to pay (WTP) estimates) change and do these changes follow

a consistent pattern? Our summary response to all three questions is: *sometimes*. Accounting for AN-A does not always improve model fit, but when it does, the improvement can be substantial. Estimated price and attribute coefficients do change, but these changes do not follow a consistent pattern either in terms of direction or magnitude. Mean WTP estimates change, but also with no discernible pattern in terms of direction or magnitude. However, in several cases, generally in those cases where accounting for AN-A improves model fit, we observe that the confidence intervals on WTP are substantially narrower. In other words, accounting for AN-A appears to produce much more precise WTP estimates. In short, we find that accounting for AN-A is not always warranted, but when it is, the key payoff appears to be more precise WTP estimates.

Literature Review

AN-A is one of a broad class of behaviors that violate the full compensatory assumption implicit in Lancaster (1966). In other words, the notion that decision-makers process and consider all information provided to them regarding alternatives does not hold. The idea that decision-makers take a more limited approach to decision-making reaches back at least as early as Dawes (1964) and Tversky (1972). Swait (2001) appears to have been the first to formalize it for DCEs, and the literature has grown rapidly ever since, due in large part to the work of Greene, Hensher, Scarpa, and several others¹. Scarpa et al. (2009) may have been the first to coin the term

¹ See McIntosh and Ryan (2002), Greene and Hensher (2003), Hensher, Rose, and Greene (2005), Rose, Hensher, and Greene (2005), Hensher (2006), Hensher, Rose, and Bertoia (2007), Campbell, Hutchinson, and Scarpa (2008), Scarpa et al. (2009), and Hess and Hensher (2010).

"attribute non-attendance", although the idea was considered in earlier papers under other names (attribute processing strategies, discontinuous preferences, etc.).

One method to account for AN-A is to elicit attribute attendance directly from respondents and then control for it during modeling (stated AN-A)². Other papers focus on identifying attribute non-attendance probabilistically via the modeling process using of latent class models (inferred AN-A). Within this modeling framework, there are a variety of specifications. For example: 1) the " 2^k model" which specifies a distinct attendance class for every possible combination of attributes (Hensher, Rose, and Greene 2012); 2) a simplified version of the 2^k model that focuses on a subset of attendance classes (Hensher and Greene 2010; Campbell, Hensher, and Scarpa 2011); 3) preference parameters constrained within classes³; 4) preference parameters constrained across classes (Hensher, Rose, and Greene 2012); 5) correlated non-attendance across attributes (Collins, Rose, and Hensher 2013); and most recently, 6) a random-parameters specification within the latent classes (Hess et al. 2013; Hensher, Collins, and Greene 2013). Both of these latter papers find that adding the random-parameters specification increases the probability of membership to the full attribute attendance class, although Hensher, Collins, and Greene (2013) find that the addition of the random-parameters component may add only marginal improvements in model fit and may serve as a confounding effect.

² See Alemu et al. (2013), Scarpa, Thiene, and Hensher (2010), and Campbell, Hutchinson, and Scarpa (2008).

³ Aggregation of common metric attributes, see Hensher, Collins, and Greene (2013) and Hensher and Greene (2010).

More recent literature has attempted to account for more complex relationships. For example: 1) including multiple decision heuristics (Baltontin, Hensher, and Collins 2017); 2) the effect of hypothetical bias on AN-A (Bellow and Abdulai 2016); 3) differences across serial and choice-task-specific AN-A measures (Colombo and Glenk 2014; Caputo et al. 2018); 4) integrating importance ranking data with AN-A information (Chalak, Abaid, and Balcombe 2016); 5) AN-A differences across attribute levels (Erdem, Campbell, and Hole 2015); 6) effects of AN-A on sensitivity to scope (Giguere, Moore, and Whitehead 2018); 7) implications of AN-A for benefit transfer (Glenk et al. 2015); 8) accounting for AN-A patterns and the underlying behavioral assumptions regarding source of AN-A (Hole, Norman, and Viney 2016; Heidenreich et al. 2017); and 9) using eye-tracking to account for AN-A (Van Loo et al. 2018). Our survey of this literature indicates that the best model specification is ultimately an empirical question, and specific to the data at hand.

Although AN-A has been examined for a wide variety of goods and services, we are aware of only one paper, Petrolia, Interis, and Hwang (2018), that applies AN-A methods directly to a marine resource, the focus of this special issue. They find that AN-A differs across elicitation types (single-choice, repeated-choice, and best-worse scaling), with more subtle differences across habitat types featured in the contingent scenarios (oyster reefs and salt marsh).

Data and Methods

Table 1 presents a summary of datasets and econometric models used in the three original studies. We discuss each study in detail below.

Petrolia, Interis, and Hwang (2014)

This survey instrument was designed to estimate attribute increment values for changes in ecosystem services associated with a proposed large-scale (234 thousand acre) coastal wetland and barrier island restoration in Louisiana's Barataria- Terrebonne estuary. The survey proposed to respondents one or more hypothetical wetland and barrier island restoration programs and asked them if they would be willing to pay a specified amount of money to implement one of the proposed restoration programs, or to implement neither of these programs, incur no cost, and allow land loss to continue at its current rate. The survey focused on three main benefits of restoration, which served as choice attributes. Specifically: 1) improved wildlife habitat, measured as the percentage of newly-constructed land generally suitable for wildlife habitat; 2) storm surge protection, measured as the percentage of residents in the area that would have improved storm surge protection; and 3) improved commercial fish harvest, measured as the percentage improvement in harvest levels of major commercial fish, such as oysters and shrimp. Although the study included both a binary-choice (referendum) version and a multinomial-choice version, we focus on the latter only. The original paper reported two sets of results, one based on the full sample, and one based on respondents for whom the survey was perceived as consequential only. For ease of discussion, these two samples are referred to here (and italicized) as the *All-Respondents Sample* and the *Consequential-Respondents Sample*, respectively.

Knowledge Networks (now GfK Custom Research) was contracted to administer the survey to its KnowledgePanel, a probability-based web panel designed to be representative of the United States (U.S.). The main survey was administered between April 21 and July 23, 2011. A total of 5,185 households were sampled, and 3,464 responded (67 percent). Of the 3,454 households, 2,067 completed the multinomial-choice version.

Conditional logit regressions were estimated that included the three non-price attributes. Each non-price attribute was specified with 3 discrete levels (low, intermediate, and high), with the low levels serving as the omitted bases. Price was specified as continuous. The model also contained controls for individual-specific characteristics. Although we retain these controls just as in the original paper, we do not report or discuss them in the paper but focus on the alternative-specific attributes.

Interis and Petrolia (2016)

This survey instrument was designed to estimate attribute increment values for ecosystem services provided by alternative coastal habitats in multiple locations. The express purpose of testing whether attribute increment values estimated using DCE methods were sensitive to the geographic location or the specific habitat providing the services. The services included improved water quality, improved flood protection, increased commercial fisheries, and increased wading bird population. In the choice exercise, respondents were asked whether they were willing to pay a specified price for one of two proposed habitat construction projects, or if they would prefer neither be implemented and to pay nothing. The two construction projects differed in the levels of ecosystem services provided and price. There were five independent samples based on combinations of project location (Barataria-Terrebonne estuary in Louisiana or Mobile Bay in Alabama USA) and habitat providing the services (oyster reefs, salt marsh, or mangroves (Louisiana only)). For ease of discussion, these five samples are referred to here (and italicized) as the *Louisiana Oyster Sample*, the *Louisiana Saltmarsh Sample*, the *Louisiana Mangrove Sample*, the *Alabama Oyster Sample*, and the *Alabama Saltmarsh Sample*. Most respondents were asked a single choice question, but some were assigned to a repeated-choice format (4 choice sets). The payment mechanism specified was a one-time payment collected on

the respondent's state tax return filed the following year. The survey was administered in May and June 2013 by GfK Custom Research to its Knowledge Panel and other respondents. Out of 8573 respondents sampled, 5366 (63 percent) completed one of the five versions described above. The final sample of respondents included 5196 respondents with no missing values for the variables of interest.

The original regressions were estimated using random parameters logit (RPL) for two reasons. It provided a convenient means of including both an error-components specification for nesting alternatives (action alternatives versus status-quo) as well as a price transformation based on the recommendations of Carson and Czajkowski (2013). The objective of this transformation was to preclude the possibility of a positive price coefficient. Operationally this required that the price coefficient be specified as lognormally-distributed (as a random parameter with zero standard deviation). This transformation is not feasible in our Latent Class (LC) AN-A models. However, omission of the transformation in the original model had only minimal effects. So, to make for a more direct comparison with the LC AN-A results, what we report here as the "original" results do not include this price coefficient transformation. Results that include the price transformation are available upon request (and can be found in the original paper). As in the original paper, we classified this model as an error-components logit (ECL). The model included three non-price attributes, each specified with 3 discrete levels, with the lowest levels serving as the omitted bases: water quality (0, 10, and 20 percent reductions in nitrogen and phosphorus), flood protection (5, 10, and 20 percent increases in number of homes protected), fish harvest (10, 20, and 30 percent increases in annual seafood catch), and bird population (0, 5, and 10 percent increases in wading bird population). Price was specified as continuous. The model also contained controls for individual-specific characteristics. As in the previous paper,

although we retained these controls just as in the original paper, we do not report or discuss them in the paper but focus to the alternative-specific attributes. Consistent with the original paper, 200 Halton draws were used for estimation.

Petrolia, Walton, and Yehouenou (2017)

The survey was designed to elicit preferences and estimate attribute incremental values for raw oysters on the half-shell among existing raw oyster consumers. The main purpose of this study was to ascertain the potential for marketing Gulf Coast oysters under brand labels in markets outside of the Gulf Coast. Attributes included oyster variety (i.e., brand or harvest location), size, saltiness level, production method (wild or cultivated), and price per half-dozen. A total of 13 oyster varieties were included in the design: 7 Gulf Coast varieties, 3 Atlantic Coast varieties, and 3 Pacific Coast varieties. Each respondent evaluated six choice sets, each containing 3 oyster alternatives.⁴ There were two separate designs based on whether a cheaper, generic Gulf

⁴ Choice set responses were elicited using the best-worst scaling (BWS) format (the multi-profile case (case III), see Flynn and Marley 2014), which included a single choice set with three alternatives, and elicited both the “best” and “worst” choice of the three alternatives, thus yielding a full ranking. This ranking was then decomposed following the method of rank-order explosion proposed by Chapman and Staelin (1982), which, in this case, yields two choice observations for each choice set evaluated: a three-alternative observation (first-best case) and a two-alternative observation (second-best case). In this particular context, respondents were asked to indicate which of the three alternatives they were “Most Likely to Buy” at the posted prices (i.e., “best”) and which of the three alternatives there were “Least Likely to Buy” at the posted prices (i.e., “worst”).

Coast oyster (typical in Gulf Coast markets but not in others) was included as one of the alternatives. The version that excluded generic Gulf Coast oysters was administered to two independent samples: a sample of non-Gulf Coast (i.e., Atlantic coast, Pacific coast, and inland) respondents, and a sample of Gulf Coast respondents. The version that included generic Gulf Coast oysters was administered to a third sample, which was comprised of another set of Gulf Coast respondents. For ease of discussion, these three samples are referred to here (and italicized) as the *Non-Generic Non-Gulf Sample*, the *Non-Generic Gulf Sample*, and the *Generic Gulf Sample*, respectively. Consistent with the other two studies, GfK Custom Research administered the survey online to a sample of households participating in their KnowledgePanel. The target population was consumers of raw oysters on the half shell. The final version was administered, in two waves, April 16–May 2 and November 7–18, 2013. A total of 6,879 panelists were sampled from GfK’s Knowledge Panel, and of these, 3,807 (55 percent) agreed to take the survey. A total of 730 passed the screening question, for a 19 percent incidence rate, and continued to complete one of the three versions as described above.

The original regressions were estimated using RPL. In the original paper, some, but not all, of the oyster variety (i.e., harvest location) parameters were randomized to account for preference heterogeneity, and, like the previous paper, the Carson and Czajkowski price transformation was implemented. Here, the oyster variety parameters were randomized according to the original paper, but as before, the price coefficient transformation was not applied for the same reasons given previously. For oyster variety, each Gulf Coast variety was modeled discretely (Champagne Bay, Apalachicola Bay, Point aux Pins, Lonesome Reef, Bay St. Louis, and Portersville Bay), with all non-Gulf Coast varieties serving as the omitted base. In

the model based on the *Generic Gulf Sample* only, non-Gulf Coast varieties were modeled explicitly, with generic Gulf Coast oysters serving as the omitted base. The size attribute was specified with 3 discrete levels (small, medium, and large), with the medium level serving as the omitted base. The saltiness attribute was also specified with 3 discrete levels (sweet, mildly salty, and salty), with mildly salty serving as the omitted base. The production method attribute had two discrete levels (wild and farm-raised), with farm-raised serving as the omitted base. Consistent with the original paper, 500 Halton draws were used for estimation.

Latent Class AN-A Model Specifications

To account for inferred AN-A, the Latent Class model is used. The model allows for discrete parameter heterogeneity by having different classes. The utility of an individual i choosing alternative j among a set of alternatives J is specified as $U_{ij} = \beta_c' \mathbf{x}_{ij} + \varepsilon_{ij}$, where β_c is a class-specific parameter vector. The standard 2^k model for AN-A is implemented by adding 1) constraints such that parameters of attributes that are not attended to in each class are constrained to zero, and 2) constraints such that non-zero parameters of attributes (those that are attended to) are restricted to be equal across classes ($\beta_c = \beta \forall c$).

The standard 2^k model indexes k according to all individual attributes and includes all attribute combinations. What we find in the literature, however, is that, even if researchers begin their analyses here, many eventually resort to using a subset of combinations only, i.e., that some of the initial classes are dropped based on an empirical, iterative process. The usual reasons given for the exclusions include nearly-zero class shares or model convergence and performance issues associated with many classes. We take a somewhat different approach to this issue: we

first categorize attributes by type and then specify classes according to these types. In other words, we redefine k to be the number of attribute types. So, Petrolia, Interis, and Hwang includes three (non-price) ecosystem-service attributes and Interis and Petrolia includes four (non-price) ecosystem-service attributes, with both including one price attribute. If our 2^k approach is applied to $k = 2$ *types* (non-price and price), there are $2^2 = 4$ classes: all attributes attended, price N-A, ecosystem service attributes N-A, and none attended. Petrolia, Walton, and Yehouenou, however, requires further delineation of non-price attributes, because different consumers tend to make choices based on either oyster variety or other non-varietal search attributes (size, saltiness, and production method), or both. So in this case, there are three attribute *types*: variety attributes, other (non-varietal) attributes, and price. Thus, applying the 2^k model to $k = 3$ *types*, there are $2^3 = 8$ classes: all attributes attended, price N-A, variety attributes N-A, other attributes N-A, variety and other attributes N-A, price and other attributes N-A, price and variety attributes N-A, and none attended.

In summary, given that the original model in Petrolia, Interis, and Hwang was conditional logit, the AN-A model is LC logit (referred to as LC AN-A). For Interis and Petrolia, the original model was ECL, so the AN-A model is an error-components LC logit (referred to as ECLC AN-A). Consistent with the original model, 200 Halton draws are used. With Petrolia, Walton, and Yehouenou, the original model was RPL, so the AN-A model is random-parameters LC logit (referred to as RPLC AN-A). Consistent with the original model, 500 Halton draws are used.

We rely on Akaike and Bayesian Information Criteria (AIC and BIC) to evaluate and compare model fit. We compare attribute increment value estimates between the base models and the LC AN-A models in terms of mean incremental attribute values and their confidence

intervals. Means are defined as the negative of the ratio of the attribute coefficient over the price coefficient. Confidence intervals are calculated using the Delta method, following the procedures given for fixed and random parameters in Bliemer and Rose (2013). Note that although the Delta method was used in Petrolia, Walton, and Yehouenou (2017), the Krinsky-Robb method was used in both Petrolia, Interis, and Hwang (2014) and Interis and Petrolia (2016). So reported confidence intervals for the original models reported here will differ somewhat from those reported in these two original papers.

Results

Petrolia, Interis, and Hwang (2014)

Consistent with the original study, two sets of regression are estimated; one for the *All Respondents Sample* and another for the *Consequential Respondents Sample*. Table 2 presents results. Model fit does not change much with the latent class models. AIC favors the LC models slightly whereas BIC favors the original models slightly. Estimated class shares are dominated by all-attended and none-attended, each taking just shy of half the total, with a small remainder captured by one of the other classes. The “none-attended” class has the largest estimated share (49 percent) for the *All Respondents Sample*, but when inconsequential responses are removed, as in the *Consequential Respondents Sample*, then the “none-attended” class share falls to 42 percent, and the “all-attended” class share increases to 54 percent, becoming the largest class. Thus, consequentiality appears to affect AN-A somehow; consequential respondents are more likely to attend to all the attributes and less likely to ignore all.

For both samples, all coefficients increase in absolute magnitude in the LC AN-A model relative to the original. In other words, positive coefficients get more positive, and negative coefficients get more negative, except one non-significant coefficient that switches from positive to negative. Given that both price and attribute coefficients increase in magnitude, the effect on attribute increment estimates is not obvious. We turn to this question next.

Changes in attribute increment value estimates are mixed. Figure 1 contains plots of estimated attribute increment value (WTP) means and 95 percent confidence intervals. For the *All Respondents Sample*, attribute increment values increase for half of the attributes (both wildlife levels and intermediate-level fish) but decrease for the other half. Confidence intervals under the LC AN-A model are generally wider. For the *Consequential Respondents Sample*, mean attribute increment values decrease in four cases, remain unchanged in one case, and increase slightly in another. Whereas the one case of an increase is marginal, three of the four cases of a decrease are on the order of an almost 50 percent reduction. Confidence intervals are generally equally-wide or wider compared to the original model.

Interis and Petrolia (2016)

Table 3 presents results for the Louisiana-based samples (*Louisiana Oyster, Saltmarsh, and Mangrove Samples*), and Table 4 presents the Alabama-based samples (*Alabama Oyster and Saltmarsh Samples*). Regarding model fit, the original models outperform the ECLC AN-A models in two out of the five samples (*Louisiana Oyster and Alabama Saltmarsh*), the ECLC AN-A models outperform the original models in two out of the five samples (*Louisiana Salt and Louisiana Mangrove*), and one is a toss-up (*Alabama Oyster*). In the two cases where model fit is improved by ECLC AN-A, there is an equitable distribution of shares across attendance class types. In two of the three models where ECLC AN-A has either worse or no better fit (*Alabama*

Oyster and Alabama Saltmarsh), the estimated classes are either "all-attended" or "none-attended".

When ECLC AN-A is used, the price coefficient increases in absolute magnitude in all cases but one (*Alabama Saltmarsh*). Regarding non-price attribute coefficients, in most cases they increase in magnitude, more than doubling in some instances. The exceptions (out of 40) are a single attribute coefficient in the *Alabama Oyster Sample*, and 7 attribute coefficients in the *Alabama Saltmarsh Sample*, where model results are almost identical (because the ECLC model detects no AN-A). In all cases, the error-components variable, *sigma*, goes to statistical zero in the ECLC AN-A models, indicating that either accounting for AN-A eliminates the need for nesting, or, as Hensher, Collins, and Greene (2013) state, one effect may be confounding the other.

Figure 2 contains plots of estimated attribute increment value (WTP) means and 95 percent confidence intervals. For samples where model fit is improved with ECLC AN-A, 14 out of 16 attribute increment values decrease. For the *Alabama Oyster Sample*, where model fit was not clearly improved by accounting for A-NA, attribute increment means and confidence intervals do not change much. Specifically, half of the means decreasing slightly, three increasing slightly, and one not changing. For the *Louisiana Oyster Sample*, where the original model outperforms the ECLC AN-A model, mean attribute increments increase in seven out of eight cases, and confidence intervals are generally wider. For the *Alabama Saltmarsh Sample*, where the original model also outperforms the ECLC AN-A model, there are only slight differences. For the *Louisiana Saltmarsh Sample*, where the ECLC AN-A model outperforms the original model, accounting for AN-A results in substantially lower means across all but one attribute, and either narrower or no-wider confidence intervals. The same is true for the

Louisiana Mangrove Sample, where the ECLC AN-A model also outperforms the original model. In all but one case, means are lower, and in all cases, confidence intervals are much narrower.

We observe that there is an intuitive relationship between the heterogeneity among samples and the changes in estimated coefficients between models. Overall, we notice that attribute increment value estimates do not change noticeably for the *Alabama Saltmarsh Sample* because there is no heterogeneity detected. Looking at changes in absolute magnitude, differences in attribute increment value estimates are smaller across samples with a larger “all-attended” class share (*Alabama Oyster and Louisiana Oyster Samples*) compared to differences for the samples with a smaller “all-attended” class share (*Louisiana Saltmarsh and Louisiana Mangrove Samples*). This result is intuitive, given that there is more heterogeneity which needs to be modeled.

Petrolia, Walton, and Yehouenou (2017)

Table 5 presents the original RPL results and the RPLC AN-A results. Model fit improves with RPLC AN-A for the *Non-generic Non-Gulf* and *Non-generic Gulf Samples* but worsens for the *Generic Gulf Sample*. Class shares appear to be equitably distributed for these data. Note that, for the *Generic Gulf Sample*, it was necessary to drop two classes to achieve stable results; we dropped the two classes that consistently showed little, if any, share being attributed to them. For the two *Non-generic Samples*, “none-attended” has the largest share (25 and 32 percent, respectively). Note that the “all-attended” class share is very low. It is only 7 percent for the *Non-generic Non-Gulf Sample* and 22 percent for the *Non-generic Gulf Sample*. For the *Generic Gulf Sample*, it is 11 percent. This is not necessarily a cause for concern; in the original study, it was hypothesized that some oyster consumers would focus on one set of attributes but not on

others. These results seem to bear this out. For the *Generic Gulf Sample*, results show that the plurality of respondents did not attend to the oyster variety attributes but rather to price and the other non-varietal attributes. Although oysters marketed along the Atlantic and Pacific coasts tend to sell under regional names, such as Wellfleets (from Cape Cod), Blue Points (Long Island), and Chincoteagues (Virginia), and often at a premium, Gulf Coast oysters are usually sold as cheaper, generic oysters. In other words, results are consistent with the notion that Gulf Coast consumers tend to pay less attention to the variety and more attention to price and other attributes.

In all cases, the price coefficient increases in absolute magnitude when RPLC AN-A is used. In all but five cases (out of 34), non-price attribute coefficients increase in absolute magnitude when RPLC AN-A is used. All the preference heterogeneity parameters, i.e., the standard deviations on the random parameters, go to statistical zero in the RPLC AN-A models.

Figure 3 contains plots of estimated attribute increment value (WTP) means and 95 percent confidence intervals. For the *Non-generic Non-Gulf Sample*, where model fit is improved with the RPLC AN-A model, means change only slightly, in most cases increasing, but confidence intervals become much narrower in almost all cases, and become much narrower for the two cases associated with attribute coefficients that are specified as random to account for preference heterogeneity (Champagne Bay and Apalachicola Bay). A similar result occurs for the *Non-generic Gulf Sample*. Specifically, means are relatively unaffected, but all confidence intervals are narrower, and all of those cases associated with the attribute coefficients specified as random are drastically narrower. Finally, for the *Generic Gulf Sample*, model fit is better under the original RPL model, and attribute increment means are largely unaffected, yet confidence

intervals on all attribute increment values are narrower, with those of the five attribute coefficients specified as random being drastically narrower.

Discussion

With some exceptions, the results indicate some general patterns when attribute non-attendance is taken into account. The first is that coefficients, both price and attributes, tend to increase in absolute magnitude. This is intuitive; when attribute non-attendance is ignored, coefficients reflect an average effect over all observations, which includes those not attending to (or, not deriving utility from) certain attributes. When accounted for, those not attending are separated out as having zero-valued coefficients, and so the magnitudes of the coefficients representing those attending necessarily increase. So this result, in and of itself, is not too surprising, and should not be interpreted to mean very much. The interesting question is what effect these changes have on attribute increment value estimates, i.e., whether the relative increase in the price coefficient dominates the relative increase in the attribute coefficients.

What we find, at least among the samples we have considered, is that there is no general directional effect on attribute increment values. Some increase, some decrease, with some large and some small. The major impacts of accounting for AN-A appear to show up in the confidence intervals surrounding these value estimates. In cases where accounting for attribute non-attendance does not clearly improve model fit, there is no clear narrowing, and in some case, widening, in confidence intervals. This is the case with both samples in Petrolia, Interis, and Hwang. It is also the case for the *Alabama Oyster*, *Louisiana Oyster*, and *Alabama Saltmarsh Samples* in Interis and Petrolia. On the other hand, in cases where accounting for attribute non-attendance improves model fit, confidence intervals are greatly narrower. This is observed for the *Louisiana Saltmarsh* and *Louisiana Mangrove Samples* in Interis and Petrolia, and the *Non-*

generic Non-Gulf and *Non-generic Gulf Samples* in Petrolia, Walton, and Yehouenou. The only exception to this pattern is observed in the *Generic Gulf Sample* in Petrolia, Walton, and Yehouenou, where although model fit is better under the original RPL model, several confidence intervals are nevertheless greatly narrower. It is also true, however, that there is no more than a 2 percent difference in model fit score (AIC and BIC) between the original and LC AN-A models. Furthermore, we observe that in all other cases where model fit is not improved by accounting for attribute non-attendance, the estimated class shares tend to follow a pattern of falling into one of two extremes: all-attended or none-attended, with very little in-between. The *Generic Gulf Sample* in Petrolia, Walton, and Yehouenou is the only one where attendance class shares are more diversified. In other words, although the model fit statistics does not indicate much improvement, the class share estimates nevertheless give stronger evidence of attribute attendance heterogeneity. In short, this last sample is somehow different from the rest. Finally, the results of Petrolia, Walton, and Yehouenou indicate a clear tradeoff in terms of accounting for preference heterogeneity, via a random-parameters specification, and accounting for AN-A. Our results, however, indicate that accounting for AN-A along with accounting for preference heterogeneity may obviate the need for the latter, and results in vastly more precise confidence intervals on attribute increment value estimates.

It should be noted that the method used to calculate attribute increment values in the latent-class models here assumes implicitly that attribute non-attendance is a heuristic. That is, respondents ignore a given attribute as a short-cut to decision-making. Hole, Norman, and Viney (2016) introduce this issue, and Heidenreich et al. (2017) expand upon it. Under this assumption, attribute increment values are defined as the ratio of the estimated attribute coefficient and the cost coefficient. But an equally-valid alternative assumption that the two

aforementioned papers highlight is that attribute non-attendance reflects preferences. In other words, respondents truly do not derive utility from changes in a given attribute. In this case, the attribute increment value should be defined as a weighted ratio, where the attribute and cost coefficients are weighted, respectively, by the probability that each is attended to.⁵ This alternative assumption can have real effects on estimated attribute increment values. Although not reported among our main results, we find no pattern in terms of direction. For example, some differences represent increases relative to those based on the heuristic assumption, whereas some represent decreases. Further, results are mixed in terms of whether these alternative values are closer or farther from the original non-attribute-attendance models. In terms of magnitude, some are very similar under both assumptions (with differences on the order of 2-10 percent), whereas some are quite different (differences on the order of 40-80 percent). However, given that we find that differences in confidence intervals comprise the main differences between models that account for attribute non-attendance and those that do not, the effect of this behavioral assumption is of lesser importance. This is because the width of confidence intervals under both behavioral assumptions are similar, meaning that the differences shown in Figures 1-3 are not much affected by this assumption. But it is important for the reader to be aware of this fact, because this is an important aspect of using latent-class models to derive attribute increment values.

⁵ These probabilities are defined, respectively, as the sum of the individual class probabilities in which each attribute is attended to.

Conclusion

In this paper, three recently published choice experiment studies focused on marine resources are revisited to take AN-A into account. Specifically, we account for inferred AN-A using latent-class models that attempt to identify classes of respondents based on attendance classes to which they are likely to belong. Overall, we find that accounting for AN-A does not always improve model fit. In some cases, model fit is a toss-up, implying that choice of model depends upon the intended purposes of the researcher, and in some cases, it is strictly worse, implying that models that focus on some other aspect of choice, such as preference heterogeneity with RPL models, is more appropriate than those focused on AN-A. Additionally, we do not find that accounting for AN-A has any clear directional effect on the magnitude of attribute increment values. We find a balanced mix of increases and decreases. Where we do find that accounting for AN-A has the biggest effect is on the confidence intervals surrounding mean attribute increment values. The confidence intervals appear to be substantially narrower in cases where apparent AN-A behavior is strong. We are not aware of any other paper focused on AN-A that has identified this effect.

We wish to make some comparisons to the conclusions of the original papers. Although we did not find any significant improvements in model fit or changes in results for Petrolia, Interis, and Hwang (2014), there are some notable differences for the other two papers. Regarding Interis and Petrolia (2016), we identified models that benefitted from accounting for AN-A and that also experienced noticeable changes in attribute increment values. We conclude that many of the attribute increment differences originally identified across habitats and locations would not have been so had they accounted for AN-A. For example, consider the Flood-15% attribute increment estimated from the Alabama saltmarsh versus Louisiana saltmarsh sample. Accounting for AN-A improved the Louisiana model and yielded an estimate about that for

Alabama. The same is true for at least four of the differences reported in the original paper when comparing habitats within the Louisiana location. We identified only one or two cases that may have gone in the opposite direction. In short, we believe that accounting for AN-A would have let the original paper make an even stronger case for the transferability of individual ecosystem service values across habitats or locations. But this would represent a minor adjustment to conclusions, not a major change in direction.

Regarding Petrolia, Walton, and Yehouenou (2017), the original paper reported a high degree of preference heterogeneity for several of the oyster varieties tested, whereas our findings indicate that after accounting for AN-A, which improved model fit in two of the three models, this preference heterogeneity vanishes. So, whereas they reported that there is evidence that there is some segment of the non-Gulf population with positive preferences for certain Gulf oyster varieties (the mean is negative), our results indicate that there is no evidence for it. By the same token, they reported that there is evidence of a segment of the Gulf population with negative preferences for most Gulf oyster varieties (the means of all but one were positive), our results indicate consistently positive preferences over all of them. Note that mean values did not change substantially, so the differences are in the variation around the mean. Again, this does not represent a major shift in direction of the conclusions of the original paper, but a marginal correction.

Our findings are limited, of course, by the choices we made and models we estimated. There is more than one way to account for AN-A. We were not able to explore stated AN-A because our samples included only very limited information for this purpose. Additionally, our analysis is incremental, as it builds on the original studies' models, which is both a strength and a weakness of the paper. While the primary strength of the approach is that it allows one to see the

marginal effect from accounting for AN-A behavior, it is also a weakness to the extent that the original studies' models may not have been flexible enough to account for heterogeneity in the choice data. Specifically, in both the Petrolia, Interis, and Hwang (2014) study that uses a conditional logit model and the Interis and Petrolia (2016) study that uses an error-components logit model, individual-level preference heterogeneity for attributes is not modeled in the AN-A models.

Also, it should be noted that all three of the original studies were conducted with a common researcher, and all three of the studies used the same survey mode, the web-enabled panel of GfK (or Knowledge Networks). These commonalities may assure that our findings are more controlled for effects of AN-A only. However, there may be elements such as question wording, choice question format, survey implementation, etc. that are not necessarily revealed for potential bias.

Although it is beyond the present scope, it is worth noting the lack of a pattern regarding socioeconomic differences. Petrolia, Walton, and Yehouenou (2017) reports that the non-Gulf sample had significantly higher income, education level, and was more male-dominated relative to the Gulf sample. However, our results indicate that both samples benefitted from the inclusion of AN-A. On the other hand, Interis and Petrolia (2016) featured three Louisiana samples with respondents randomly assigned to them. The Louisiana oyster sample did not benefit from AN-A inclusion, but the Louisiana saltmarsh and mangrove samples did. Likewise, the Alabama saltmarsh sample did not benefit from AN-A inclusion, but the Alabama oyster sample did. So here we have samples drawn from the same socio-demographic pools with apparently different AN-A behavior. Finally, Petrolia, Interis, and Hwang (2014) featured a sample and a sub-sample, with the sub-sample comprised of respondents who self-reported as

perceiving the survey to be consequential. Assuming that this sub-sample represents a somewhat different type of respondent, the results indicate nevertheless no obvious difference in AN-A behavior. Nevertheless, the literature provides some indications of who may engage in AN-A behavior. Balbontin, Hensher, and Collins (2017) and Heidenreich et al. (2018) link it to experience with the good. Alemu et al. (2013) point to protest behavior. Bello and Abdulai (2016) link AN-A to hypothetical bias. Heidenreich et al., citing the work of Saelensminde (2002), speculate as to the role of educational differences, and Carlsson, Kataria, and Lampi (2010) find limited evidence that education, as well as age, may have an effect. On the other hand, Scarpa, Theine, and Hensher (2010) find that multiple socioeconomic characteristics explain AN-A.

In closing, our results indicate that models accounting for AN-A are not necessarily warranted in all cases. Even in the case of Interis and Petrolia, where although there were five independent samples, the questionnaires differed only slightly, either in terms of the specific habitat providing the same ecosystem services, or the specific geographic location at which the services are provided (by the same habitat), the AN-A behaviors were not consistent. Three samples were improved by accounting for AN-A and two were not. Similarly, across the three samples in Petrolia, Walton, and Yehouenou, using three very similar questionnaires, two models were improved, one was not. As with most empirical work, the best model depends on the question being asked and the data being considered. The issue of attribute non-attendance is no exception.

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Table 1
Summary of datasets and econometric models used in the original studies

	<i>Petrolia, Interis, and Hwang (2014)</i>	<i>Interis and Petrolia (2016)</i>	<i>Petrolia, Walton, and Yehouenou (2017)</i>
Goods valued	Coastal wetlands and barrier islands in Louisiana's Barataria-Terrebonne estuary	Oyster reefs, salt marsh, and mangroves in Louisiana and Alabama	Gulf oysters for consumption
Ecosystem services / Attributes	Wildlife habitat, storm surge protection, commercial fish harvest, and cost	Water quality, flood protection, commercial fisheries, wading bird population, and cost	Harvest location/brand, size, saltiness, production method (wild or cultivated), and cost
Experimental design	D-efficiency	D-efficiency	S-efficiency
Response rate	67%	63%	55%
Econometric model	Conditional logit	Error-components logit	Random parameters logit

Table 2
CL and LC AN-A regression results for Petrolia, Interis, and Hwang (2014)

	<i>All Respondents (N = 1,588)</i>						<i>Consequential Respondents (N = 1,097)</i>					
	CL			LC AN-A			CL			LC AN-A		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
Price	-0.002	***	0.00	-0.01	***	0.00	-0.003	***	0.00	-0.01	***	0.00
Wildlife_intermediate	0.27	***	0.09	1.86	**	0.82	0.30	***	0.11	0.88	**	0.34
Wildlife_high	0.21	*	0.11	1.45	**	0.71	0.38	***	0.14	1.29	**	0.63
Storm protection_intermediate	0.37	***	0.08	1.34	*	0.71	0.41	***	0.10	0.65	**	0.31
Storm protection_high	0.16		0.14	-0.26		0.71	0.42	**	0.16	0.65		0.44
Fisheries productivity_intermediate	0.53	***	0.11	2.44	***	0.64	0.51	***	0.13	1.65	***	0.63
Fisheries productivity_high	0.47	***	0.13	1.66	**	0.66	0.56	***	0.15	1.14	**	0.54
Class Share												
All A				0.41						0.54		
Price N-A				0.00						0.04		
Ecosystem Services N-A				0.10						0.00		
None A				0.49						0.42		
AIC	2863.09			2849.06			1889.97			1883.47		
BIC	2974.92			2976.86			1994.01			2002.39		
LL	-			-			-923.98			-917.74		
	1410.55			1400.53								

*, **, *** indicate statistical difference at the 10%, 5%, and 1% level.

Table 3

ECL and ECLC AN-A regression results for Interis and Petrolia (2016) Louisiana samples

	Louisiana Oyster (N = 1,254)						Louisiana Saltmarsh (N = 1,016)						Louisiana Mangrove (N = 488)					
	ECL			ECLC AN-A			ECL			ECLC AN-A			ECL			ECLC AN-A		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
Price	-0.01	***	0.08	-0.02	***	0.00	-0.01	***	0.23	-0.05	***	0.01	-0.01	***	0.19	-0.08	***	0.02
Water_10%	0.50	***	0.13	1.12	***	0.32	0.47	***	0.15	1.65	***	0.61	1.06	***	0.23	2.83	***	0.48
Water_20%	0.74	***	0.14	2.27	***	0.66	0.80	***	0.16	3.35	***	0.88	1.12	***	0.26	3.11	***	0.58
Flood_10%	0.70	***	0.12	1.45	***	0.30	0.56	***	0.16	1.24	***	0.43	0.77	***	0.22	1.65	***	0.36
Flood_15%	0.94	***	0.15	1.47	***	0.33	0.92	***	0.18	2.50	***	0.83	0.70	**	0.27	0.88	**	0.37
Fish_20%	0.32	***	0.12	1.07	***	0.29	0.33	***	0.14	2.67	***	0.96	0.04		0.23	1.17	***	0.38
Fish_30%	0.73	***	0.12	1.73	***	0.34	0.40	***	0.15	2.07	**	0.86	0.39	*	0.23	1.94	***	0.42
Bird_5%	0.63	***	0.13	2.04	***	0.51	0.37	**	0.16	1.77	**	0.74	0.40	*	0.21	2.08	***	0.47
Bird_10%	0.55	***	0.12	1.75	***	0.56	0.61	***	0.15	1.72	***	0.46	0.28		0.19	1.04	***	0.40
Sigma	7.50	***	1.96	0.00		0.11	4.10	***	0.78	0.00		0.12	4.04	***	1.13	0.00		0.20
Class Share																		
All A				0.47						0.22						0.13		
Price N-A				0.09						0.28						0.42		
Ecosystem Services N-A				0.18						0.14						0.24		
None A				0.26						0.36						0.21		
AIC	1887.19			1957.90			1733.88			1660.60			738.52			709.60		
BIC	2015.54			2101.70			1856.97			1798.44			843.27			826.92		
LL	-918.59			-950.97			-841.94			-802.29			-			-		
													344.26			326.80		

*, **, *** indicate statistical difference at the 10%, 5%, and 1% level.

Table 4

ECL and ECLC AN-A regression results for Interis and Petrolia (2016) Alabama samples

	<i>Alabama Oyster</i> (N = 1,395)						<i>Alabama Saltmarsh</i> (N = 489)					
	ECL			ECLC AN-A			ECL			ECLC AN-A		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
Price	-0.01	***	0.09	-0.02	***	0.01	-0.01	***	0.18	-0.01	***	0.00
Water_10%	0.68	***	0.11	1.57	***	0.40	0.75	***	0.21	0.73	***	0.19
Water_20%	0.94	***	0.13	2.22	***	0.45	0.63	***	0.23	0.60	***	0.22
Flood_10%	0.27	***	0.10	0.11		0.23	0.35	*	0.20	0.31	*	0.18
Flood_15%	0.51	***	0.13	0.68	*	0.35	0.65	**	0.28	0.58	***	0.21
Fish_20%	0.27	**	0.11	1.19	***	0.34	0.62	***	0.21	0.62	***	0.19
Fish_30%	0.33	***	0.10	0.65	**	0.25	0.98	***	0.21	1.00	***	0.19
Bird_5%	0.20	*	0.11	0.22		0.25	0.93	***	0.25	0.84	***	0.21
Bird_10%	0.53	***	0.11	1.45	***	0.44	1.28	***	0.22	1.26	***	0.20
Sigma	3.68	**	1.56	0.00		12.37	1.56		1.11	0.00		0.12
Class Share												
All A				0.57						1.00		
Price N-A				0.00						0.00		
Ecosystem Services N-A				0.01						0.00		
None A				0.42						0.00		
AIC	2468.09			2461.70			831.54			838.90		
BIC	2583.38			2592.68			923.77			943.73		
LL	-			-			-			-		
	1212.05			1205.83			393.77			394.46		

*, **, *** indicate statistical difference at the 10%, 5%, and 1% level.

Table 5

RPL and RPLC AN-A regression results for Petrolia, Walton, and Yehouenou (2017)

	<i>Non-generic Non-Gulf</i> (N = 2,937)						<i>Non-generic Gulf</i> (N = 1,059)						<i>Generic Gulf</i> (N = 2,992)					
	RPL			LCRP AN-A			RPL			LCRP AN-A			RPL			LCRP AN-A		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
Price	-0.09	***	0.07	-0.40	***	0.03	-0.11	***	0.12	-0.39	***	0.09	-0.09	***	0.13	-0.61	***	0.05
Champagne Bay	-0.24	**	0.10	-1.72	***	0.37	0.78	***	0.29	2.52	***	0.38	0.30	*	0.16	0.18		0.23
Apalachicola Bay	-0.49	***	0.10	-1.86	***	0.29	0.46		0.30	1.85	***	0.39	0.70	***	0.22	0.78	***	0.24
Point aux Pins	-0.48	***	0.10	-2.00	***	0.31	0.35		0.30	1.63	***	0.42	-0.22		0.16	-0.37	*	0.22
Lonesome Reef	-0.46	***	0.10	-1.77	***	0.30	0.65	*	0.35	1.66	***	0.41	-0.02		0.17	-0.32		0.23
Bay Saint Louis	-0.58	***	0.10	-2.07	***	0.43	0.48	*	0.27	1.93	***	0.37	0.03		0.12	0.08		0.23
Portersville Bay	-0.54	***	0.10	-2.21	***	0.33	-0.18		0.23	0.25		0.40	-0.25		0.15	-0.42	*	0.25
Non-Gulf													-0.40	*	0.21	2.56	***	0.21
Small	-0.50	***	0.09	-0.94	***	0.19	-0.42	*	0.22	-1.22	**	0.59	-0.70	***	0.16	-1.43	***	0.30
Large	-0.11		0.08	0.20		0.18	-0.28		0.21	0.07		0.37	0.10		0.18	-0.41	**	0.20
Sweet	0.06		0.09	0.64	**	0.31	0.17		0.22	0.75		0.75	-0.10		0.17	0.03		0.25
Salty	-0.51	***	0.08	-1.33	***	0.25	0.14		0.21	-0.18		0.50	0.05		0.15	-0.10		0.21
Wild	0.19	***	0.07	0.83	***	0.23	0.33	**	0.15	0.75		0.57	0.41	***	0.11	0.21		0.18
SD Champagne Bay	0.60	***	0.22	0.00		0.15	1.47	***	0.33	0.00		0.26	1.16	***	0.23	0.00		0.15
SD Apalachicola Bay	0.67	***	0.18	0.00		0.15	1.72	***	0.42	0.00		0.23	2.04	***	0.34	0.00		0.17
SD Point aux Pins							1.59	***	0.40	0.00		0.23	0.75	**	0.32	0.00		0.16
SD Lonesome Reef							1.74	***	0.42	0.00		0.23	1.18	***	0.21	0.00		0.15
SD Bay Saint Louis							1.29	***	0.37	0.00		0.25						
SD Non-Gulf													2.85	***	0.19	0.00		0.10

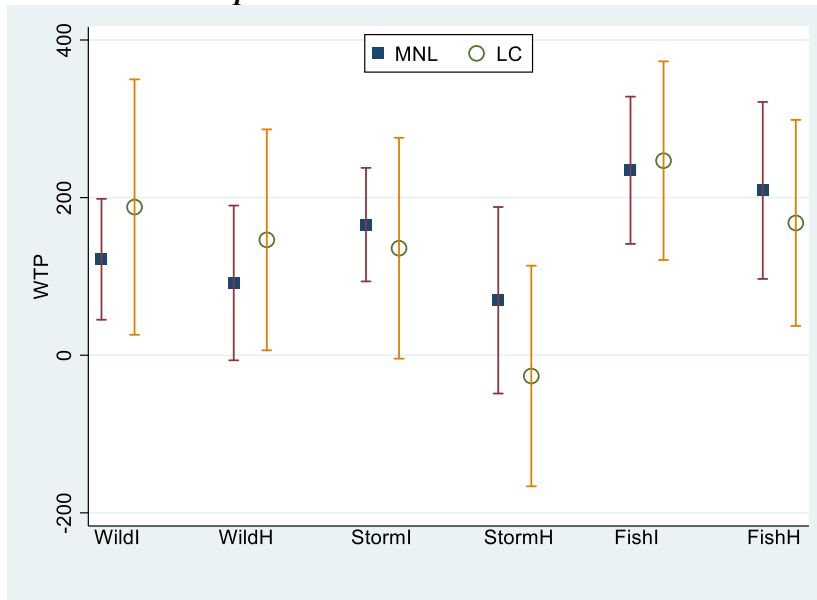
Table 5, continued.

Class Share						
All A		0.07		0.22		0.11
Others N-A		0.05		0.00		
Variety N-A		0.15		0.05		0.41
Price N-A		0.07		0.25		0.14
Variety and Others N-A		0.10		0.07		
Price and Others N-A		0.14		0.00		0.11
Price and Variety N-A		0.17		0.09		0.12
None A		0.25		0.32		0.11
AIC	5040.42	4754.00	1789.85	1746.30	4458.61	4526.30
BIC	5124.21	4879.66	1874.26	1865.45	4566.68	4664.42
LL	-2506.21	-2355.99	-877.93	-849.15	-2211.31	-2240.17

*, **, *** indicate statistical difference at the 10%, 5%, and 1% level.

Figure 1. Means and 95 percent confidence intervals for attribute increments (WTP) under original MNL specification and LC-AN-A specification for Petrolia, Interis, and Hwang (2014). Panel A shows results for the *All Respondents Sample*; Panel B, for the *Consequential Respondents Sample*.

Panel A: *All Respondents*



Panel B: *Consequential Respondents*

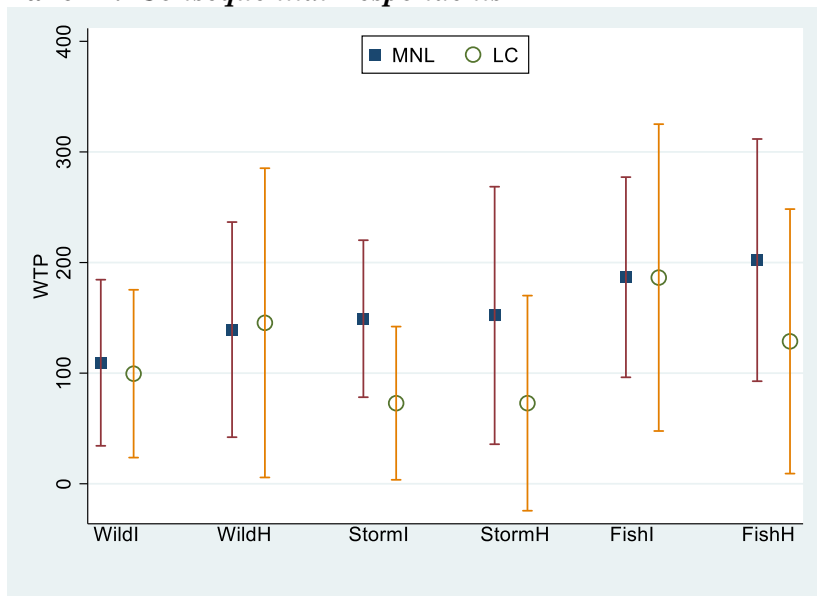
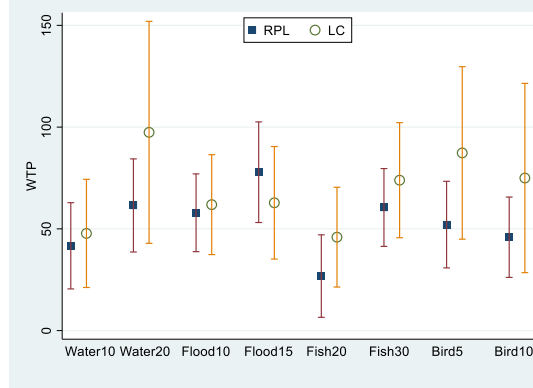
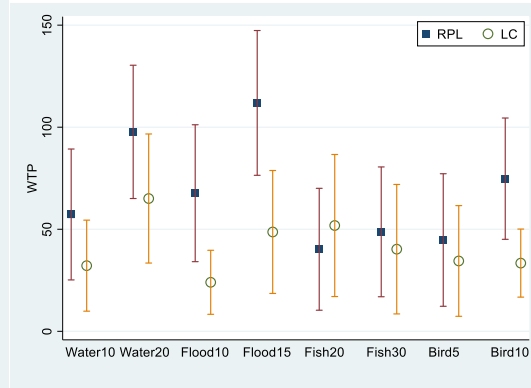


Figure 2. Means and 95 percent confidence intervals for attribute increments (WTP) under original RPL specification and LC-AN-A specification for Interis and Petrolia (2016). Panel A shows results for the *Louisiana Oyster Sample*; Panel B, *Louisiana Saltmarsh*; Panel C, *Louisiana Mangrove*; Panel D, *Alabama Oyster*; Panel E, *Alabama Saltmarsh*.

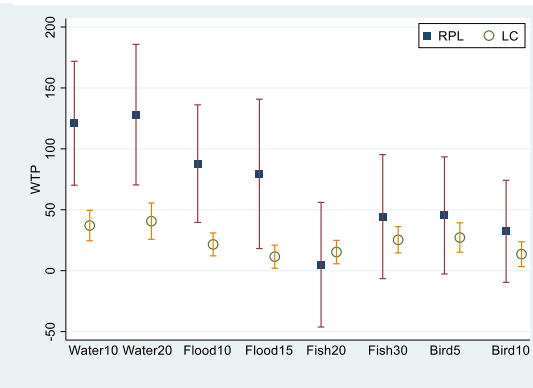
Panel A: *Louisiana Oyster*



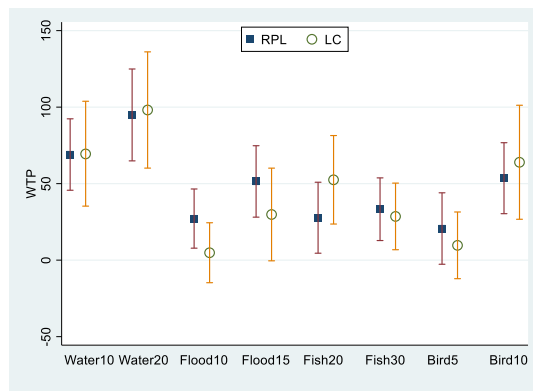
Panel B: *Louisiana Saltmarsh*



Panel C: *Louisiana Mangrove*



Panel D: *Alabama Oyster*



Panel E: *Alabama Saltmarsh*

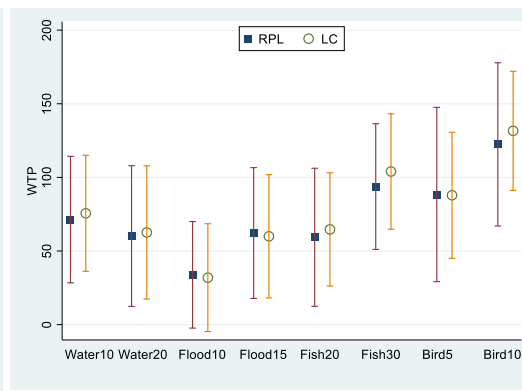
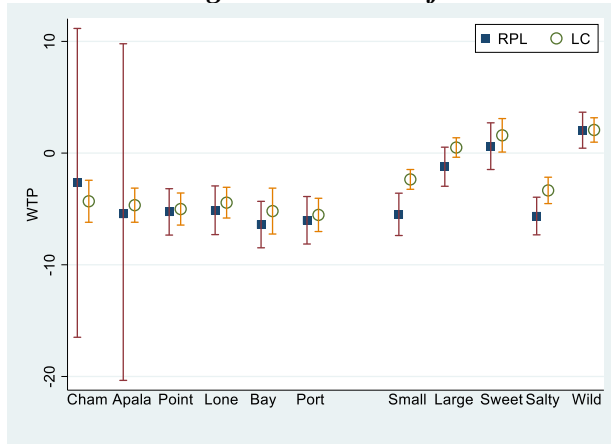
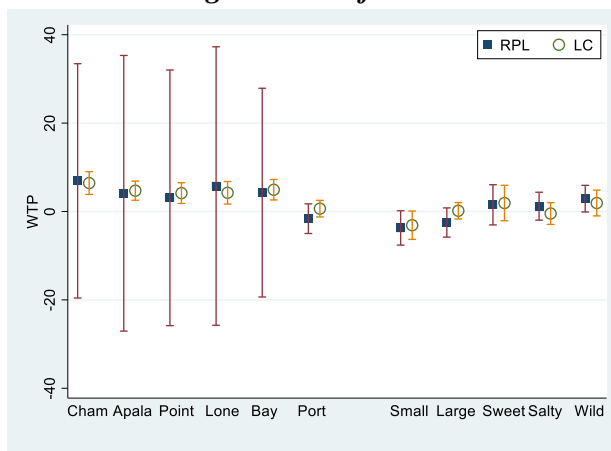


Figure 3. Means and 95 percent confidence intervals for attribute increments (WTP) under original RPL specification and LC AN-A specification for Petrolia, Walton, and Yehouenou (2017). Panel A shows results for the *Non-Generic Non-Gulf Sample*; Panel B, *Non-Generic Gulf*; Panel C, *Generic Gulf*.

Panel A: *Non-generic Non-Gulf*



Panel B: *Non-generic Gulf*



Panel C: *Generic Gulf*

