STATED PREFERENCE METHODS FOR ENVIRONMENTAL MANAGEMENT: RECREATIONAL SUMMER FLOUNDER ANGLING IN THE NORTHEASTERN UNITED STATES

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I. Introduction

Environmental managers are becoming increasingly aware that environmental policies must be crafted in a way that incorporates the human dimensions of the ecosystem. Failure to incorporate stakeholder preferences into management measures can lead to policies that fail because people's preferences, motivations, and behavior concerning their use of the environment were not properly considered even if defensible natural science approaches were incorporated in the management decision.

In this paper, we present a new method for quantifying angler preferences for fisheries management. The method, called the Stated Preference Discrete Choice Technique (SPDC) (Louviere et. al) is a particular form of conjoint analysis, which has broad application to measuring preferences for all sorts of goods including both market and non-market goods. The method has been used applied in a wide variety of settings (for example, appliance choice (Ben-Akiva et al.), yogurt (Guadagni et al.), and light-rail transportation (Preston), and environmental valuation (Adamowicz et al.)). For resource managers, the method provides useful information about new policies, non-observable ranges for management tools, and policies having multiple attributes.

The SPDC technique does rely on respondents making choices over hypothetical scenarios. For the case of recreational fishing, respondents are asked to choose among hypothetical trips, each completely described by site attributes (e.g., cost of travel to the site, expected catch, etc.). The National Marine Fisheries Service (NMFS) has for some time been collecting data on actual fishing choices made by recreational anglers. By observing these choices, analysts are able to use revealed preferences (RP) techniques to measure preferences. The primary advantage of RP techniques is the reliance on actual choices made by fishermen, avoiding the problem of strategic responses (Blamey and Bennett) perhaps inherent with SPDC techniques. The strength of RP techniques is also its weakness. Relying on observable trips limits an analysis to observable states of the world. Therefore, RP techniques may not be suitable for quantifying preferences for attributes where no variation exists or for which the attribute cannot be observed. For summer flounder fishing, the fishery studied in this report, this was indeed a problem.

Summer flounder is one of the most sought after recreationally caught fish along the eastern seaboard of the United States. It is typically in the top three species in terms of anglers targeting it per year according to NMFS (personal communication, NMFS). NMFS has for some time been concerned with the overall exploitation level of summer flounder by both commercial and recreational fishermen along the Atlantic coast. The agency and councils have been gradually tightening regulations for all fishing activity in an effort to conserve the stock. Recently, interest has shifted to understanding angler preferences and motivations for fishing and fisheries management in an effort to comply with administrative law requirements, and to craft more successful and acceptable policies. This interest was the impetus for this study.

Initial attempts at quantifying behavioral responses to management regulations focused on using RP techniques using observable fishing choices coupled with the effective management regime at the angler's chosen fishing site. RP methods failed largely because of very little spatial or temporal variation in management regulations. This is largely by design, however, as the agency and councils attempt to set uniform spatial regulations (across states) to avoid confusion and enforcement problems. Table 1 shows regulations in the Northeastern United States for summer flounder. Attempts by the author to quantify behavioral responses due to changing bag and size limits using RP data failed, even after introducing variation in bag and size limits using variation in open seasons.

Table 1. Summer Flounder Regulations, 2000[1]

State	Minimum Size Limit (inches)	Possession Limit	Open Season
Massachusetts	15.5	8	May 10 - Oct. 2
Rhode Island	15.5	8	May 10 - Oct. 2
Connecticut	15.5	8	May 10 - Oct. 2
New York	15.5	8	May 10 - Oct. 2
New Jersey	15.5	8	May 6 - Oct. 20
Delaware	15.5	8	May 10 - Oct. 2
Maryland Bays	15	8	May 15 - Dec. 31
Maryland Coastal	15.5	8	April 15 - Dec. 11
Potomac River	15.5	8	May 15 - Dec. 31
Virginia	15.5	8	March 29 - July 23 Aug. 2 - Dec. 31
North Carolina	15.5	8	Jan. 1 - Dec. 31

Source: Atlantic States Marine Fisheries Commission, personal correspondence, May 14, 2001.

Consequently, attention shifted toward the use of SPDC techniques to enable the investigation of new management options and to introduce variation in bag and size

[1] For the period 1996-1998, there was even less variation in regulations: states had no closed seasons and the identical minimum size and possession limits. Minimum size limits ranges were from 14 to 15 inches and possession limits ranged from 8 to 10 fish.

limits so that management could explore “what if” scenarios before enacting regulations. In addition to guiding the reader through the SPDC method, the paper will offer some rigorous validity testing for the method itself. Specifically, we will test whether there is a divergence of parameters and welfare estimates from the SPDC method versus the RP method.

Our findings show that the SPDC technique is very useful at quantifying tradeoffs among various summer flounder management alternatives and for recovering welfare and participation change estimates. While our findings indicate that parameter and welfare estimates do differ somewhat from that found from the RP method, the results demonstrate that these differences are quite small and that for practical uses of the models, the differences are of such small magnitude that policy guidance coming from either approach would be quite similar.

The reader should note that SPDC techniques could be applied to a wide-range of policy issues facing the agency in addition to recreational issues including commercial fishery management in the context of area management, gear restrictions, etc. Similarly, it could be applied to critical marine habitat or marine mammal issues.

The organization of the paper will proceed as follows. We will describe the complete process of SPDC development including a theoretical argument for the need to quantify preferences and a review of methods for quantifying preferences (Section II); compare RP techniques to SPDC and showing how the SPDC method was adapted for a study of preferences for summer flounder management in the Northeaster United States (Section III); describe the experimental design of this project (Section IV) and models of angler behavior (Section V); discuss results and application to evaluating policy (Section VI); and conclude with recommendations for future SPDC studies (Section VII).

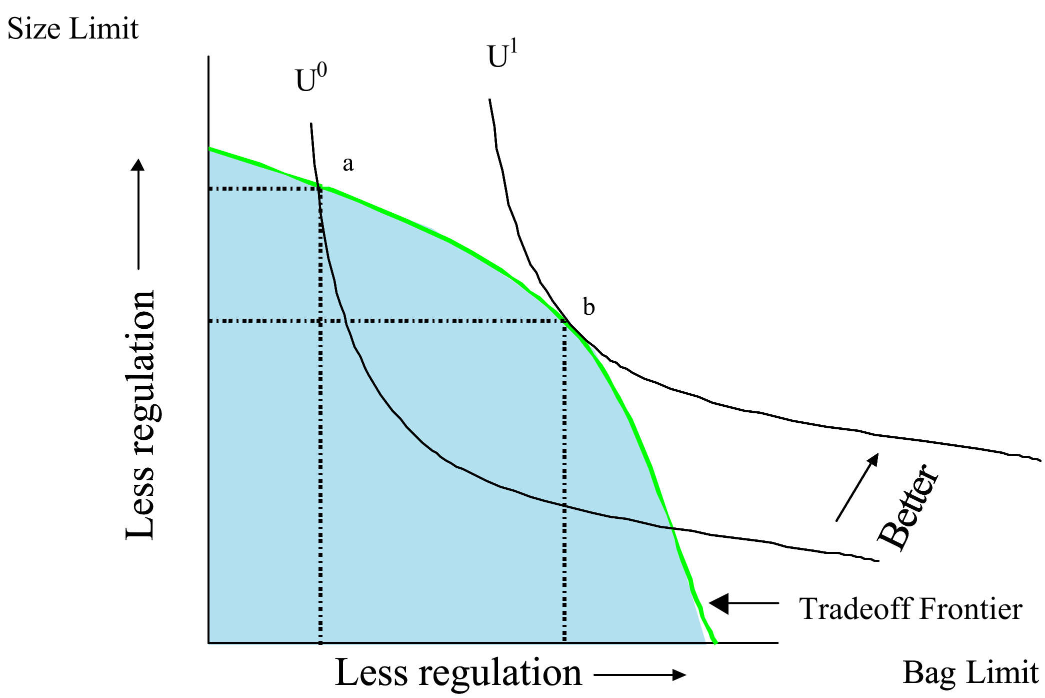
II. A Review of Approaches for Quantifying Preferences for Fisheries Management

Why should managers care about incorporating angler preferences and behavior into fisheries management? Fisheries management is something of a misnomer, since policy is directed at fishermen or the activities of humans having some adverse affects on fish populations or habitat. Consequently, it is really people that we are managing. In the absence of man's intervention in the fisheries ecosystem, there would not be a need for fisheries management. From this perspective, it is obvious that an understanding of people's behavior is important for effective fisheries management.

Such a perspective does not preempt the role of sound natural science information in the policy making process. Knowledge of the natural system is obviously important to understand the impacts of fishing and the capacity of the resource. However, in the absence of knowledge about those we are managing, placing limits on fishing activity can lead to management failure. Just as individuals and corporations find and exploit loopholes in tax laws, so to do affected fishermen react and change their behavior once regulations are imposed on them. It is vital to understand these reactions when designing environmental policy.

So how can natural/physical science and the human components of the management problem be reconciled? Figure 1 shows a stylized representation of how these concepts can be combined to bring about effective policy. Suppose population dynamics scientists determine the combination of bag and size limit regulations for a species that will achieve a target mortality level. This mortality level is chosen to ensure the conservation of the species. In the absence of information about angler preferences concerning bag or size limits, no point on the frontier is more preferred to any other one from the physical science perspective, since all points both inside and on the frontier ensure a sustainable fish population. In such as setting, it is likely that a non-optimal management level, such as point a, will be chosen. Point a is non-optimal because for the same conservation level, we could move to point b and achieve a higher level of well-being for a representative angler since $U^1 > U^0$, where curves U^1 and U^0 represent levels of well-being associated with different levels of size and bag limits. These curves are termed indifference curves by economists, because anglers are equally well off with any combination of bag and size limits implied by a given indifference curve, U. At point a, anglers are more restricted with regard to bag limits than size limits. Anglers would prefer to tighten size limits and loosen bag limits and move toward point b.

Figure 1. Reconciling human preferences and environmental constraints.



Another advantage of considering stakeholder preferences in management decisions is the degree to which it can foster buy-in into management and stakeholder acceptance for policy. Additionally, there are legal requirements that the NMFS must consider stakeholders when forming management decisions.

There are several ways of incorporating people's preferences of the natural system each having it's own pluses and minuses. For example, an approach required by law for many federal environmental policies- the public meeting- allows affected parties to voice concerns about potential management options. The approach allows all affected parties to participate if they wish, but questions remain as to how representative the information is and if he who shouts loudest is heard most.

Another approach is to ask anglers whether they favor or oppose management options (public opinion survey). For example, one might ask a random sample of anglers the degree to which they favor or oppose bag or size limits. These questions allow managers to gain information on anglers' preferences for bag or size limits, but does not reveal their preferences to management options where both bag and size limits might be considered nor are preferences revealed for how preferences for bag or size limits might change as regulations are tightened. One could imagine that anglers might be more opposed to bag limits that eliminate all take-home fish but potentially more supportive of a slight decrease in bag limits. This approach also relies on a representative sample of anglers. However, vocal anglers may still dispute results from such a survey if their preferences are quite different from the sample's.

The Revealed Preference Approach

An approach used recently by the NMFS relies on observing actual angler behavior to infer something about their preferences for recreational fishing and fishing regulations. The revealed preference approach (hereafter referred to as RP), as it is called, requires a representative sample of anglers. For recreational angling, "representative" can be thought of along several strata such as geographical location of fishing, time of year, and the type of fishing. To estimate RP models, data must exist on catch, location and time of fishing, place of residence, the degree to which an angler "gave up" wages to take a trip, type of fishing, information about environmental characteristics about the fishing site, and fishing regulations at the site fished.[2]

With this information in place, statistical models of the demand for recreational fishing trips are estimated that describe tradeoffs anglers make with regard to expected catch, cost of travel to site, management regulations, environmental conditions, and other factors deemed important to describe recreational site choice (Hicks et al., Haab et al., McConnell et al.). The model, once estimated, allows preferences to be quantified so that management options can be ranked, anglers' value of changing environmental conditions can be estimated (useful, for example, to answer questions such as 'what is the value of recreational fishing?' or 'what was the loss to recreational anglers due to an oil spill in Rhode Island?').

The RP methodology relies on variation in the natural environment so that the statistical model can discern how the various factors important for describing recreational

[2] For examples of RP applications and discussion of some important issues related to RP modeling relevant for sportfishing, see Bockstael et al., Green et al., Haab and Hicks, Hauber and Parsons, Jones and Lupi, Kaoru and Smith, Kling and Thomson, Parsons and Needelman, Parsons et al., Parsons and Hauber, Pendleton and Mendelsohn, and Whitehead and Haab.

fishing sites influence the choice. If no variation is found in the data (e.g., fish stocks are uniformly distributed and catchable) then the model will fail to quantify the effect of that factor. For example, recreational angling regulations for bag and size limits in the Northeastern United States for most species are set uniformly across states, and open and closed seasons closely mirror each other: there is no variation.

Similarly, RP approaches, based upon observable data at a site, are limited to analyzing the effect of actual factors at a site. For example, if managers were considering new management tools such as property right regimes, then current marine recreational data of fishing behavior would provide little information about anglers' preferences for them since anglers are not currently making recreational fishing choices in the context of property right management regimes. Therefore, observable data on angler behavior offer very little or no variation with regard to many management tools so that using RP approaches to estimate angler preferences for management is problematic at best and impossible at worst.

The Stated Preference Approach

Stated preference techniques rely on anglers' responses to hypothetical scenarios. For example, the researcher might describe a hypothetical fishing trip to an angler and ask the angler whether they would take the trip or not. Stated preference techniques have two major classes of elicitation techniques to get at anglers' preferences for fisheries management. The first type, contingent valuation, measures the value of a change from the status quo to some other state of the world. For example, one might ask anglers to consider their current trip and ask them their willingness to pay to avoid a decrease in the bag limit for striped bass for that trip. This contingent valuation question is designed to quantify the economic loss of going to a more restrictive management position. The technique is not well suited to measuring preferences for all of the attributes of the fishing experience (expected catch, cost of travel to site, management regulations, environmental conditions, etc.), but this technique is useful for exploring new management tools or examining willingness to pay in the context of tightening or loosening regulations.

Another stated preference methodology, Stated Preference Discrete Choice (SPDC) techniques have been applied to environmental management problems such as Alaska fishing (Herman), hunting in Canada (Adamowicz et al.), and Maine fishing (Roe et al.). Like contingent valuation, SPDC techniques applied to fishing management gain information about preferences by analyzing responses to hypothetical fishing trips. Further, SPDC considers a fishing trip as a bundle of attributes describing a trip. Using experimental design techniques, anglers are given trip comparisons that are optimal in the sense that they require the respondent to make tradeoffs across the different trip attributes simultaneously. Therefore, it is possible to examine how preferences for a management measures such as bag limits might change as other management changes, as environmental conditions change, or as the cost of the trip changes. Additionally, new policy-relevant attributes can be examined; for example, anglers might be asked to consider a trip under the existing management regime and one with a new management tool in place (for example, gear or area restrictions). Like contingent valuation, SPDC is based upon hypothetical, not real behavior. Consequently, questions could be raised about the veracity of results based upon this type of data.

III. Revealed and Stated Preference Techniques for Marine Recreational Fishing

The use of revealed preference methods in economics is extensive. Applications include demand analysis (food demand, housing demand, and demand for other consumer goods), production analysis (agricultural and industrial production), and analysis of labor market choices. These models focus on observing choices made by individuals and attempt to relate choices to observed factors about the choice in order to estimate a quantitative relationship. Recreation demand analysis was the first use of revealed preference methods for non-market goods. Hotelling was the first to suggest that demand for national parks was probably a factor of the cost of accessing the park as well as environmental and other factors associated with the choice to visit a park or not.

In a marine recreational fisheries recreation demand setting, the use of revealed preference methods require extensive data on the individual, the recreation site, the state of the environment at that site, and similar information for substitute recreational alternatives. The random utility framework, in particular, requires extensive data, on each and every recreational alternative available to the individual. Perhaps the most burdensome requirement in the context of recreational fishing is the characterization of the quality of the fishing experience. Many studies have used the expected catch for the trip as a proxy for the quality of a fishing trip. The formulation of expected catch requires a time series of biological catch-effort data at a site to produce a meaningful measure of expected catch (McConnell, Strand, and Blake-Hedges).

NMFS Data Collection Efforts

The NMFS' Division of Fisheries Statistics and Economics, Office of Science and Technology has for some time undertaken data collection on recreational angling. Since 1994, this data collection effort has been expanded to include economic data to enable the estimation of economic valuation and impact models in support of characterizing the economic importance of recreational fishing and for fisheries management (see Hicks et al., 2000). The initial analysis of the first data collection effort, undertaken in the Northeastern United States in 1994, revealed that developing species-specific models of angler behavior and economic value was severely hampered by data limitations. Additional research has shown that models aggregating over species, while very useful for characterizing total economic value, are a relatively poor proxy for species-specific models needed for guidance of management. Additional work using data from other regions of the country has revealed similar problems in developing species-specific management models.

In response to these problems, the NMFS Fisheries Statistics and Economics Division (F/ST1) began a new data collection effort in a way complementary to the ongoing data collection on recreational anglers. The effort consisted of adding a mail survey to the MRFSS field survey. In the field, anglers were asked questions enabling the estimation of the total value models so that the historical time series could be maintained; in the mail survey anglers were presented with questions about a specific species. These questions consisted of attitudes and awareness about catch and release fishing, management tools, and stated preference questions related to potential management measures aimed at summer flounder. These questions varied attributes relating to a fishing trip; among the attributes were bag and size limits for summer flounder. The questions were framed in such a way that preferences for management tools could be estimated, welfare measures obtained, and a participation model could be estimated.

The SPDC portion of the mail survey was created using experimental design techniques in order to improve the efficiency of the tradeoffs people had to make concerning fishing and fishing management. Clearly the ability to control the tradeoffs respondents make is a major advantage to SPDC methods. Choice experiments are designed to introduce variation in the factors researchers want to explore. This is obviously a major advantage relative to RP methods where researchers are at the mercy of variation and trade-offs that are observable in the field. The ability to design tradeoffs nearly places SPDC in the realm of experimental economics. In SPDC, we can investigate 'new' attributes (what if there were a recreational fishing tradeable quota) or attributes out of observable ranges (an 80 inch size limit)- with SPDC we aren't limited to the current state of the world when finding out about people's preferences.

In RP models we use 'real' choices people make. To estimate models of behavior, researchers make assumptions about what information is relevant for the person's recreation choice. For example, the analyst must decide: the relevant substitute sites the individual considered, the environmental quality indicators important to the individual, the formation of expectations about quality indicators, and hope that important factors not observable are not correlated with the observable variables.

In SPDC, all the information is given to respondents. It is a hypothetical technique; people are not making real economic choices. Therefore, it is important to frame questions properly (e.g., need the ‘right’ attributes, and the ‘right’ ranges of these attributes). The questionnaire must be clear since it is containing all of the information for the choice experiment. In a travel cost setting, in order to get enough variation in variables of interest, e.g., bag and size limits, an analyst might need time series or spatial data, which opens up potential statistical pitfalls. For the NMFS’s needs, the SPDC technique’s primary advantage is the ability to value new or out of range attribute levels and for attributes with little or no variation.

IV. Stated Preference Experimental Design

To collect the SPDC data, the choice was made to leverage the Marine Recreational Fisheries Statistics Survey (MRFSS) for two reasons. First, the MRFSS had already been used extensively to obtain data for RP methods, those models existed, and it was felt that it provided a mature methodology from which to begin a pilot project using SP methods. Additionally, there were cost advantages associated with going with the well-established MRFSS survey. The primary advantage of leveraging the MRFSS was that it afforded the opportunity to collect both SP and RP data *for the same fishermen*. Having this data would allow hypothesis testing on whether SP and RP data provided similar results for both parameter and welfare estimates.

Once the decision had been made to collect data via the MRFSS survey, the question was how best to do it. The MRFSS has several vehicles for collecting data, each having its own strengths and weaknesses. The field intercept survey collects catch/effort and economic data from fishermen in the field. It is well suited for RP methods because the economic add-on questions seek factual information from the respondent about his employment situation, income, and whether he is primarily engaged in fishing. SP questionnaires typically require respondents to digest information designed to "setup" the hypothetical question they will be asked. Additionally, SPDC methods present multi-attribute recreation trips and ask respondents which one they would have chosen. Taken in tandem, it is difficult to implement an SPDC survey in combination with the MRFSS field intercept. If one factors the time cost of the additional SPDC information that one must read to respondents, and the time it takes respondents to compare the hypothetical trips, conducting the SPDC survey in the field is not a suitable method for collecting the data.

The MRFSS also collects data via a random phone survey. The advantage to this approach is that one can collect data via a random sample of anglers. For many of the reasons listed above, it is not possible to conduct the SPDC survey on the phone. One could conduct a mail follow-up to the random phone survey to obtain the SPDC data, but one would also need to collect data on actual trip choices if a rigorous comparison of RP and SPDC methods needs to be made.

In 1999, a field test was undertaken in Ocean City, Maryland. The field test consisted of adding SPDC questions to the field portion of the survey. Findings indicated that fishermen responded well to the SPDC questions but it did take them quite a bit of time to digest the trip comparison information and make a decision. It was felt by survey statisticians that the resulting downtime for interviewers could potentially jeopardize the scientific integrity of the field survey by biasing the data collection effort. Based on this information, it was decided that the intercept survey should be used to collect RP data on respondents (as it had been used in the past), and then a mail follow-up survey should be conducted to obtain SPDC data.

Based upon the results of the initial field test, extensive survey revisions were undertaken. At this time, the focus was on properly identifying the attributes of the hypothetical recreation trip that were important for the angler's trip decision. It was clear that the SPDC model needed to be able to quantify preferences for size and bag limits since they were the primary tools used by management (though season limits are also used extensively). To get at season limit regulations and to make the model amenable to predicting changes in participation, the SPDC comparison, in addition to two hypothetical trips, asked anglers to consider a 'Don't Go' option, whereby they could opt out of fishing if regulations or some other factors moved in an unfavorable enough direction (for more discussion on the importance of an 'opt out' choice, see Banzhaf et al).

Survey Field Test and Focus Group

Pretests were given to employees of the National Marine Fisheries Service in the Office of Science and Technology. These surveys are available from the author. The intent of these surveys was to further hone the instrument, question format, readability of the questions, and meaningfulness of attributes and attribute definition. This was a highly iterative process designed to further the instrument's development as far as possible before the focus group meetings held in Baltimore, Maryland in March of 2000.

The goal of the focus group was to further refine the entire instrument and the SPDC questions. None of the principal investigators were present in the room during the focus group session; however, the principal investigators could view respondents through a one-way mirror (of which the respondents were made aware). A moderator's guide was prepared (see Appendix A). There were four focus groups each of approximately 10 participants each. Focus groups were stratified according to age and income. Respondents were randomly recruited and screened based upon their knowledge and participation in fishing and their availability within the stratas described above (the focus group screening instrument can be found in Appendix A).

All portions of the survey were under consideration for change as a result of feedback from the respondents. Two versions of the survey were prepared for the focus group. The primary difference between the two was factors included in the hypothetical choice comparisons (the two versions can be found in Appendix A). Table 2 contains the attributes and definitions considered in the focus group experiment. Our experience in the field and in in-house pretests indicated that Survey 1, which did not tell fishermen how many of the summer flounder they caught were of legal size, was problematic, leading to confusion among respondents who for the most part thought that all of the summer flounder caught were of legal size. Under this improper assumption, the respondents were not required to make the proper trade-offs regarding minimum size limits.

Consequently, in the focus group we first gave respondents Survey 1, and then probed whether they thought the described trips gave them all the necessary information to make a choice comparison. Next, we then gave them Survey 2 with no explanation other than it was a slightly different version of the survey. Many respondents did not notice that another attribute had been added, but when probed about the difference between Surveys 1 and 2, noticed that there was an addition of an attribute. When probed about their assumptions concerning the number of legal sized fish in Survey 1, most had indeed assumed that all of the caught fish were of legal size. This confirmed our suspicion that the addition of the attribute in Survey 2 was necessary to get at the full range of preferences for fisheries management.

Respondents were also asked about ranges of attributes including the appropriateness of the cost of the trip, catches for summer flounder, etc. Additionally, respondents were probed about the appearance of the survey and cover letter, as well as how effectively it conveyed information to the reader. These steps were taken to insure as high a response rate as possible.

In addition to the SPDC portion of the survey, focus group participants were asked a variety of questions related to opinions about fisheries management, targeting habits, fishing habits and avidity, and catch and release practices. These questions were designed to collect valuable information for fisheries management, establish a rough baseline of fishing behavior, and get respondents thinking about their fishing in preparation for the SPDC questions. Placing these questions in sequence before the SPDC questions was done intentionally.

Table 2. Focus group SPDC questions: attributes and definitions

Attribute	Definition	Survey 1	Survey 2
Cost of traveling to a site	Includes gas, wear and tear on your vehicle and other expenses you might have from traveling to and from a fishing site. This cost does **NOT** include expenses for food, ice, or fishing equipment.	Yes	Yes
Bag limit for summer flounder	The most summer flounder an angler can legally keep per day of fishing due to regulations.	Yes	Yes
Minimum size limit for summer flounder	Summer flounder smaller than a minimum size limit must be released.	Yes	Yes
Likely catch of summer flounder	Fishermen never know exactly how many summer flounder they will catch when they take a trip. Often, they have an idea of how many fish they are likely to catch.	Yes	Yes
Likely fishing success for all other species	When taking a trip, fishermen might also be interested in fishing for species besides summer flounder. Fishing success refers to the expected number of fish caught for all other species that you might encounter for a typical trip in your area.	Yes	Yes
Likely Number of summer flounder of legal size	Fishermen also are never sure of the size of summer flounder they will catch. Often they might be aware of differences in locations that might lead to differences in the sizes of fish caught.	No	Yes

After analyzing the results of the focus group, it was found that even with such a small sample, the model performed quite well with regard to sign and significance of coefficients. The final list of attributes was chosen based upon two presiding considerations. First and foremost, attributes were chosen and defined to make the hypothetical trip comparison meaningful for anglers. After meeting this consideration, attributes were defined to make the comparison consistent with the RP models that have been used in past studies. Following feedback from the focus group, the questionnaire was finalized in March of 2000. Appendix B contains a final instrument used for the conjoint study[3]. Table 3 provides the definitions and ranges of attributes used in the study.

Table 3. Final Attributes, Definitions, and Ranges for SPDC Survey

Attribute	Definition	Ranges
Cost of traveling to a site	Includes gas, wear and tear on your vehicle and other expenses you might have from traveling to and from a fishing access site (such as tolls, ferry fees, and parking fees). This cost also includes expenses for food, ice, and fishing equipment used on this trip. The cost **does not** include guide or boat fees.	{$5, $20, $30, $40, $55}
Bag limit for summer flounder	The most summer flounder an angler can legally keep per day of fishing.	{1, 4, 6, 8, 12} (fish)
Minimum size limit for summer flounder	Summer flounder smaller than a minimum size limit must be released.	{12, 14, 15, 16, 18} (inches)
Likely catch of summer flounder	Anglers never know exactly how many summer flounder they will catch when they take a trip. However, they often have an idea of how many fish they are likely to catch.	{2, 5, 8, 11, 14} (fish)
Likely fishing success for all other species	When taking a trip, anglers might also be interested in catching species besides summer flounder. Fishing success refers to the expected number of fish caught for all other species that you might encounter for a typical trip in your area.	{Below Average, Average, Above Average}
Likely Number of summer flounder of legal size	Anglers also are never sure of the size of summer flounder they will catch. However, they often might be aware of differences in locations that might lead to differences in the sizes of fish caught.	{0, 1, 3, 6, 10} (fish)

Final Design

Once the attributes and attribute levels were finalized, the final design needed to be created. Based upon our feedback from focus groups and other survey pre-tests, it was determined that respondents should only receive four of the SPDC questions. This level was determined because of two primary reasons: 1) survey fatigue on the part of

[3] The questionnaire in Appendix B is only 1 of 18 versions distributed to anglers.

respondents might lead to 'poor' responses if any more SPDC questions were offered to them and 2) for each two SPDC questions added, the survey is lengthened by one page. Any lengthening of the survey might signal to respondents that the survey is too time consuming to complete. Upon opening a package, the primary indicator of how much time a survey will take to complete is the size and thickness of the instrument. The two factors taken in combination led us to the conservative number of four SPDC trip comparisons per respondent.

Given these constraints, the challenge was to design a survey that would enable the quantification of preferences for fisheries management tools and the other attributes identified in the previous step. Since each respondent was getting a relatively low number of SPDC questions, we decided to divide the survey into blocks (or unique versions of the survey), with each block having different levels of attributes for the four trip comparisons. Using the SAS QC module, we used PROC Factex to generate a Type V resolution candidate design. This ensured that we could estimate all main and cross effects for attributes in the model. The candidate design created by PROC Factex is a starting point design and is smaller than a full factorial design that would have exceeded the memory and disk space available on the computer used for this experiment (6 gigabytes). The next step was to pair down the candidate design into the best design possible given the fact that we were limited to 4 (questions) x 18 (unique sets of questionnaires)= 72 unique trip comparisons.

Clearly, increasing the number of blocks increases the efficiency of the design matrix since increasing the number of unique trip comparisons allows for more tradeoffs by respondents. However, increasing the number of blocks increases survey costs because each respondent is tracked during several stages of mailings according to their assigned block (discussed in detail below). Using SAS Proc Optex, we took the candidate design set and created the best design set we could based upon the concept of D optimality.

Once attributes, their levels, and model specifications are known then one needs to choose the final design. Table 4 shows some of the optimality criteria that are commonly used when comparing design candidates. The first two, A and D optimality, are information based candidates. That is, designs are chosen in a way that maximizes the information matrix or equivalently, minimizes the variance. U and S optimality are known as distance based criteria, since they seek to spread or group candidates designs according to the degree of coverage a given design has over the attribute space. D optimality, the most widely used criteria method, is used in this study. We iterated the PROC Optex procedure 1000 times and chose the best design out of those 1000 runs.

Table 4. Optimality Criteria*

Criterion	Goal	Formula
D-optimality	Maximize determinant of the information matrix	$\max\lvert X'X \rvert$
A-optimality	Minimize the sum of the variances of estimated coefficients	$\min \text{ trace } (X'X)^{-1}$
U-optimality	Minimize distance from design (D) to candidates (C)	$\min \sum_{x \in C} d(x, D)$
S-optimality	Maximize distance between design points	$\min \sum_{Y \in D} d(Y, D-Y)$

*taken from the SAS/QC Usage and Reference Manual Volume I.

Final Stated Preference Questionnaire

Once these steps were completed, the final version of the questionnaire was produced using Microsoft Publisher and mail merge techniques. Figure 1 shows an example of one of the actual trip comparisons used in the SPDC instrument.

Respondents were asked:

"Suppose **last August** that you could have chosen ***only*** from the recreational opportunities described below. Please review the trip descriptions and answer the two questions at the bottom of the table."

After respondents viewed the three options, they were asked to indicate "Which trip do you most prefer." All respondents were referred to consider the choice of trips relative to August 1999. This was done to anchor all respondents to the same time period versus adding time period explicitly as an additional attribute in the choice experiment. August was chosen because it is the generally the peak season for summer flounder fishing. This setup was chosen to avoid having respondents getting an instrument whose catch ranges were not believable during the periods in either early spring or late December. The chosen layout of the SPDC question is very similar to that used in Adamowicz et al.

Figure 2. An actual SPDC trip comparison.

	Trip A	Trip B	Trip C
Cost of traveling to the site	$ 40	$ 40	Do something else, but not take a saltwater fishing trip.
Likely total catch of summer flounder	8 fish	11 fish	
Minimum size limit for summer flounder	14 inches	15 inches	
Bag limit for summer flounder	12 fish	6 fish	
Likely number of summer flounder of legal size	3 fish	3 fish	
Likely fishing success for all other species	Average	Above Average	

Employees of F/ST1 used Microsoft Publisher to put together all opinion-related questions, SPDC questions, and demographic questions into a booklet format in a size very close to that recommended by Dillman, and Dillman and Salant and produced the final survey. Because a mail survey was used to contact people who had been intercepted in the field and who had agreed to participate, a modified Dillman method approach was employed in an effort to maximize the survey response rate (Table 5). The first step was to recruit field intercept respondents at the time of the field survey. Once respondents agreed to participate in the follow-up survey they were given a survey brochure that very briefly described that they would soon receive a mail survey that would help the NMFS know more about what they thought about fisheries management. It was a full-colored tri-fold brochure that was primarily designed to help respondents recall at the time of opening the mail survey that they had agreed to participate.

Table 5. Mail survey steps and response rates

Action	Time Administered
Survey Brochure	At time of field intercept
First Mailing	No more than one month after intercept
Post Card	Two weeks after the mailing of the First Mailing
Second Mailing	Two weeks after mailing of the Post Card

Overall response rates[4]	Months	Response Rate
Wave 2	March-April	58.4%
Wave 3	May-June	56.3%
Wave 4	July-August	55.7%
Wave 5	September-October	59.6%
Wave 6	November-December	53.5%
Average Response Rates		56.8%

At the end of each month, all intercepted anglers who agreed to participate in the SPDC survey were mailed the survey instrument along with a cover page that reiterated many of the points made in the survey brochure and reinforced the notion that each respondent's opinion mattered. Following a two-week period, respondents who had not yet responded to the first mail survey were sent a postcard reminder that reinforced the points made in earlier cover letters and brochures. If after two weeks from the date of mailing the postcard, respondents had still not returned a survey, a second survey was sent to them along with a slightly different cover letter that contained similar points as previous information, but in slightly more forceful language. Prior to the beginning of the initial mailing each survey respondent was randomly assigned a survey version (also referred to as a block). A database tracked all subsequent mailings to individuals according to their block number. This ensured that if the second mailing was necessary, respondents would receive the same version of the survey that they were assigned in the first mailing.

V. Model of Angler Behavior

Both the RP and SPDC models employ discrete choice statistical techniques to estimate models of behavior. The discrete choice technique assumes that anglers must choose between a number of discrete alternatives (or in the case of recreational fishing, fishing sites). Anglers' utility from choosing a particular site is dependent on the attributes associated with each site. For models of recreational angling, the angler's vector of site-specific attributes, **X**, is typically assumed to be populated by data such as the cost of traveling to the site, indications of the site's fishing quality, and other site-specific attributes. In the discrete choice framework, the angler is assumed to choose the site i from among a set of sites S that maximizes his utility. Assume that the angler's indirect utility function for site i is given by

$$V(\beta, \mathbf{X}_i) = v(\beta, \mathbf{X}_i) + \varepsilon_i \tag{1}$$

where $\mathbf{X_i}$ is the vector of site and individual-specific attributes associated with site i, β is a vector of preference parameters on the observable portion of the individual's indirect utility function, $v(\beta, \mathbf{X}_i)$. Finally, ε_i is the unobservable portion of the individual's indirect utility function and is assumed to be site specific. The angler then compares all potential choices in his choice set, S, and chooses the best site, i:

$$V(\beta, \mathbf{X}_i) > V(\beta, \mathbf{X}_j) \;\; \forall j \in S, i \in S \tag{2}$$

The challenge is to take the model given by (1) and (2) and develop a statistical model that will enable the recovery of the behavioral parameters, β. Of course, the structure of the model will depend heavily on assumptions about the form of the site-

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[4] Incorrect addresses are not included in the calculation of response rates. For the entire survey, there were

specific error term, ε_i. In this paper, we use two forms of the error structure, the Type II Generalized Extreme Value distribution (GEV) and the more restrictive Type I GEV distribution (independent logit). The independent logit specifies the probability of choosing site i as

$$\Pr ob(i) = \frac{e^{v(\beta,\mathbf{x}_i)}}{\sum_{j\in S} e^{v(\beta,\mathbf{x}_j)}} \tag{3}$$

A well-known restriction associated with the model given in (3) is that it implies the Independence of Irrelevant Alternatives restriction (IIA). The implication of this is that the ratio

$$\frac{\Pr ob(i)}{\Pr ob(j)} = \frac{e^{v(\beta,\mathbf{x}_i)}}{e^{v(\beta,\mathbf{x}_j)}}$$

is independent of site-specific attributes for all other alternatives. This means that the probability ratio would remain unchanged as other sites in S are dropped or as additional sites are added. Many empirical applications have demonstrated violations of this assumption.

To relax the IIA restriction, analysts have turned to the nested logit model. The nested logit model divides the choice set S into M subsets. Each subset is comprised of sites/alternatives grouped according to similarity. The IIA restriction is binding for sites within a subset m, but not for site comparisons in different subsets of the choice set. If the analyst designs the choice structure appropriately, then IIA restrictions can be eliminated for cases where it is thought to be problem. The nested logit model is

---

5009 surveys sent out and 150 bad addresses.

equivalent to assuming that the error terms are distributed as Type II GEV. Given this assumption, the probability that an angler is observed choosing site ni can be written[5]:

$$\mathrm{Prob}(ni) = \frac{e^{s_n*(a_n+v(\beta,\mathbf{X}_{in}))}\left[\sum_{j\in S_n} e^{s_n*(a_n+v(\beta,\mathbf{X}_{jn}))}\right]^{(1/s_n)-1}}{\sum_{m=1}^{M}\left[\sum_{j\in S_m} e^{e^{s_m*(a_m+v(\beta,\mathbf{X}_{mj}))}}\right]^{1/s_m}} \qquad (4)$$

Notice that restricting each scale parameter, s_i=1, and each alternative specific constant, a_i=0, collapses the model back to that found in (3). Therefore, the logit model is seen as a special case of the nested logit model. The parameter s is referred to as the scale parameter and is the inverse of what McFadden terms the inclusive value parameter.

The RP Econometric Model

Recent work using revealed preference techniques in a marine fisheries setting has attempted to provide information that is useful for management and able to analyze issues that are species-specific (Schumann; Hicks and Steinback). Findings for these models are two-fold:

1) If management measures or stock conditions change at a species-specific level, then species-specific models of angler behavior are important to develop since aggregate species models perform poorly, and

2) Species-specific models using RP data are very hard or impossible to estimate because of (a) the large number of species targeted and

[5] For the results presented later, s_i=1 if the 'Don't go' option is chosen, and s_i=s if either of the the stated preference trips are chosen.

caught by marine anglers, (b) management measures do not vary much for a particular species, and (c) data requirements to characterize fishing quality for all sites on a species-by-species basis are burdensome.

Given these factors, it was clear that developing a useful summer flounder model would be at best very difficult to implement. Attempts to estimate the discrete choice RP model with bag and size limits explicitly included as factors in the model failed because of a near complete lack of variation in the management data. Therefore, a simpler RP model is developed that enables anglers to substitute between summer flounder and other species they may want to target. We assume that when fishing, anglers choose sites based upon all species regardless of what they choose to target.

Consequently, anglers consider the fishing quality for summer flounder as well as the fishing quality for all other species they could catch at the site. Additionally, anglers are concerned about the cost of taking a trip to site i. We experimented with other variables thought relevant for explaining the RP decision, such as county of boat mooring and county-specific variables describing the degree of tourist versus fishing destinations, etc. Including these variables did not affect the findings of the paper, but did greatly reduce the number of observations for the RP model, since the sample had to be reduced to include only those having responded to the RP economic or SPDC survey. For these reasons, a simple choice structure was chosen to make the RP model as close to the SPDC model as possible, making the statistical comparison as transparent as possible. The RP variable definitions are given in Table 6. The overall goal in developing the RP model was to estimate a model that would be useful to enrich the SPDC experiment and to test for parameter homogeneity across the two techniques.

Table 6. RP Variable Definitions.

Variable Name	Definition
TC_RP_i	Travel Cost based on RP data to Site i. Equals roundtrip distance to site i times the rate of $0.33 per mile.
SF_RP_i	Average Catch per trip per wave at site i for summer flounder based on RP data. Average taken over the period 1997-2000.
OC_RP_i	Average Catch per trip per wave at site i for all other species based on RP data. Average taken over the period 1997-2000.

The definition of the indirect utility function for the RP model is defined as follows:

$$V(\beta, \mathbf{X}_i^{rp}) = \beta_{tcost}^{rp'} * TC\_RP_i + \beta_{sf}^{rp'} * SF\_RP_i + \beta_{oc}^{rp'} * OC\_RP_i + \varepsilon_i \qquad \text{(1 RP)}$$

and the parameters to be estimated are given by $\beta_{tcost}^{rp'}, \beta_{sf}^{rp'}$, and $\beta_{oc}^{rp'}$. Notice that this indirect utility function is linear with regard to the travel cost coefficient. This assumption ensures a closed form solution for the welfare estimates that follow. For the RP model, we assume a non-nested choice structure implied by (3) by estimating a multinomial logit model using maximum likelihood techniques.

It should be noted that the parameters listed in (1 RP) can be rewritten as follows: $\{\beta_{tcost}^{rp'}, \beta_{sf}^{rp'}, \beta_{oc}^{rp'}\} = \{\lambda\beta_{tcost}^{rp}, \lambda\beta_{sf}^{rp}, \lambda\beta_{oc}^{rp}\}$. The parameter λ is often referred to as the scale factor and is tied directly to the data source from which the data are estimated. The parameter λ is inversely related to the variance of the error term in the model (Louviere et al.) and is impossible to identify if one were only going to estimate model (1 RP). For this reason, most applications of discrete choice models do not explicitly include the scale factor in their model notation. However, when combining SPDC and RP models, the scale factor must be explicitly accounted for during estimation.

The SP Econometric Model

Alternative specific attributes associated with the SPDC survey were carefully defined in the design phase of survey development. They are given in Table 7. Notice because the final estimated model estimates cross effects for some factors, the definitions differ somewhat from Table 3.

Table 7. SPDC Variable Definitions (all data levels used in model are as given in the questionnaire and Table 3).

Variable Name	Variable Definitions
TC_SP_i	Cost of trip.
SF_SP_i	Average summer flounder catch per trip.
BAG_SP_i	Summer flounder bag limit.
$SZNM\_SP_i$	Minimum size limit for summer flounder interacted with likely number of legal size summer flounder
OCA_SP_i	=1 if Likely fishing success for other species was 'Above Average', =0 otherwise.
OCB_SP_i	=1 if Likely fishing success for other species was 'Below Average', =0 otherwise.
$HOME\_SP_i$	=1 if respondent chose 'Don't Go' Option,=0 otherwise
λ^{sp}_{go}	Scale parameter for the go/don't go decision stage of the model. Only estimated for nested models.

The model estimates the effect of other catch as categorical, and normalizes on an average level of catch for all other species. Additionally, crossing the minimum size limit variable with the expected number of legal-sized summer flounder best captured the size limit effect. This variable can be thought of as a proxy for the amount of take-home fish an angler expects to receive. Attempts to estimate the model with minimum size limits and numbers of summer flounder of legal size as separate attributes failed. It appeared that once respondents were told how many of the caught summer flounder were of legal size, they viewed the minimum size limit as a quality attribute: the higher the size limit the bigger the fish you were allowed to keep. However, based upon findings from the focus group about motivations for fishing for summer flounder (of which one of the main motivations was to take fish home), this specification seems to be a good way to capture how size limits are a consideration for site choice.

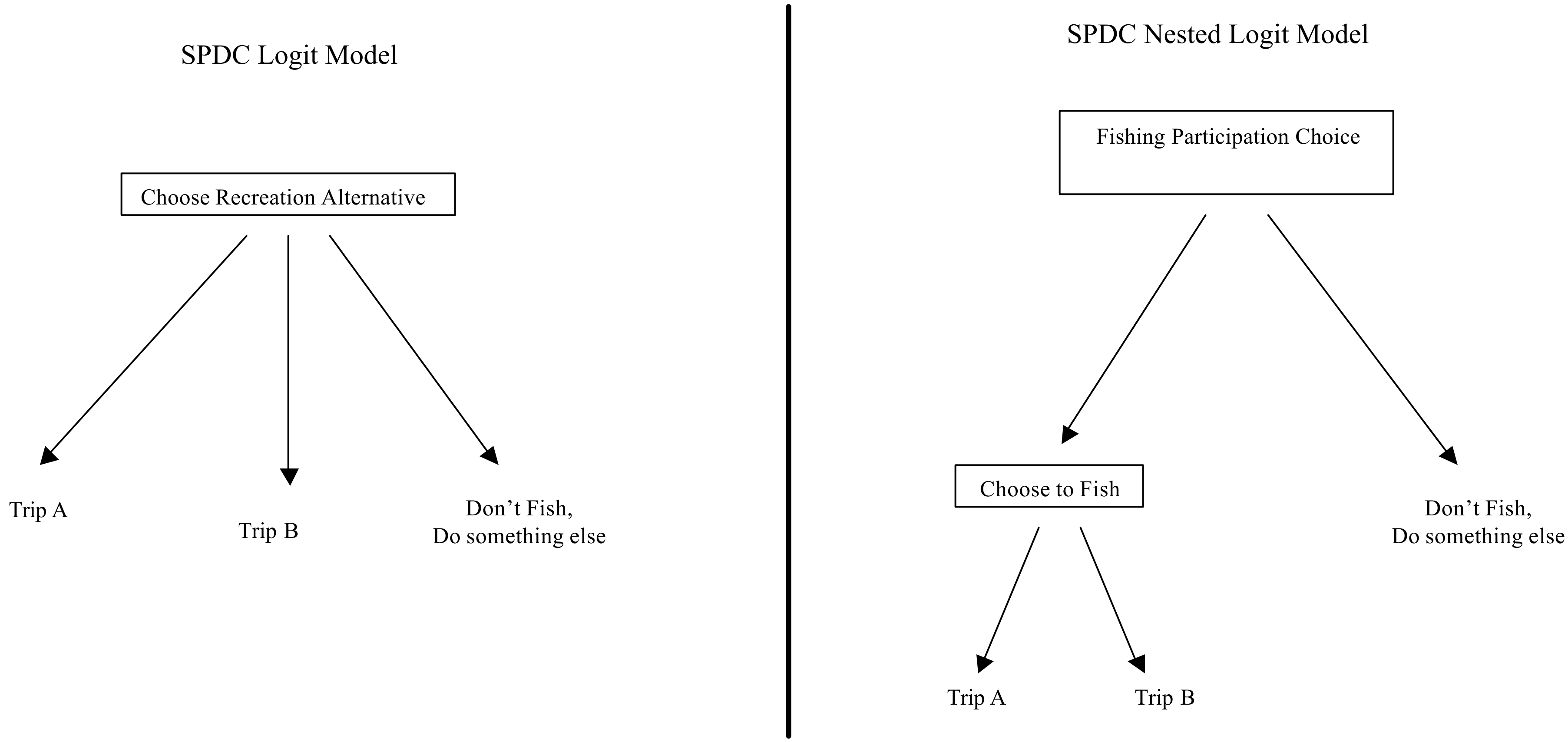
The estimated stated preference model is given in equation (1 SP).

$$\begin{aligned} V(\beta^{sp'}, \mathbf{X}_i^{sp}) = (1 - home\_sp_i) * (\beta_{tcost}^{sp'} * TC\_SP_i + \beta_{sf}^{sp'} b\_sp\_sf * SF\_SP_i \\ + \beta_{bag}^{sp'} * BAG\_SP_i + \beta_{sznm}^{sp'} * SZNM\_SP_i \\ + \beta_{oca}^{sp'} * OCA\_SP_i + \beta_{ocb}^{sp'} * OCB\_SP_i) \\ + \beta_{home}^{sp'} * HOME\_SP_i + \varepsilon_i \end{aligned} \tag{1 SP}$$

This specification ensures that if respondents choose the 'Don't Go' option, their indirect utility function is simply $V(\beta^{sp}, \mathbf{X}_i) = \beta_{home}^{sp'} + \varepsilon_i$. The 'Don't Go' option is clearly a very different option that choosing either Trip A or Trip B (see Figure 2). It seemed intuitive that the ratio $\frac{P(\text{Don't Go})}{P(\text{Trip A})}$ could very well not be independent of the attribute levels of Trip B (violating the IIA restrictions). We estimated two versions of the SPDC model, a non-nested and nested model. Figure 3 shows the choice structure for the two models. All nested models were estimated using full information maximum likelihood techniques.

As is the case for the revealed preference data, a scale factor is implicit in all of the parameters associated with equation (1 SP). When estimating each data source separately, neither scale factor is identifiable. To test to see if underlying parameters are statistically the same, one must account for the scale factor when placing restrictions on the parameters across data sources.

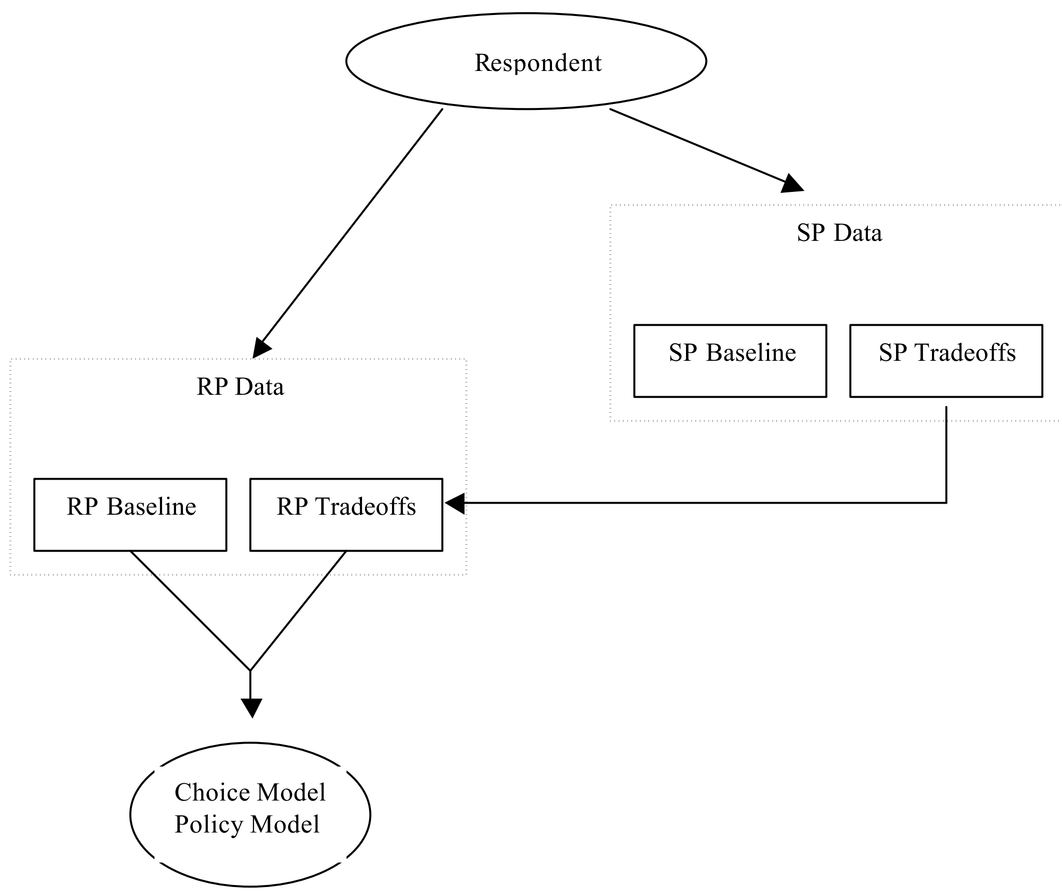
Figure 3. Visual depiction of alternate SPDC choice structures.



Combining the RP and SP Models

Because of the lack of variation in bag and size limits for summer flounder, we have to 'enrich' the RP data in order to quantify how anglers make tradeoffs regarding factors influencing their fishing decisions. The enrichment process we have been advocating is to use the SPDC methodology to find out about anglers' preferences for bag and size limits and their participation choice. To better understand the data enrichment scheme, Figure 4 shows how these techniques fit together.

Figure 4. Data enrichment for fisheries management policy analysis (from Louviere et al.)



The RP methodology is employed to test for parameter homogeneity across the two techniques, and to help identify the relative scale factor across the two models. Furthermore, the RP data are necessary to characterize actual baseline conditions for welfare and other policy analysis. Making policy changes to hypothetical trips is not meaningful since all of the SPDC trip attributes are hypothetical. Louviere et al. provide an excellent description of the data enrichment paradigm across RP and SP data sources.

Another important consideration, given our data collection process, is the choice of sample for tests of parameter homogeneity, welfare measures, and participation changes. We have several different samples from which to estimate parameters. First, we estimate the SPDC and RP models totally independent of each other. We then use the estimated parameters (and associated choice structure) to estimate welfare and participation changes for all RP observations[6]. This model ignores any efficiency gains one may obtain from estimating the models simultaneously, but does use the RP data to construct a meaningful baseline for welfare analysis. This method, however does not adjust parameter estimates obtained from the SPDC estimation to reflect the underlying scale of the RP data.

Next, we estimate combined RP and SPDC models for only those respondents where a complete set of RP and SPDC responses exists (2,154 individuals). These models restrict the travel cost and summer flounder catch parameters to be equal across the two datasets while accounting for differences in the scale parameter. We also estimate the combined RP and SPDC models for all RP responses. For these estimations, there were 22,857 RP individuals and 2154 SPDC individuals. Recall that each SPDC

[6] Louviere et al. refers to this as his data enrichment paradigm #2.

respondent received four trip comparisons. For our sample of SPDC respondents, each respondent completed 3.84 of the trip comparison questions on average.

To understand the exact specification of the various models employed, how the scale factor was estimated, and the restriction used, consider combining the SPDC logit model with the RP model of site choice. Following the exposition in Louviere et al., let the vectors $\mathbf{X}_{\mathbf{i}}^{\mathbf{SP}}$ and $\mathbf{X}_{\mathbf{i}}^{\mathrm{RP}}$ be the common data elements for which one wishes to test for parameter homogeneity and let the vectors $\mathbf{Z}_{\mathbf{i}}^{\mathbf{SP}}$ and $\mathbf{Z}_{\mathbf{i}}^{\mathbf{RP}}$ contain data elements assumed to have their own separate parameters in the model. Given our assumption about the error structure, we can write the choice probabilities for the RP and SPDC models as follows:

$$
\begin{aligned}
P_i^{RP} &= \frac{\exp(\lambda^{RP}(\beta^{RP}\mathbf{X}_{\mathbf{i}}^{\mathbf{RP}} + \omega^{RP} Z_{\mathbf{i}}^{\mathbf{RP}}))}{\sum_{j\in S^{RP}} \exp(\lambda^{RP}(\beta^{RP}\mathbf{X}_j^{\mathbf{RP}} + \omega^{RP} Z_j^{\mathbf{RP}}))} \quad \forall i \in S^{RP} \\
P_i^{SP} &= \frac{\exp(\lambda^{SP}(\beta^{SP}\mathbf{X}_{\mathbf{i}}^{\mathbf{SP}} + \omega^{SP} Z_{\mathbf{i}}^{\mathbf{SP}}))}{\sum_{j\in S^{RP}} \exp(\lambda^{SP}(\beta^{SP}\mathbf{X}_j^{\mathbf{SP}} + \omega^{SP} Z_j^{\mathbf{SP}}))} \quad \forall i \in S^{SP}
\end{aligned}
\tag{5}
$$

Using the data enrichment method, we pool the data sources and restrict $\beta^{RP} = \beta^{SP}$. We cannot identify both scale factors, so we normalize on the scale of the SP data by setting $\lambda^{SP} = 1$. The likelihood function for this pooled model (assuming that the error terms are independent across the data sources) can then be written

$$
\begin{aligned}
L(\lambda^{RP},\beta,\omega^{SP},\omega^{RP};X_{\mathbf{i}}^{\mathbf{SP}},X_{\mathbf{i}}^{\mathbf{RP}},Z_{\mathbf{i}}^{\mathbf{RP}},Z_{\mathbf{i}}^{\mathbf{SP}}) = &\sum_{n\in N^{RP}} \sum_{P_i\in S^{RP}} y_{in} P_{in}^{RP}(\lambda^{RP},\beta,\omega^{\mathbf{RP}};X_{\mathbf{i}}^{\mathbf{RP}},Z_{\mathbf{i}}^{\mathbf{RP}}) + \\
&\sum_{n\in N^{SP}} \sum_{P_i\in S^{SP}} y_{in} P_{in}^{SP}(\beta,\omega^{\mathbf{SP}};X_{\mathbf{i}}^{\mathbf{SP}},Z_{\mathbf{i}}^{\mathbf{SP}})
\end{aligned}
$$

where y_{in}=1 if person n chooses alternative i, 0 otherwise. Notice we are summing across all observations and summing over all choice alternatives in both the RP and SPDC data.

Using maximum likelihood techniques, the function is then maximized with respect to $\lambda^{RP}, \beta, \omega^{SP}$, and ω^{RP}.

With the likelihood function estimated, hypothesis testing for parameter homogeneity can proceed. This process is described in detail in Louviere et al. Let the log likelihood function value for the restricted model, where $\beta^{RP} = \beta^{SP}$ is imposed, be denoted by L^{Joint}. Let L^{SP} and L^{RP} be the log likelihood values for the SPDC and RP models estimated independently. To test for parameter homogeneity, calculate the test statistic, $-2[L^{SP}+L^{RP}-L^{Joint}]$ which is distributed as $\chi^2_{(n-1,\alpha)}$, where n is the number of restrictions in the model and a is the level of significance desired. To accept the hypothesis of parameter homogeneity, the calculated test statistic must be smaller than the critical value. This specification allows the recovery of the relative scale parameter between the two data sources. As we have specified the model, any estimate of the scale factor greater than one implies that the variation of the RP data is greater than the SP data.

Welfare and Participation Change Estimation

Welfare estimation for potential policy changes using the data enrichment methods described above requires careful thought about how the RP and SPDC models fit together. Since welfare measurement compares a change in the state of the world (usually as a result of a policy change) to a baseline condition, the characterization of the baseline is important. To calculate baseline conditions to be useful in tandem with parameters of the SPDC format requires variables to be site-specific. The MRFSS data used in this study are aggregated at the county level when defining sites (some counties are aggregated further, see Hicks et al. for county aggregation definitions). For our study, there are 39 potential fishing sites available to individuals from New Hampshire to Virginia. In order to characterize baselines, average catch per trip for summer flounder and for all other species was calculated for each site. Additionally, travel costs were computed for each respondent to each site using zipcode centroids for the respondent's residence and county of fishing. Once pairs of zipcode centroids were recovered, travel distance to each site was computed using PC Miler (a PC software program).

Additionally, baseline management information was collected (See Table 1). Although this information provided no variation capable of estimating behavioral parameters using RP data, it was quite useful for establishing baselines for each site. Therefore, the complete array of RP information was necessary in order for the calculation of welfare estimates as a result of policy changes. This made estimation of the RP models relatively easy to do. Welfare changes were estimated by altering a set of management measures (bag and size limits or seasonal closures) relative to baseline levels.

To give the reader a better understanding of the mechanics of welfare measurement and the data enrichment process undertaken here, consider the model presented in equation (5). To motivate the issues of data enrichment in the context of welfare measurement, assume that all parameters, including those of interest to fisheries management, are identifiable from the RP data. Following Hanemann, the welfare change (compensating variation) of moving from condition $\mathbf{X}_i^{RP,0}$ to condition $\mathbf{X}_i^{RP,1}$ can be written as

$$W = \frac{\ln(\sum_{j\in S^{RP}} \exp(\lambda^{RP}(\beta^{RP}\mathbf{X}_j^{\mathbf{RP},1} + \omega^{\mathbf{RP}} Z_j^{\mathbf{RP}}))) - \ln(\sum_{j\in S^{RP}} \exp(\lambda^{RP}(\beta^{RP}\mathbf{X}_j^{\mathbf{RP},0} + \omega^{RP} Z_j^{\mathbf{RP}})))}{-1*\beta_{tcost}^{rp}} \qquad (6)$$

Of course, the parameters relevant for management cannot be recovered using RP estimation. Given this limitation, there are two ways of incorporating the SPDC information. First, we could calculate the baseline as described above and simply replace the RP parameters with those estimated from the SPDC model to obtain the equation

$$W = \frac{\ln(\sum_{j\in S^{RP}} \exp(\lambda^{SP}(\beta^{SP}\mathbf{X}_j^{\mathbf{RP},1} + \omega^{\mathbf{SP}} Z_j^{\mathbf{RP}}))) - \ln(\sum_{j\in S^{RP}} \exp(\lambda^{SP}(\beta^{RP}\mathbf{X}_j^{\mathbf{RP},0} + \omega^{\mathbf{SP}} Z_j^{\mathbf{RP}})))}{-1*\lambda\beta_{tcost}^{sp}} \qquad (7)$$

The problem with this approach is that it ignores the effect of the scale parameter. Even if the underlying behavioral responses are equal ($\beta^{SP} = \beta^{RP}, \omega^{\mathbf{SP}} = \omega^{\mathbf{RP}}$), the estimate of compensating variation and choice probabilities could be quite different because of a failure to account for the scale factor.

If preference homogeneity were found and the scale factor across the RP and SPDC data sources is accounted for, the appropriate welfare measure is

$$W = \frac{\ln(\sum_{j\in S^{RP}} \exp(\lambda^{RP}(\beta\ \mathbf{X}_j^{\mathbf{RP},1} + \omega^{\mathbf{SP}} Z_j^{\mathbf{RP}}))) - \ln(\sum_{j\in S^{RP}} \exp(\lambda^{RP}(\beta\ \mathbf{X}_j^{\mathbf{RP},0} + \omega^{\mathbf{SP}} Z_j^{\mathbf{RP}})))}{-1*\lambda^{rp}\beta_{tcost}} \qquad (8)$$

where the scale factor is recovered from the RP data and the constraint $\beta^{SP} = \beta^{RP}$ is imposed. We estimate welfare changes using both equation (7) and (8) for each of the SPDC models.

Additionally, predictions of participation changes are recovered using estimated choice probabilities. When management measures are tightened, the probability of choosing the 'Don't Go' increases since it is relatively more attractive. The mean value of the probability of choosing the 'Don't Go' option is calculated. We interpret this value as the ratio of the sample who would have chosen not to go fishing as regulations are tightened. This ratio can be multiplied by the predicted population of summer flounder trips in the Northeastern United States to estimate participation changes.

Associated with defining policy changes is mathematically relating size with quantities caught for summer flounder. Recall that the model interacts minimum size limits with the expected number of legally sized fish. Therefore, as minimum size limits are increased, presumably the expected number caught of legal size would decrease because of the size distribution of the summer flounder stock. Using size distributions obtained from NMFS, we developed an algorithm that calculates this interaction variable when policies change size limits.

VI. Results

The discussion above refers to a large number of models to be estimated ranging from stand-alone RP and SPDC models to jointly estimated ones. We also vary the sample sizes for many of the jointly estimated models to include only those observations for which RP and SPDC observations exist to models that include the full sample of RP observations. The goal of this extensive empirical analysis is to investigate the conditions under which preference homogeneity can be shown to exist and to provide information about future work involving SPDC modeling. Important policy relevant questions will hopefully be answered such as the consistency of results across SPDC and RP methods, the implications for welfare analysis if parameter homogeneity is rejected, and the appropriate choice structure for the SPDC models. Table 8 describes in detail all of the estimated models. For each of the models listed below, we will investigate differences in welfare, changes in participation, and parameter estimates in order to get at some of these questions.

Table 8. Estimated Models

Model	Description	Sample
I. SPDC	Discrete choice model of site and participation choice based upon SPDC experimental design.	N=2154 SPDC respondents
II. Nested SPDC	Nested discrete choice of participation and then site choice based upon SPDC experimental design.	N=2154 SPDC respondents
III. RP (SPDC Sample)	Discrete choice model of site choice. Based upon observable choices of Northeast and Mid-Atlantic recreational angling.	N=2154 SPDC respondents
IV. RP (All RP Sample)	Discrete choice model of site choice. Based upon observable choices of Northeast and Mid-Atlantic recreational angling.	N=22857 RP respondents
V. RP/SPDC (SPDC Sample)	Jointly estimated RP and SPDC site/participation models.	N=2154 SPDC respondents
VI. RP/Nested SPDC (SPDC Sample)	Jointly estimated RP and SPDC site/participation models. The SPDC model is nested at the participation decision level.	N=2154 SPDC respondents
VII. RP/SPDC (All RP Sample)	Jointly estimated RP and SPDC site/participation models.	N=2154 SPDC respondents, 22857 RP respondents
VIII. RP/Nested SPDC (All RP Sample)	Jointly estimated RP and SPDC site/participation models. The SPDC model is nested at the participation decision level.	N=2154 SPDC respondents, 22857 RP respondents
IX. RP (All RP Sample) Choice Based	Discrete choice model of site choice. Based upon observable choices of Northeast and Mid-Atlantic recreational angling. Corrected for choice-based sampling.	N=22857 RP respondents
X. RP/Nested SPDC (All RP Sample) Choice Based	Jointly estimated RP and SPDC site/participation models. Corrected for choice-based sampling.	N=2154 SPDC respondents, 22857 RP respondents

SP and RP Model Estimates

To start, we estimated separately Models I through IV. First, we constructed the data necessary to estimate the RP choice structure. To do this, we calculated travel cost and expected catch rates (for both summer flounder and all-other fish species) for counties from New Hampshire to Virginia. Summer flounder recreational angling occurs further south than Virginia, but our data was limited in its southern extreme because of regional designations in data collection techniques. However, it is felt that the region examined in this study captures the primary area of summer flounder fishing and therefore the preferences of anglers potentially impacted by policy.

The RP models are presented in Table 9 (denoted by models III and IV). Model III contains the results of the site choice model for those respondents who were observed in both the RP and SPDC data sources. This effectively 'throws out' some RP data that could be useful in identifying behavioral parameters for anglers' site choices. However, it does allow for the more restrictive test of parameter homogeneity- where parameter estimates are compared across the same respondents. The travel cost and other catch coefficient are significant at the 5% level, but the parameter on summer flounder catch is not significant. Other studies have shown that identifying species-specific parameters is difficult at best and can be even more problematic if less than the full dataset is used for estimation. The complete RP data set is used in the estimation of model IV. In this model, all parameters are significant at the 5% level. For both of the RP models, anglers are more likely to visit closer sites, those with higher levels of summer flounder, or other catch if the other factors are held constant.

Table 9 provide the estimation results for the SPDC models: the non-nested model, Model I and the nested version, Model II (recall the alternative choice structures depicted in Figure 3).[7] For each respondent, the data provided information on the version of the survey administered, so that the appropriate experimental design could be matched to responses. For the 'Don't Go' option, we specified a dummy variable to capture any unobservable effects particular to the participation decision in the model. This was done for the nested and non-nested versions of the model. The nested model was included in order to relax the IIA restriction, which was discussed previously. All parameters in both models are significant at the 5% level. The estimate on the scale parameter for the nested model, λ_{go}^{sp} is greater than one (a required condition for a well behaved utility function). We tested the restriction that λ_{go}^{sp} =1 (which would result in the standard non-nested model) and found that the nested model was indeed the preferred model at the 5% level of significance ($?^2$~4.19).

All signs are as expected. Anglers tend to prefer closer sites, those with higher levels of catch, and those with less restrictive levels of management (higher bag limits and lower minimum size restrictions). The choice specific dummy on the 'don't go' option is always negative, indicating that all things equal, the angler is more likely to choose to participate than not.

Jointly Estimated Model Results

Similar results, found in Table 10, were obtained from jointly estimated models using the sample of respondents in the SPDC models (Models V and VI). These models

[7] The reader should note that Hausman tests were performed to test the appropriateness of the IIA restriction (comparing models I and II; V and VI; and VII and VIII). In all cases the non-nested models violated the IIA assumption at the 95% level of significance.

were obtained by jointly estimating the RP and SPDC models while placing restrictions on the travel cost and summer flounder catch coefficients. All parameters are significant at the 5% level. Again, the nested model is preferred to the non-nested model at the 5% level of significance ($?^2$~3.86). Using the full sample of RP data (which effectively brings the most information to the model), Models VII and VIII were obtained by jointly estimating the RP and SPDC models, with the same restrictions as those found in Models V and VI. The results are quite similar to the other jointly estimated models. This time, the nested model is preferred to the non-nested model at the 10% level of significance.

Table 9. RP and SPDC estimation results (t statistics in parenthesis)*.

	I	II	III	IV
Parameter	SP	Nested SP	RP (SPDC sample)	RP (All RP sample)
β^{sp}_{tcost}	-.0140	-.0118		
	(-14.10)	(-8.74)		
β^{sp}_{sf}	.0601	.0515		
	(12.95)	(8.82)		
β^{sp}_{bag}	.0708	.0606		
	(15.47)	(9.48)		
β^{sp}_{sznm}	.0080	.0068		
	(19.25)	(9.73)		
β^{sp}_{oca}	.2358	.2040		
	(5.18)	(4.88)		
β^{sp}_{ocb}	-.4186	-.3558		
	(-9.91)	(-7.55)		
β^{sp}_{home}	-.8168	-1.0352		
	(-11.53)	(-8.30)		
λ^{sp}_{go}		1.2079		
		(10.17)		
β^{rp}_{tcost}			-.0271	-.0240
			(-20.85)	(-60.73)
β^{sp}_{sf}			.0331	.0728
			(1.13)	(7.07)
β^{sp}_{oc}			.0515	.0595
			(4.44)	(16.31)
$?^{RP}$				
χ^2(all parms=0)	4095.52	4099.71	534.17	4577.03
N (people)	2154	2154	2154	22857
N (discrete choices)	8279	8279	2154	22857

*All estimates were obtained using full information maximum likelihood estimators written in Gauss v. 3.5 and the Gauss Constrained Maximum Likelihood Module v 1.

Table 10. Joint Estimation of RP and SPDC Models (t statistics in parenthesis)*.

	Subset of obs where SP and RP data exists, n=2154		All obs, SP n=2154; RP n=22857	
	V	VI	VII	VIII
Parameter	RP/SP	RP/Nested SP	RP/SP	RP/Nested SP
β^{sp}_{tcost}	-.0145	-.0124	-.0147	-.0126
	(-16.11)	(-8.86)	(-16.33)	(-9.69)
β^{sp}_{sf}	.0570	.0491	.0553	.0477
	(12.67)	(8.77)	(13.17)	(8.83)
β^{sp}_{bag}	.0707	.0608	.0707	.0609
	(15.37)	(9.50)	(15.37)	(9.52)
β^{sp}_{sznm}	.0082	.0070	.0083	.0071
	(20.50)	(10.01)	(20.75)	(10.14)
β^{sp}_{oca}	.2345	.2039	.2338	.2038
	(5.15)	(4.85)	(5.14)	(4.84)
β^{sp}_{ocb}	-.4229	-.3615	-.4250	-.3646
	(-10.09)	(-7.63)	(-10.17)	(-7.69)
β^{sp}_{home}	-.8558	-1.0623	-.8759	-1.0772
	(-12.46)	(-8.74)	(-13.48)	(-9.03)
λ^{sp}_{go}		1.2005		1.1964
		(10.23)		(10.25)
β^{rp}_{tcost}	-.0145	-.0124	-.0147	-.0126
	(-16.11)	(-8.86)	(-16.33)	(-9.69)
β^{sp}_{sf}	.0570	.0491	.0553	.0477
	(12.67)	(8.77)	(13.17)	(8.83)
β^{sp}_{oc}	.0245	.0208	.0362	.0310
	(3.71)	(3.47)	(10.97)	(7.95)
?^{RP}	1.8307	2.1480	1.6202	1.8935
	(12.62)	(8.44)	(15.81)	(9.27)
χ^2(all parms=0)	4622.22	4626.17	8667.80	8671.67
N (people)	SP=RP=2154	SP=RP=2154	SP=2154 RP=22857	SP=2154 RP=22857
N (discrete choices)	SP=8279 RP=2154	SP=8279 RP=2154	SP=8279 RP=22857	SP=8279 RP=22857
Restrictions	b_sp_tcost= b_rp_tcost b_sp_sfcatch= b_rp_sfcatch	b_sp_tcost= b_rp_tcost b_sp_sfcatch= b_rp_sfcatch	b_sp_tcost=b_rp_tcost b_sp_sfcatch= b_rp_sfcatch	b_sp_tcost=b_rp_tcost b_sp_sfcatch= b_rp_sfcatch

*All estimates were obtained using full information maximum likelihood estimators written in Gauss v. 3.5 and the Gauss Constrained Maximum Likelihood Module v 1.

Table 11. Joint Estimation of RP and SPDC Models correcting for choice-based sampling (t statistics in parenthesis)*.

		All obs, SP n=2154; RP n=22857
	IX	X
Parameter	RP Correcting for Choice-based Sampling*	RP/Nested SP Correcting for Choice-based Sampling*
β^{sp}_{tcost}		-.0134 (-9.57)
β^{sp}_{sf}		.0412 (8.77)
β^{sp}_{bag}		.0614 (9.45)
β^{sp}_{sznm}		.0075 (10.71)
β^{sp}_{oca}		.2028 (4.77)
β^{sp}_{ocb}		-.3766 (-7.80)
β^{sp}_{home}		-1.1358 (-9.96)
λ^{sp}_{go}		1.1791 (10.24)
β^{rp}_{tcost}	-.0550 (-75.99)	-.0134 (-9.57)
β^{sp}_{sf}	.1337 (9.95)	.0412 (8.77)
β^{sp}_{oc}	.0289 (4.90)	.0071 (4.44)
$?^{RP}$		4.0751 (9.43)
χ^2(all parms=0)	27863.21	31943.56
N (people)	22,857	SP=2154 RP=22857
N (discrete choices)	22,857	SP=8279 RP=22857

*Alternative specific constants included to correct for choice-based sampling are available from the author.

There are significant similarities across the jointly estimated models. All signs are as expected. Anglers tend to prefer closer sites, those with higher levels of catch, and those with less restrictive levels of management (higher bag limits and lower minimum size restrictions). The choice specific dummy on the ‘don’t go’ option is always negative, indicating that all things equal, the angler is more likely to choose to participate than not.

The marginal value coefficients, found by dividing a coefficient with the absolute value of the travel cost coefficient are also quite similar across the models. Summer flounder catch (in the range of \$3.95 to \$3.78), bag limits (in the range of \$4.81 to \$4.90), and size limits interacted with expected number of legal size fish (in the range of \$0.56 to \$0.57) are all quite close to one another across the jointly estimated models. The only discernible pattern when comparing the models is that the stand-alone SPDC models (Models V and VI), which imposed no restrictions on the parameters, tended to lead to higher marginal value estimates. We also compared the marginal value estimates of summer flounder catch from the RP models to all of the other models (Table 11). Findings show that the RP estimates of the marginal value of summer flounder catch are lower than any found using the SPDC data.

For the restricted models in Table 10, the scale factor ($?^{RP}$) is always greater than one and the estimated magnitudes (in the range of 1.62 to 2.15) indicate that the variance of the RP data is on average nearly three times that found in the SP data. Tests for homogeneity of parameters across the different models, while accounting for this difference in the scale factor, were performed. Using Models V-VIII, tests were performed for each model to examine if the more restrictive model (where the scale factor is estimated and restrictions are placed across the RP and SPDC models) is preferred to separate estimation of the models. All tests for preference homogeneity on the travel cost and summer flounder catch parameters failed at the 10% significance level using the statistical test described above.

Choice-based sample models

One reason that tests for parameter homogeneity might fail is because of problems with the RP sample (Louviere et al.). The intercept survey used to gather the RP data is inherently a choice-based sample. The difficulty with choice-based samples is that the probability of observing an individual choosing a particular fishing site is a function of the individual's preferences and the probability that a particular choice is sampled (Ben-Akiva and Lerman). Since we aggregate over intercept sites in this study and define sites at a county level, it is believed that difficulties associated with choice-based sampling can largely be avoided. Ben-Akiva and Lerman show that if the fraction of the sample is equal to the fraction of the population of anglers at a site, then there is no problem recovering unbiased parameter estimates for anglers' preferences. If this condition does not hold, Ben-Akiva and Lerman demonstrate that including alternative specific constants to the model will yield unbiased estimates for anglers' parameter estimates if the model is conditional logit (as the RP model is).[8] We therefore estimate the RP model using all observations and include alternative specific constants (reported as Model IX).

Using this RP model, we also estimate the joint nested SPDC/RP model to see if correcting for choice-based sampling leads to acceptance of parameter homogeneity. Additionally, comparing models IX and X in Table 11 to the other models might shed some light on whether there is a serious problem with choice-based sampling as it relates to welfare and parameter estimates. We find that the hypothesis of parameter homogeneity must be rejected even after correcting the RP model for parameter homogeneity. Perhaps more interesting is a comparison of the parameter and welfare estimates across the models implicit in Table 12 and Figure 4. Figure 4, in particular, shows that the welfare measure for Model IX (the RP model correcting for choice-based sampling) lies within the 95% confidence intervals of the other two RP models (Models III and IV). Similarly the welfare measure for the jointly estimated model accounting for choice-based sampling lies within the 95% confidence intervals of all but one of the jointly estimated models (Model VI is the only exception). Our findings, while certainly not definitive on the issue of choice-based sampling, indicate that in practical terms, accounting for choice-based sampling has little impact on model outputs of interest to the agency. This means that it appears that using intercept data for the RP models (see Hicks et al.; Haab et al.; and McConnell and Strand) is a reasonable way to proceed for estimates of welfare due to environmental or policy changes.

Welfare and Participation Change Estimates

The implications of the rejection of the hypothesis of parameter homogeneity are two-fold:

(1) While all signs for parameters across the RP and SP models agree, there is a small but statistically significant divergence in their actual magnitude.

(2) Despite the findings that parameter estimates are not homogenous across data sources, the RP estimation provides no way to estimate management-specific behavioral parameters.

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[8] The Ben-Akiva and Lerman discussion summarizes results demonstrated by McFadden, who shows that the alternative specific constants are biased but can be corrected using sample weights, which were calculated by the author from a combination of the random phone and intercept data.

The challenge is to reconcile these seemingly contradictory items in a reasonable way. Since the ultimate goal of this research was to provide a tool that would provide fishery-specific, policy-relevant input, we will next examine differences in the predictions of welfare and participation changes across the different models. To accomplish this, we begin by examining the differences between predicted welfare change in the RP and all SPDC models due to a change in environmental conditions affecting summer flounder catch. Results are presented in Table 12 for two policies that increase summer flounder catch by 25% and 50%.

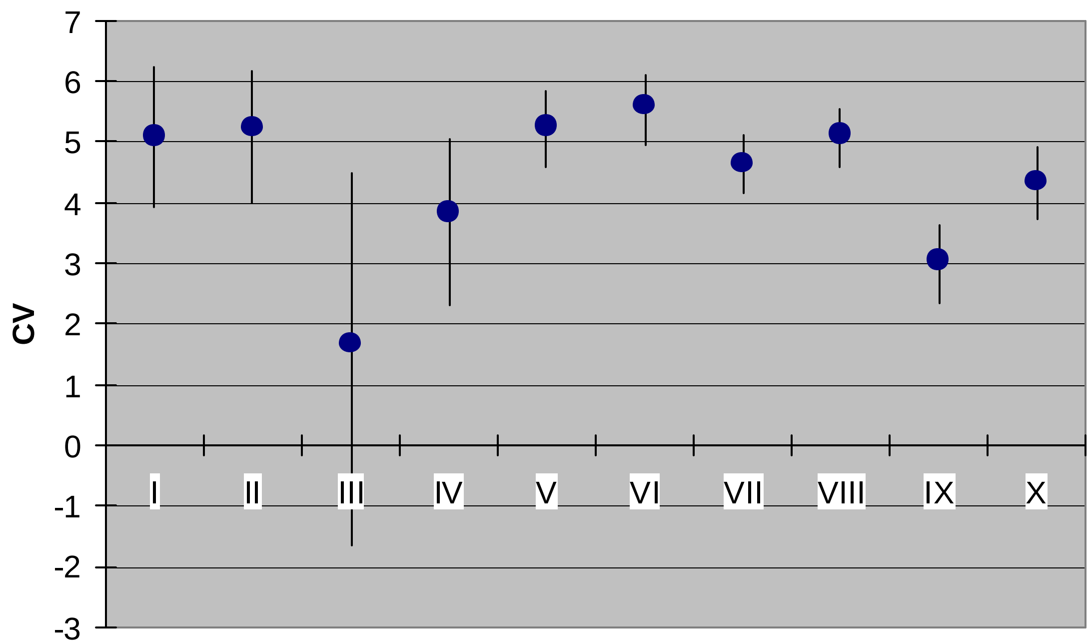
The results show that estimates across all of the models, despite rejecting the hypothesis of preference homogeneity, are remarkably close, even when comparing the RP models with the other models in the paper. Ninety-five percent confidence intervals were constructed using the Krinsky-Robb technique with 200 draws of the parameter vector. There is some overlap in the confidence intervals depending on the actual model compared. The mean CV for the full RP model (whose welfare estimates are statistically different from zero) is very close to residing inside the

Table 11. Measures of Compensating Variation for a change in environmental quality*,.**

Quality Change	RP Models			SPDC Models		Data Enrichment Models Subset of RP Obs		Data Enrichment Models All RP Obs		
	III Subset of RP Obs.	IV All RP Obs.	IX All RP Obs CB Sampling	II Nested	I Non-nested	VI Nested	V Non-nested	VIII Nested	VII Non-nested	X Nested CB Sampling
Marginal Value of s. flounder catch	$1.22	$3.03	$2.43	$4.36	$4.29	$3.95	$3.93	$3.78	$3.76	$3.07
+25% Δ in s. flounder catch	0.83 (-.82,2.20)	1.90 (1.14,2.49)	1.52 (1.16,1.80)	2.60 (1.97,3.04)	2.52 (1.94,3.08)	2.74 (2.42,2.98)	2.58 (2.26,2.86)	2.52 (2.26,2.71)	2.29 (2.04,2.51)	2.15 (1.85,2.42)
+50% Δ in s. flounder catch	1.69 (-1.64,4.48)	3.85 (2.30,5.06)	3.06 (2.34,3.62)	5.25 (3.99,6.16)	5.09 (3.92,6.23)	5.61 (4.94,6.11)	5.26 (4.60,5.84)	5.14 (4.60,5.53)	4.65 (4.15,5.11)	4.36 (3.74,4.91)

*Confidence intervals computed using the Krinsky-Robb method with 200 draws. Because of the many models presented in this report, 200 draws and calculations per welfare measure presented seems a reasonable trade-off between precision and computation time.
**The number of legal sized fish is not allowed to change in this measure.

Figure 4. Welfare Measures for a 50% increase in Summer Flounder Catch



95% confidence intervals for every other model estimated. Comparing results across all of the SPDC models shows that, regardless of the definition of sample sizes or nesting structure, welfare estimates are not too different from each other. There are a few comparisons that are significantly different, but these models are virtually identical to one another.

To further examine how the each of the seven SPDC models perform, we examine participation and welfare measures for potential policy changes that fisheries managers might want to consider. We alter the bag and minimum size limits relative to baseline levels in Table 13. The first row of the table is associated with more restrictive policies that are loosened as one moves down the rows in the table. Findings indicate that anglers are willing to pay more to avoid more restrictive bag limits than size limits. However, anglers are willing to pay significant amounts to avoid either type of policy. Examining the relative performance across models, findings indicate that again the results are strikingly similar across models. Nearly without exception, mean measures of CV fall within the 95% confidence intervals of the the other SPDC models in the Table. Figures 5 and 6 show the relationships between point estimates of CV and the associated 95% confidence intervals in graphical terms for Options 1 and 2 respectively. The figures show that all models are internally consistent with each other. The 95% confidence intervals for Models I and II are wider than the jointly estimated models because the joint models bring more information to the estimates and therefore greater precision to the welfare estimates.

Changes in participation (defined here as trips) estimates for the same policies are reported in Table 13. These estimates were computed by calculating the probability of choosing the ‘Don’t Go’ option for each person in the RP data both before and after a policy change. We then calculate the mean difference in predicted probability over the entire sample to obtain an estimate of the proportion of trips that would change as a result of the policy. This method is perhaps best suited for policies that reduce the number of trips (associated with tighter management regulations) since the RP data is by definition a sample of people who have chosen to recreate; however, Table 13 shows trip changes for hypothetical policies both increasing and decreasing season length.

Figure 5. Option 1 Welfare Estimates
(-1 bag limit, -1 month season length)

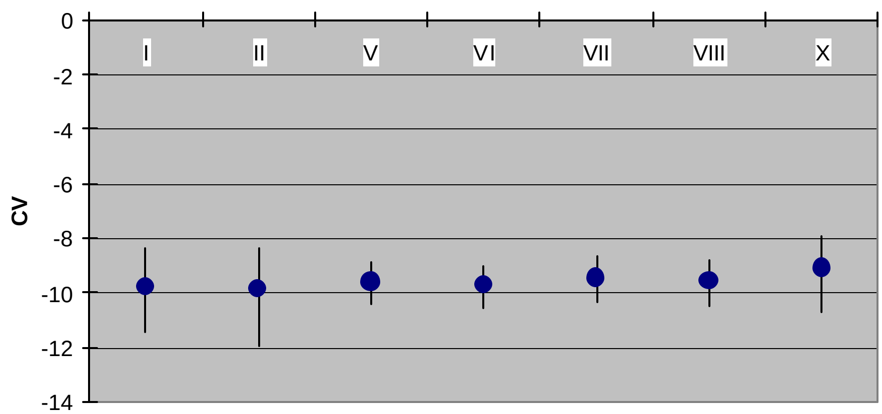


Figure 6. Option 2 Welfare Results
(-1 bag limit, +1 size limit, -1 month season length)

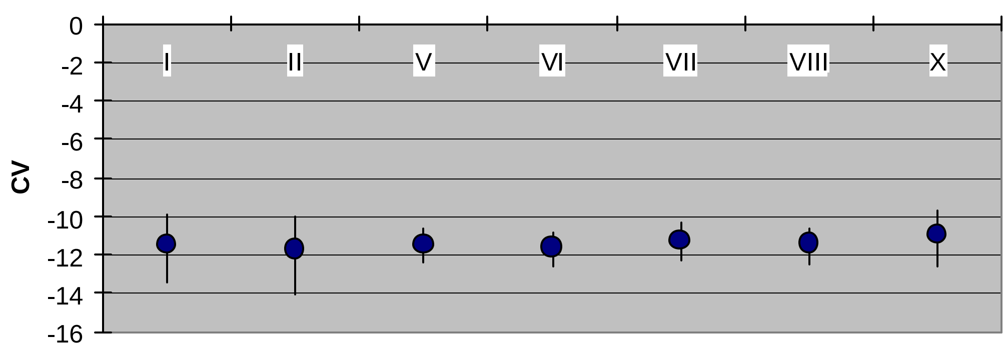


Table 13. Measures of CV for some selected policy changes (95 % confidence intervals in parenthesis) *.

				I	V	VI	VII	VIII	II	X
Option	Bag Limit Δ	Size Limit Δ	Season Δ (Months)	SP Non-nested	RPSP Non-nested Small Sample	RPSP Nested Small Sample	RPSP Non-nested Large Sample	RPSP Nested Large Sample	SP Nested	RPSP Nested Large Sample with CB Sampling
1	-1	0	-1	-$9.78	-$9.60	-$9.71	-$9.45	-$9.55	-$9.87	-$9.09
				(-$11.47 -$8.37)	(-$10.42 -$8.87)	(-$10.58 -$9.04)	(-$10.33 -$8.65)	(-$10.49 -$8.84)	(-$11.95 -$8.38)	(-$10.68 -$7.92)
2	-1	1	-1	-$11.49	-$11.47	-$11.66	-$11.25	-$11.43	-$11.69	-$10.97
				(-$13.42 -$9.94)	(-$12.43 -$10.65)	(-$12.62 -$10.89)	(-$12.28 -$10.35)	(-$12.47 -$10.64)	(-$14.07 -$10.06)	(-$12.65 -$9.68)
3	0	-1	0	$2.92	$3.25	$3.43	$3.13	$3.30	$3.12	$3.30
				($2.51 $3.38)	($3.00 $3.52)	($3.17 $3.69)	($2.86 $3.42)	($3.03 $3.56)	($2.65 $3.62)	($2.84 $3.74)
4	0	0	-1	-$5.71	-$5.60	-$5.67	-$5.52	-$5.58	-$5.76	-$5.30
				(-$6.68 -$4.91)	(-$6.08 -$5.19)	(-$6.16 -$5.28)	(-$6.02 -$5.07)	(-$6.11 -$5.18)	(-$6.95 -$4.89)	(-$6.20 -$4.66)
5	0	1	-1	-$7.42	-$7.47	-$7.63	-$7.32	-$7.47	-$7.59	-$7.20
				(-$8.67 -$6.48)	(-$8.08 -$6.98)	(-$8.20 -$7.15)	(-$7.99 -$6.78)	(-$8.09 -$6.97)	(-$9.03 -$6.59)	(-$8.26 -$6.38)
6	0	1	0	-$1.95	-$2.13	-$2.23	-$2.06	-$2.16	-$2.10	-$2.18
				(-$2.31 -$1.71)	(-$2.31 -$1.99)	(-$2.40 -$2.09)	(-$2.26 -$1.91)	(-$2.33 -$2.01)	(-$2.54 -$1.81)	(-$2.51 -$1.93)
7	1	-3	0	$15.45	$16.91	$17.77	$16.32	$17.12	$16.03	$16.74
				($13.34 $17.85)	($15.62 $18.23)	($16.62 $18.99)	($14.94 $17.72)	($15.96 $18.41)	($13.77 $18.70)	($14.73 $18.82)
8	1	-1	0	$7.67	$7.91	$8.13	$7.71	$7.92	$7.91	$7.70
				($6.48 $8.75)	($7.26 $8.47)	($7.60 $8.69)	($7.02 $8.31)	($7.33 $8.52)	($6.76 $9.30)	($6.74 $8.70)
9	1	0	0	$4.74	$4.65	$4.69	$4.57	$4.61	$4.78	$4.38
				($3.97 $5.48)	($4.24 $5.02)	($4.28 $5.04)	($4.13 $4.97)	($4.17 $4.98)	($3.94 $5.69)	($3.75 $5.05)
10	1	1	0	$2.79	$2.51	$2.45	$2.51	$2.44	$2.67	$2.19
				($2.13 $3.36)	($2.17 $2.81)	($2.05 $2.74)	($2.13 $2.84)	($2.02 $2.76)	($1.96 $3.42)	($1.62 $2.85)
11	1	2	0	$1.68	$1.32	$1.20	$1.35	$1.24	$1.47	$0.97
				($1.05 $2.32)	($0.98 $1.65)	($0.81 $1.49)	($0.99 $1.710)	($0.82 $1.55)	($0.70 $2.22)	($0.35 $1.63)
12	1	3	0	$1.07	$0.65	$0.51	$0.70	$0.57	$0.80	$0.28
				($0.42 $1.71)	($0.30 $1.00)	($0.12 $0.80)	($0.31 $1.09)	($0.15 $0.87)	($0.04 $1.56)	(-$0.37 $0.96)
13	2	1	0	$7.54	$7.17	$7.15	$7.09	$7.06	$7.46	$6.59
				($6.10 $8.86)	($6.42 $7.80)	($6.37 $7.73)	($6.27 $7.76)	($6.25 $7.69)	($6.00 $9.01)	($5.40 $7.98)

Table 13, cont. Measures of CV for some selected policy changes (95 % confidence intervals in parenthesis)*.

				I	V	VI	VII	VIII	II	X
Option	Bag Limit Δ	Size Limit Δ	Season Δ (Months)	SP Non-nested	RPSP Non-nested Small Sample	RPSP Nested Small Sample	RPSP Non-nested Large Sample	RPSP Nested Large Sample	SP Nested	RPSP Nested Large Sample with CB Sampling
14	3	-3	0	$25.03	$26.32	$27.25	$25.57	$26.44	$25.71	$25.66
				($21.23 $28.62)	($24.21 $28.21)	($25.45 $29.13)	($23.34 $27.57)	($24.61 $28.39)	($21.99 $30.06)	($22.47 $29.01)
15	3	-1	0	$17.21	$17.27	$17.57	$16.92	$17.20	$17.54	$16.56
				($14.45 $19.66)	($15.76 $18.51)	($16.26 $18.79)	($15.31 $18.26)	($15.81 $18.57)	($14.85 $20.56)	($14.49 $18.98)
16	3	0	0	$14.26	$13.99	$14.11	$13.21	$13.87	$14.39	$13.21
				($11.94 $16.51)	($12.77 $15.12)	($12.87 $15.16)	($12.43 $14.96)	($12.56 $14.99)	($11.87 $17.14)	($11.29 $15.24)
17	3	3	0	$10.57	$9.97	$9.91	$9.87	$9.81	$10.38	$9.07
				($8.46 $12.50)	($8.87 $10.88)	($8.77 $10.78)	($8.67 $10.89)	($8.60 $10.76)	($8.22 $12.63)	($7.31 $11.17)

*Confidence intervals computed using the Krinsky-Robb method with 200 draws.

Table 14. Measures of changes in trips for some selected policies (95% confidence intervals reported in parenthesis)*.

				I	V	VI	VII	VIII	II	X
Option	Bag Limit Δ	Size Limit Δ	Season Δ (Months)	SP Non-nested	RPSP Non-nested Small Sample	RPSP Nested Small Sample	RPSP Non-nested Large Sample	RPSP Nested Large Sample	SP Nested	RPSP Nested Large Sample with CB Sampling
1	-1	0	-1	-100,467	-92,609	-64,492	-96,373	-72,591	-140,564	-40,017
				(-114,866 -84,555)	(-103,735 -80,194)	(-73,374 -55,469)	(-108,399 -82,713)	(-82,543 -62,292)	(-164,747 -105,171)	(-79,420 -9,620)
2	-1	1	-1	-114,894	-105,219	-73,633	-109,883	-83,189	-161,133	-43,237
				(-130,725 -96,814)	(-117,233 -91,823)	(-82,576 -63,395)	(-122,959 -95,174)	(-93,778 -71,060)	(-187,052 -123,976)	(-85,368 -10,642)
3	0	-1	0	22,365	17,982	13,057	19,669	15,464	32,553	3,999
				(19,270 25,689)	(16,079 20,254)	(10,873 15,886)	(17,514 22,155)	(12,925 18,733)	(28,050 37,825)	(1,376 8,942)
4	0	0	-1	-66,748	-66,065	-45,912	-67,586	-50,776	-95,126	-32,318
				(-76,496 -55,795)	(-74,226 -56,907)	(-52,063 -39,641)	(-76,278 -57,706)	(-57,499 -43,783)	(-112,565 -69,988)	(-65,541 -7,347)
5	0	1	-1	-80,305	-77,299	-54,050	-79,781	-60,341	-114,709	-35,005
				(-91,413 -67,594)	(-86,225 -67,331)	(-60,871 -46,274)	(-89,345 -69,081)	(-67,789 -51,540)	(-133,357 -88,121)	(-70,460 -8,252)
6	0	1	0	-15,520	-12,731	-9,199	-13,854	-10,842	-22,684	-3,006
				(-17,508 -13,109)	(-14,022 -11,250)	(-10,592 -7,435)	(-15,291 -12,213)	(-12,384 -8,819)	(-26,135 -18,637)	(-5,772 -800)
7	1	-3	0	109,098	80,192	57,509	89,341	69,483	157,170	17,635
				(96,830 123,991)	(72,727 90,709)	(47,358 69,117)	(80,669 101,245)	(57,187 83,228)	(138,674 179,025)	(5,974 39,015)
8	1	-1	0	57,975	43,263	30,597	47,794	36,631	82,309	10,790
				(51,227 65,161)	(39,086 48,420)	(25,555 35,843)	(43,040 53,527)	(30,718 42,683)	(71,956 92,596)	(3,442 23,667)
9	1	0	0	36,996	27,315	19,025	30,104	22,725	51,377	7,477
				(32,449 42,150)	(24,591 30,429)	(16,177 21,963)	(27,102 33,725)	(19,171 26,366)	(43,195 60,336)	(2,260 16,233)
10	1	1	0	22,435	16,021	10,869	17,640	12,973	29,817	4,991
				(18,252 27,981)	(14,095 18,550)	(9,256 12,808)	(15,390 20,681)	(10,922 15,412)	(22,645 38,847)	(1,495 10,347)
11	1	2	0	14,008	9,411	6,114	10,367	7,300	17,312	3,491
				(9,714 19,341)	(7,688 11,699)	(4,893 7,580)	(8,294 13,252)	(5,707 9,198)	(10,349 26,598)	(861 6,831)
12	1	3	0	9,236	5,645	3,410	6,228	4,078	10,218	2,616
				(4,616 14,870)	(3,829 7,986)	(2,129 4,789)	(3,979 9,063)	(2,338 5,883)	(2,546 19,552)	(597 5,288)
13	2	1	0	58,048	41,562	28,679	45,999	34,409	79,735	11,663
				(50,287 68,256)	(37,098 46,640)	(24,217 33,369)	(40,970 51,903)	(28,909 40,152)	(64,361 96,999)	(3,446 25,412)

Table 14, cont. Measures of changes in trips for some selected policies (95% confidence intervals reported in parenthesis)*.

Option	Bag Limit Δ	Size Limit Δ	Season Δ (Months)	I SP Non-nested	V RPSP Non-nested Small Sample	VI RPSP Nested Small Sample	VII RPSP Non-nested Large Sample	VIII RPSP Nested Large Sample	II SP Nested	X RPSP Nested Large Sample with CB Sampling
14	3	-3	0	167,611	114,623	81,053	129,425	99,321	241,982	26,088
				(149,798 188,025)	(104,391 128,389)	(66,954 96,211)	(117,266 145,096)	(82,132 117,466)	(212,267 271,477)	(8,620 58,023)
15	3	-1	0	122,703	85,648	59,960	95,895	72,812	174,528	21,261
				(109,397 138,237)	(77,012 95,131)	50,014 69,684	(86,457 106,539)	(60,995 84,169)	(150,652 198,825)	(6,737 47,069)
16	3	0	0	104,259	73,120	50,880	18,953	61,579	146,631	18,953
				(91,997 118,492)	(65,781 81,305)	42,795 58,715	(73,779 90,952)	(51,683 71,250)	(123,881 171,059)	(5,861 41,846)
17	3	3	0	79,841	56,082	38,618	62,296	46,506	109,487	15,591
				(68,986 94,831)	(50,024 63,031)	32,574 44,906	(55,441 70,438)	(39,013 54,199)	(87,247 134,632)	(4,601 34,260)

*Confidence intervals computed using the Krinsky-Robb method with 200 draws.

Figures 7 and 8 (and in more detail, Table 14) show that the choice of model structure and sample can lead to different estimates of participation changes. The most striking results in these figures are the relative performance between the model that corrects for choice-based sampling (Model X) and the other models. Note that Model X includes alternative-specific constants that in effect allocate the sample into fishing sites based upon the sample weights. Consequently, the predicted option of 'Don't Go', for which there is no RP alternative specific constant, gets a much lower probability of being chosen compared to the other models in the figures. The choice of model structure, whether nested or not, does not seem to affect participation estimates in a systematic way.

We have also computed participation and welfare changes for quite a number of potential policies to develop a response surface based upon CV. Assuming that policies with higher CV are preferred to policies with lower CV, we found that all models predict the same ordering of policy alternatives from most preferred to least preferred. Coupling this with the finding that the RP and the SPDC models predict levels of CV very close to one another provides evidence that the SPDC enrichment models are a defensible way of incorporating respondents preferences despite the rejection of preference homogeneity across the RP and SPDC models.

Also of interest is the finding that SPDC models I and II, which are estimated independently of the RP data, perform reasonably well with regard to management-relevant measures. Therefore, based on this example, it would seem that estimating only the SPDC model and applying those parameter estimates to the baseline as defined by the RP data is a reasonable way to proceed for policy analysis.

Figure 7. Option 1 Participation Change Estimates (-1 bag limit, -1 month season length)

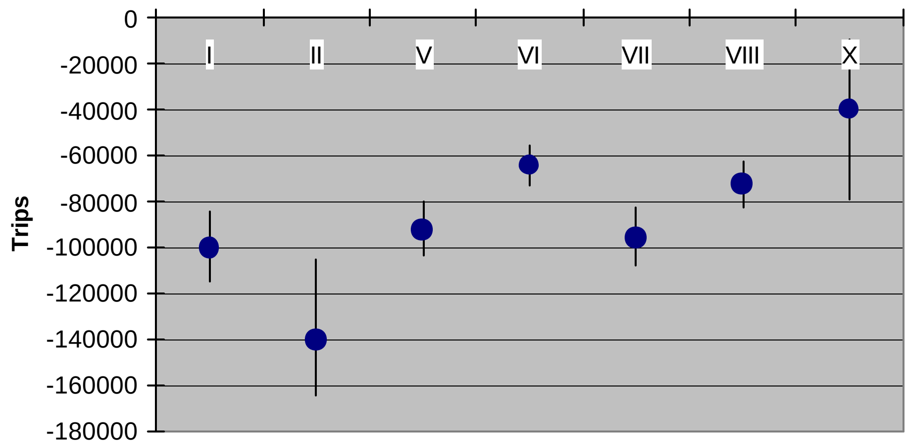
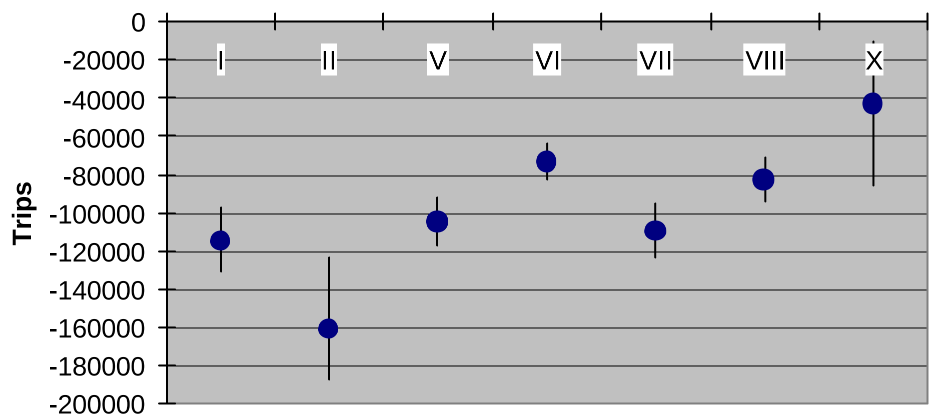


Figure 8. Option 2 Participation Change Estimates (-1 bag limit, +1 size limit, -1 month season length)



VII. Recommendations and Conclusion

This paper presents a methodology for quantifying people's preferences for environmental conditions or management that are not readily identifiable using real-world observations. For many reasons, including lack of variation or the exploration of a new management technique, RP methods may not provide adequate information for natural resource managers. The SPDC technique presented here provides a rigorous way of estimating preferences for important attributes like this. The experimental design technique, used for constructing hypothetical comparisons of trips, is a very powerful and efficient way to collect data with the additional advantage of minimal burden on respondents.

Additionally, we have shown that the existing data collection programs within NMFS can be used to readily collect data necessary for the implementation of an SPDC project. The intercept survey is an extremely effective way of gathering information about the real choices that people make regarding recreational angling. Combining the intercept survey with a mail data collection methodology for the collection of the SPDC survey proved to be an effective way of combining these data sources.

Despite the findings of preference heterogeneity across the RP and SPDC data sources, the results also show that while statistically different, nearly without exception the models predict welfare changes on par with each other. As for model structure and the choice of sample, the SPDC models all predict quite similar welfare changes for every policy examined. Perhaps the only discernible difference between alternative model structures was in the effect of choice-based sampling on predicted participation changes. These results showed that the models are amenable to capturing the effects of regulations on participation and that these effects are statistically different from zero. These estimates do not take into account how trip avidity might change as a result of changing regulations, since we model participation changes contingent on the number of trips, or choice occasions, observed in the sample.

The results also suggest that this technique is potentially very useful for a whole host of other management problems facing NMFS ranging from marine protected areas for commercial fishing, marine mammal protection, turtle protection, to potential gear restrictions on commercial fishermen. Because the technique does not necessarily require a large body of baseline data, it can be used to quickly assess people's preferences for the environment and fisheries management.

For future use of this methodology, several recommendations can be made based upon the results found here. We first critique the setup of this survey relative to testing for parameter homogeneity across models.

- The researcher should always try and maximize the number of restrictions across the RP and SPDC models if the goal is to test for parameter homogeneity. It would have been easy to enter expected catch for other species as a quantitative rather than qualitative variable in SPDC model. This would have allowed further testing for parameter homogeneity or for testing for parameter homogeneity among subsets of parameters. However, we constructed the other catch variable as qualitative for a reason. We felt and heard from focus group respondents that a qualitative variable would lessen the burden on respondents.
- The finding that the variance of the RP data was roughly three times that of the SPDC data is not surprising. However, steps can be taken to perhaps improve the RP data by careful attention to sampling and consideration of additional variables that should be included in the model. NMFS would be well served to collect site-

specific data on factors that may differentiate one site from another. These items may not necessarily be directly related to fishing but could include information such as the presence of beaches, number of boat ramps, a resort area, and other amenities. This work could be undertaken independently of any ongoing data collection efforts and could perhaps be collected solely using GIS techniques. It should be noted that this recommendation is directed at the RP estimation and is relevant for all of the RP work NMFS does.

- It our belief that NMFS needs to conduct a careful examination of the effect of choice-based sampling on RP Estimation. This process could use existing data collected by the MRFSS to approximate the sampling weights employed by the survey (as we did in Models IX and X). Note this recommendation again applies to any RP research undertaken. The issue with choice based sampling has nothing to do with the avidity bias issue. Rather, the issue is that when we estimate a choice probability we want it to be independent of the probability of being sampled. Despite accounting for the issue of choice-based sampling during estimation of parameters, welfare changes, and participation changes, findings show that except for predicted trip changes, there was little practical difference between models that did and did not account for the choice-based sample nature of the RP data. These findings, while preliminary, support the NMFS' current use of RP models of angler behavior for use in the calculation of welfare measurement relevant for management.
- When defining the experimental design matrix in the SPDC study, be explicit about cross and higher order effects for which you might want to test. While a

careful tradeoff needs to be made between survey length, number of questions per respondent, and the cost of administering different versions of a survey, NMFS could use SPDC techniques to estimate non-linear and cross effects that are simply not possible to quantify in an RP model. Of course, the question of how relevant these higher order effects might be for management relevant advice is still open to debate. While we were able to quantify a cross effect with no difficulty, we did not use an optimal design for this purpose, so there was some loss in efficiency.

Next we discuss recommendations relative to SPDC modeling that may call for departures from, rather than modifications of, the current methodology.

- Related to the issue of choice-based sampling is the issue of using the MRFSS random digit dial survey to identify respondents. Once identified, respondents are asked about a recent trip to obtain RP data and then could be asked SPDC questions about hypothetical trips or both. The advantage of using this approach is that it is a random sample of anglers. The issue of inland versus coastal anglers might be problematic and a thorough assessment of this issue should be undertaken before using this methodology.
- The random digit dial approach can also be used to formulate a better participation model in concert with site choice modeling. The current model did a relatively poor job of predicting participation changes, since the sample only consisted of current participants.

- This project was designed to look at only one species. It is conceivable that NMFS will expand the methodology to include other attributes such as other species (or target species) or modes of fishing (e.g., from shore, boat, etc.). There is some evidence that 'branding' alternatives in an SPDC model can be a very important way of getting respondents to organize information and get at their preferences. The methodology in this paper simply treats hypothetical trips as generic goods: they are solely described by their attributes. By branding a fishing trip, one might include attributes such as species or mode and label the hypothetical trip accordingly. The 'brands' are still simply attributes, but changes in labeling and organization of the hypothetical alternatives will become important.

This project has demonstrated the utility of applying stated preference methods to environmental management problems facing NMFS. The results show that the method yields internally consistent and useful results for a wide range of management options, that would not otherwise be quantifiable using revealed preference techniques. The approach can be expanded to include many other issues facing the agency such as spatial management, marine protected species, etc. Because the stated preference discrete choice method can be used independently of the revealed preference approach, it is possible to assess a problem quickly when no observable data on angler or commercial fishing behavior have been collected. The experimental design aspects of the stated preference technique allow investigators to maximize the information they collect from respondents, meaning that precise estimates can be obtained from relatively small samples. For all of these reasons, the stated preference discrete choice method should be considered a useful tool for tackling NMFS' many management problems.

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