ABSTRACT. In this manuscript we explore the consequences to different income groups of various policies to reduce overfishing in the Gulf marine recreational fishery. To do so we estimate a discrete choice model of marine recreational fishing demand allowing for incomplete data and a non-constant marginal utility of income. By allowing the marginal utility of income to vary across three categorical income groups, our model allows us to explore the distributional consequences of various fee schemes and other policy programs that would change catch in the fishery. We find that flat fees have a strong proportional effect on the participation of shore fishermen, where low-income anglers predominate, and a relatively small impact on the expensive charter fishing mode. We also find that the welfare consequences of declining catch rates would fall disproportionately on low-income anglers. (JEL Q51, Q22)

I. INTRODUCTION

Congestion and overfishing are serious issues in marine fisheries across the globe, and while the commercial fishery is often blamed, there is increasing recognition that recreational fisheries are contributing to these problems but may also play a role in their solution (Coleman et al. 2004). Hence, in addition to longstanding regulations of the commercial sector, recreational fisheries are increasingly being controlled by government actions. For example, in the Gulf of Mexico, several existing recreational fisheries are closed periodically as a way to ensure that total harvests do not exceed the total allowable catch, which is set at a level to ensure the sustainable growth of the fish stock (Gulf of Mexico Fishery Management Council 2004). Such regulations are equivalent to quantity rationing schemes, which have a negative stigma among economists because they may lead to inefficient resource allocation and encourage wasteful rent-seeking behavior. A fee-based approach might be an alternative way to reduce recreational effort that would avoid the inefficiencies that arise because of closures, promoting use by the highest-value anglers. Partly in response to budgetary pressures in the United States, managers of public recreational resources are turning more and more to park entrance fees and fishing license fees to supplement their endowments and government allowances (More 2002).

However, in contrast to quantity rationing, fees have a negative stigma among many recreational users, government officials, and other non-economists. In the recreation and leisure literature and amongst many policy makers, the use of fees is criticized on the grounds of equity because they may exclude the poorest user groups from use of resources (More and Stevens 2000). Though economists who estimate welfare impacts (gains or losses in benefits) rarely do so, it is sometimes important to examine the distributional impact of a policy (see Arrow et al. 1996). We examine the various consequences of such a fee approach on three income groups in this manuscript: we explore whether the burden of fishing fees falls...
disproportionately hard on lower income people. We also examine the anglers’ maximum willingness to pay (WTP) to avoid a decline in catch rates.

To examine income effects requires departure from the usual recreation modeling approaches. Revealed preference models of recreation demand are often estimated using discrete choice approaches (or random utility models/RUMs), and unfortunately since the beginning of the use of these, the marginal utility of income is typically assumed to be constant (e.g., Caulkins, Bishop, and Bouwes 1986; Bockstael, Hanemann, and Kling 1987). There are very few exceptions.1 In contrast, in our variant on the random utility model income effects are allowed so that distributional consequences can be explored.

The remainder of the paper is organized as follows. In the next section we provide some additional background and a review of some of the relevant literature.2 We then present the model, a discussion of the 1997 Marine Recreational Fishery Statistics Survey (MRFSS) data set that we use, and finally, our empirical results. To preview these: we find that a flat fee imposed on all modes of fishing can be quite effective in reducing recreation demand for recreational fishing in the Gulf of Mexico. When we look at the impacts across different income groups, we find that in the Gulf a fee on fishing would tend to affect the behavior of low-income anglers more than that of high-income anglers. The welfare cost of such fees to high-income anglers is greater in absolute terms, but smaller relative to their income. We also look at anglers’ WTP to prevent a decline in catch rates and find that, as with the welfare costs of a fee, these impacts also vary by income groups. Finally, there is evidence here that because mode choice varies across income groups, policies that seek to take into account the equity impacts can be targeted at specific modes of fishing.

II. ADDITIONAL BACKGROUND AND LITERATURE

To begin, we first briefly consider the RUM and the role income plays and second, some literature on imposing fees in the recreational setting. The use of the RUM in recreation demand or travel cost models is now quite well documented in the literature and we will not provide an extensive review of such literature here, as that has been done in numerous other papers (see, e.g., the introductory chapter in Hanley, Shaw, and Wright 2003 and references therein). The RUM has a few distinct advantages over some other types of models applied to recreation demand (specifically the single-site count data approach) in that it handles substitution among sites rather well. However, in virtually all existing recreation demand models that have been estimated using the RUM-based approach, income effects are assumed to be absent, or at least assumed not to matter when choosing among various sites to visit. We are aware of very few estimated RUM models that appear in published or unpublished papers that allow for a non-constant marginal utility of income.3 This is probably not a matter of carelessness or an oversight on the part of modelers: incorporating income effects generally leads to some very difficult technical issues (for discussion see Herriges and Kling 1999; McFadden 1999; Shaw and Ozog 1999). To incorporate income effects, our econometric model below draws on recent work by Morey, Sharma, and Karlstrom (2003) and Morey, Sharma, and Mills (2003) that incorporate income effects in

1 The random utility model’s leading competitor these days is probably some sort of count-data model and within that structure, income plays a role that is often difficult to discern, especially in the single-site count data model.

2 The usual apology to those authors of important papers we missed pertains.

3 Shonkwiler and Shaw (2003) consider the impact of a $5 increase in the fee at one of the Columbia River main-stem reservoirs within a finite mixture model that allows for income effects, but this is quite different than the usual RUM model. They find that recreational users within one regime lose almost twice the consumer’s surplus as those in another income regime.
a simple fashion. Morey and his colleagues assume that utility is "a piece-wise linear spline function" of expenditures. In this case, the change in the marginal utility of money is assumed to be a step function of the amount of the individual's income. This piece-wise spline approach is used to introduce an income effect below. The approach is well suited for our data set, where income is available categorically. We use this approach within the context of a repeated discrete choice version of the RUM that is geared to the data that we have.

**Fee Impacts**

Distributional consequences of environmental or resource programs have been considered in a variety of settings, including tradable pollution permits, the share of water shortages, and in situations where "grandfathering" allocation schemes are allowed (see Rutström and Williams 2005). The distributional impacts of recreation fees, in the context of well-developed utility-theoretic recreation demand models, have not been frequently addressed in the mainstream literature on non-market valuation. One notable exception is the contingent valuation study by Adams et al. (1989): their study of hunting and fees illustrates that lower income groups have higher losses than higher income hunters when a flat "per-head" fee is imposed on them.

Several authors of leisure studies (Reiling et al. 1996; Bowker, Cordell, and Johnson 1999; More and Stevens 2000) have concluded that implementation of a fee or an increase in a fee would lower recreational participation by low-income people. More and Stevens (2000) found that a $5 daily fee to access public lands would affect almost half of the low-income people as compared to a smaller portion (33%) of high-income people. Reiling et al. (1996) estimated that recreational demand for public lands on the part of low-income groups is more elastic than that of middle or high income groups, which implies that low income people would be more responsive to a price increase. These studies support the notion that income inequity is problematic in recreational activities. In contrast to these studies, Kyle, Graefe, and Absher (2002) find no significant correlation between household income and willingness to pay for fees, and Winter, Palucki, and Burkhardt (1999) found that income was less helpful in understanding public response to fees than a measure of social trust. Because the RUM we develop is almost entirely driven by the data we have for this analysis, we next describe key features of it before we describe the model.

**III. KEY DATA FEATURES/MODEL**

To estimate recreational demand, one would ideally like to know the destination, the frequency, and what mode is chosen for each and every trip an individual takes, for as long a time period as is possible. Such accurate diary data are rarely available to those interested in recreation, for the simple reasons that collecting it can be complicated, there are limits to respondent recall, and attrition among recreational users that remain in the sample for the entire length of the period is common; for all these reasons such data collection efforts are likely cost-prohibitive to most researchers. Hence, it is often the case that data are gathered by making trade-offs between study and survey cost, accuracy for the information that is collected, and focus on one or more important policy issues.

The key policy issues of interest to us here ultimately relate to management of the Gulf-marine fishery, which is suffering from overfishing. The data used here come from the 1997 Marine Recreational Fishery Statistics Survey (MRFSS) questionnaire. We use this data set as the only data currently available to examine several policies of interest in the Gulf marine fishery. Here are the key features of the data that come from this survey:

1. Anglers were intercepted at some site, in some mode of fishing:  

   4 As will be shown below, our econometric model has a correction for potential intercept bias.
2. The destination of, and mode of fishing for this intercept trip is known;
3. Anglers are asked the total number of trips they took over a two month period;
4. Anglers are asked how many of these total trips are also to the intercept destination; and
5. Anglers are not asked the specific destinations and modes of the total remaining trips, aside from those that were taken to the intercept site.

Because of the lack of knowledge about the specific destinations on all trips, this is far from ideal data. We nevertheless use it to analyze various policies, in lieu of doing no research that may shed light on them, or undertaking an expensive new data collection effort, which would entail a brand new survey and sample. Morey, Shaw, and Rowe (hereafter, MSR 1991) developed a statistical and theoretical model that takes advantage of data of exactly this type because it was also data from the exact same type of questionnaire, and we therefore follow very closely the discrete choice/RUM they developed. The history of the MRFSS data set is discussed in Hicks et al. (2000) and the data used here are in fact from the 1997 study (also discussed in detail in Whitehead and Haab 1999), which uses add-on questions to the standard intercept data. Other specific details about the data used here are given below, and next we lay out the model.

Random Utility Model of Fishing Participation, Site, and Mode Choice

In the MSR (1991) model, the assumption was made that anglers engage in a pattern corresponding to a repeated decision, leading to a “repeated” discrete choice or random utility model of recreation demand. The repeated choice model framework is adopted by Morey, Rowe, and Watson (1993), Parsons, Jakus, and Tomasi (1999), Shaw and Ozog (1999), and a host of others (see Morey 1999 for discussion). Within the repeated choice framework, the season is divided up into choice occasions so that not more than one trip can be taken during a single choice occasion. Note that even with a sample of anglers who were intercepted on site, most anglers will not participate in fishing on every choice occasion. However there were a few anglers that took as many as sixty-one fishing trips during a two-month interval; so a choice occasion is equivalent to a “trip” in our analysis.

In our context, an individual making repeated choices confronts two simultaneous decisions: whether to go recreational fishing at all during some choice occasion, and if she (reader: freely substitute “he” below) does so, choose the site and mode that will be used for fishing. The mode choices include whether to fish from shore, from a private-rental boat (private boat hereafter), or a from charter boat. In principle, anglers could choose to travel to one of 38 possible counties along the Gulf, from Louisiana to Florida. However, because only day trips are included in our analysis, anglers tended to fish as sites near to their homes. Of all intercept trips, 84% were to one of the three nearest counties, the nearest six counties accounted for 95% of all trips and no one ventured beyond the tenth nearest site. To capture the diversity of sites while maintaining a fairly small set of choices, each angler is treated as choosing from one of seven destinations corresponding to the six nearest sites or some other site. The characteristics of the seventh site for each angler (travel cost and catch rate) are set using a weighted average for the seventh to tenth closest sites (Table 1). Of course, for each angler in the sample the set of sites considered is different.

The econometric model estimated below is based on one presented in the appendix to MSR (1991), which takes full advantage of the partial data available here. To our

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5 Texas fishing trips were not included in the survey.
6 Choosing which sites to put in the model was complicated and involved choices of aggregation and selection because of the size of the “Gulf” marine fishery. The focus here is on income effects, and we readily admit there may be interesting extensions involving aggregation schemes and potential bias (see Haener et al. 2004; Parsons and Hauber 1998).
knowledge this model has not been estimated before. It essentially reduces to estimating two conditional probabilities. First, individual \( i \) has a probability of not going fishing on any given choice occasion, equal to \( p_{nf}^{i} \). On any choice occasion she can alternatively take a trip to a destination we observe, or to a destination we do not observe. The maximum number of trips an individual can take over the period is \( T \).

There are \( J \) total destinations and \( M \) possible modes that an angler might use. Hence, if \( K_{i} \) is the number of trips individual \( i \) takes over the period for which the destination and mode are observed (the intercept destination) and \( y_{jmi} \) is the number of trips to observed site \( j \) using mode \( m \) taken by individual \( i \), then:

\[
P_{i}(x, \beta, T) = \left\{ \begin{array}{c} \frac{K_{i}!}{\prod_{j=1}^{J} \prod_{m=1}^{M} \left( \pi_{jmi} \right)^{y_{jmi}}} \\
\prod_{j=1}^{J} \prod_{m=1}^{M} \left( \pi_{jmi}^{y_{jmi}} \right) \end{array} \right\}
\]

The probability has three main parts: the first part relates to the probability of not fishing on a given choice occasion; the middle part pertains to the probability of fishing, but at some other unobserved destination; and the last part is the usual \( K \) trial multinomial on observed destination trips (McFadden 1976). This specification takes full advantage of the data that we have from this survey. Those data that we have preclude estimation using some other, more recently developed choice modeling approaches.7

The use of the probability in equation [2] in the likelihood function would suffer from intercept bias since those that fish more

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**TABLE 1**

**DISTRIBUTIONS AND VARIABLE SUMMARY STATISTICS**

<table>
<thead>
<tr>
<th>Mode Distribution (Intercept Trips) (trips)</th>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charter</td>
<td>156</td>
<td>4.2</td>
</tr>
<tr>
<td>Private-rental</td>
<td>2,691</td>
<td>72.8</td>
</tr>
<tr>
<td>Shore</td>
<td>847</td>
<td>22.9</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Site Distribution (Intercept Trip) (trips)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st closest site</td>
</tr>
<tr>
<td>2nd closest site</td>
</tr>
<tr>
<td>3rd closest site</td>
</tr>
<tr>
<td>4th closest site</td>
</tr>
<tr>
<td>5th closest site</td>
</tr>
<tr>
<td>6th Closest Site</td>
</tr>
<tr>
<td>Rest of 7th to 10th closest sites</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Income Distribution (anglers)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than $35,000 (DM₀)</td>
</tr>
<tr>
<td>$35,001 to $75,000 (DM₁)</td>
</tr>
<tr>
<td>Greater than $75,001 (DM₂)</td>
</tr>
</tbody>
</table>

Note: Variable names in parentheses where appropriate.

We assume that the vector of random variables for these observed trips is randomly drawn from a Type I Extreme Value distribution. We estimate the probability that individual angler \( i \) chooses to fish at site \( j \), using mode \( m \) for her intercept trip, \( \pi_{jmi}^{*} \). This, in absence of other features, would lead to the conventional conditional multinomial logit model. However, we also have information about trips to “some site” of unknown destination. Ignoring these data, all we would know is the destination on trips to the intercept site. Let \( Q_{i} \) be the number of trips taken to destinations we do not observe (all other destinations and modes). The marginal distribution of \( Q_{i} \) is assumed to follow the binomial. The probability of observing individual \( i \)’s choices, \( y_{jmi} \) can be written

\[
P_{i}(x, \beta, T) = \left\{ \begin{array}{c} \frac{K_{i}!}{\prod_{j=1}^{J} \prod_{m=1}^{M} \left( \pi_{jmi} \right)^{y_{jmi}}} \\
\prod_{j=1}^{J} \prod_{m=1}^{M} \left( \pi_{jmi}^{y_{jmi}} \right) \end{array} \right\}
\]

7 Note that if the popular nested logit specification were used, for example, this would have the advantage of breaking the independence of irrelevant alternatives (IIA) assumption, but for any nesting structure we can think of, this would come at the expense of having to use an average of all prices and catch rates and some aggregate of the unobserved destination sites. As we do not know the other destinations, this assumption seems rather unacceptable. In any case, concerns about aggregation issues (see footnote 6) would quickly be exacerbated, likely overwhelming any gains from nesting.
often are more likely to be interviewed. Hence, in the likelihood function estimated, we introduce a correction for potential intercept bias, replacing the distribution of unobserved trips with a sampling distribution that assumes being in the sample is proportional to the total number of trips one takes.\(^8\) With this assumption, the modified likelihood function becomes

\[
L_k = \prod_{i=1}^{N} \left( \frac{(K_i + Q_i + 1)}{(1 - \pi_i^m)} (T - K_i + 1) \right) P(x, \beta, T).
\]

In order to estimate the probabilities of making the mode/site and participation choices, a functional form for the indirect utility function must be specified. Applying the typical linear specification of a RUM model to the problem of mode choice, the utility of an angler on choice occasion \(t\) is a function of the individual’s fishing budget in period \(t\), \(B_{tm}\) and whether or not a particular site \(j\) and mode \(m\) has been chosen for the intercept trip at a personal cost of \(P_{jmi}\), with catch rates \(CR_{jmi}\). That is, we write \(U_{0ti} = x_0 + \beta(B_{ti})\) if the angler does not fish, and \(U_{jmti} = x_m + \beta(B_{ti} - P_{jmi}) + \gamma CR_{jmi} + \epsilon_{jmti}\) if the angler chooses site \(j\), mode \(m\), where \(\epsilon_{jmti}\) is the error term, capturing unexplained variation in the utility when the angler chooses to fish, presuming we know the destination/mode. The coefficients \(x_0\) and \(x_m\) can be functions of variables describing the angler, the mode, or the season.

An angler will not fish if the reservation utility, \(U_{0ti}\), is greater than the utility enjoyed in all of the modes. Hence the probability that an angler does not fish, \(\pi_i^m\), is the probability that \(U_{0ti} > U_{jmti}\), for all other modes, so \(\pi_i^m\) is a decreasing function of the difference \(U_{jmti} - U_{0ti}\). This difference can be simplified to

\[
U_{jmti} - U_{0ti} = (x_m - x_0) - \beta P_{jmi} + \gamma CR_{jmi} + \epsilon_{jmti}. \tag{3}
\]

As in MSR (1991) it is assumed that the non-fishing utility is deterministic so that the error in this equation is captured in the single error term, \(\epsilon_{jmti}\). There is a straightforward interpretation of equation [3]. The identifiable difference between the \(x\)'s in the parentheses can be thought of as the utility gain achieved by fishing in site \(j\) and using mode \(m\). The \(-\beta P_{jmi}\) term reflects the cost in terms of decreased utility that the angler must pay in order to gain the benefits of the fishing trip.

The usual assumption in the applied literature is that the marginal utility of income is constant so that \(\beta\) is the same for all possible uses of income or income levels. This specification implies, therefore, that if an angler’s fishing costs increase by one dollar, his or her utility declines by a fixed amount that does not vary across incomes or for any other reason. Because the marginal utility of income may actually vary over incomes, we relax this assumption.

To allow for some variation in the marginal utility of income, we adopt Morey, Sharma, and Karlstrom (2003) and Morey, Sharma, and Mills (2003)’s linear spline function approach in which the marginal utility of income varies for different income brackets. If this approach is adopted, then an angler’s utility (temporarily suppressing the coefficient on and the catch rate variable) taking a trip to site \(j\), mode \(m\) would be written

\[
U_{jmti} = x_0 + \beta_0(B_{ti} - P_{jmi}) + \epsilon_{jmti}
\]

\[
\text{if } (B_{ti} - P_{jmi}) \leq M_0
\]

\[
= x_0 + \beta_0 M_0 + \beta_1(B_{ti} - M_0 - P_{jmi}) + \epsilon_{jmti}
\]

\[
\text{if } M_0 < (B_{ti} - P_{jmi}) \leq M_1, \tag{4}
\]

\[
= x_0 + \beta_0 M_0 + \beta_1 (M_1)
\]

\[
+ \beta_2(B_{ti} - M_1 - P_{jmi}) + \epsilon_{jmti}
\]

\[
\text{if } M_1 < (B_{ti} - P_{jmi})
\]

where \(M_0\) and \(M_1\) are threshold points where it is assumed that the marginal utility of income changes. Using this approach and assuming that travel costs do not change an individual’s income bracket, the

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\(^8\) See the intercept bias correction discussed in MSR (1991), their equation 14, and the relevant text where results are discussed.
usual utility difference equation becomes

\[ U_{jmti} - U_{0t} = (x_m - x_0) - \beta_k P_{jmti} + e_{jmti}, \]

where \( k=0,1,2 \) for the three different income categories.

IV. DETAILS ON THE DATA, ESTIMATION, AND EMPIRICAL RESULTS

Data Details

Anglers in 1997 MRFSS intercept survey were contacted at a variety of locations including docks, marinas, and other sites along the Atlantic and Gulf Coasts (except along the Texas coast). Interviews were spread unevenly throughout the year with a greater proportion conducted in the Sep–Oct and May–Jun waves (19.84% and 19.79%, respectively) and the fewest in the coldest and hottest months, Jan–Feb and Jul–Aug (12.89% and 14.29%, respectively). However, during any given month we assume that interviewers were told to spend the same amounts of time at each type of mode, as was true in earlier MRFSS survey efforts (see MSR’s related footnote 10, 1991, p. 189). The follow-up economic survey was conducted over the telephone. The data are divided into six waves, each lasting two months each.

The questions in the survey include those about general characteristics of respondents, their number of fishing days within the previous two months, the specific information on intercept trips, that is, what mode of fishing they engaged in, when they went fishing, and the number of fish that they caught.\(^9\) Here we focus on single-day trips for a sample of anglers living in four states along the Gulf of Mexico coast. After eliminating incomplete observations there are 3,694 observations on anglers remaining (see Table 1 for some summary statistics). As such, this is one of the larger samples of anglers we have ever worked with, which certainly adds some computational burdens, but also adds the benefit of reduced sampling error, as compared to working with only hundreds of anglers, as researchers often must do.

Anglers that were interviewed reported fishing an average of 7.1 days during a two-month fishing period. As is standard procedure in the repeated framework, we divide the overall period into choice occasions, such that no angler can take more than one fishing “trip” on a choice occasion, resulting in 61 choice occasions. The most commonly chosen mode of fishing for anglers in our sample on the observed intercept trip was using a private boat (72.8%), which is not surprising since about 63% of anglers in the overall sample owned a boat. The other mode is charter boat (4.2%), with the remainder fishing from the shore (22.9%).

The focus here is on income and the survey questionnaire identified income in 11 categories, which we aggregate into three broad categories: low (less than $35,000), middle ($35,001 to $75,000), and high (greater than $75,001). These income levels correspond roughly to the 50% and 80% thresholds for U.S. households reported in the U.S. Census Bureau’s Current Population Survey.\(^10\) Because 34% of respondents in the sample do not reveal their income, the log linear ordinary least squares regression model suggested and estimated by Haab, Whitehead, and McConnell (2000) is used to impute missing income values. After using imputed income, those in the lowest income category constitute 47.9% of the total sample. The middle income category contains 42.3% of the respondents, and the remainder of those in our sample (9.8%) falls into the highest income category. These income levels are identified by the dummy variables: \( DM_0=1 \) if household income is less than $35,000, \( DM_1=1 \) if household income is $35,001 to $75,000 and \( DM_2=1 \) if household income is greater than $75,001.\(^11\)

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\(^9\) Unfortunately, we do not have information to calculate catch rates by species.

\(^10\) In 1997, 50% of the U.S. households had an income less than $40,699, 80% less than $78,638 - See (http://www.census.gov/hhes/income/histinc/eh1.html).

\(^11\) The dummy variable trap is avoided because there no default coefficient.
Construction of Travel Costs/Catch Rate Variables

Travel costs to the three modes for seven destinations near the angler’s home (the intercept destinations) are constructed using distances calculated using the Zipfip program. Other expenses and boat fees varying by mode are computed simply as the sample average. In addition, the opportunity cost of an individual’s time in travel to and from the site is factored in using assumed travel speeds and reported wage rates as the opportunity cost of time per hour, if these are available in the individuals’ responses. For individuals not reporting wage rates but reporting annual income we used average hourly income instead, and for those reporting neither wage nor income, we used a hedonic regression to predict their wage rate per hour. Retirees are assumed to have an opportunity cost of time equal to the minimum wage rate. It is noteworthy that the average cost of fishing from a charter vessel is considerably more than all other modes, and sometimes an order of magnitude more costly than the cost of shore fishing.

As mentioned above, the mode-site catch rates used are the average of reported catch rates for each site and mode. When, for a given mode-site combination, only a few individuals report catch, the average reported catch could be problematic. As our sample is rather large, this was not a major problem, but when less than 20 observations were available, observations from adjacent site(s) were included until at least 20 observations were obtained. In this way, a catch rate was available for each of the 38 counties and for each of the three modes.

Estimation and Empirical Results

The final empirical specification of the probability of not fishing and the probability of site/mode choice can be written as:

\[
\pi_{mji} = \frac{1}{\sum_{m=1}^{M} \sum_{j=1}^{J} \exp \left[ \alpha_{0m} - \alpha_{0} + \gamma (\text{CatchRate}_{ij} - \text{CatchRate}_{mji}) - (\beta_{0}DM_{0} + \beta_{1}DM_{1} + \beta_{2}DM_{2}) \right]}.
\]

and

\[
\pi_{ij} = \exp \left\{ -\sum_{m=1}^{M} \sum_{j=1}^{J} \exp \left[ \alpha_{0m} + \gamma \text{CatchRate}_{mji} - (\beta_{0}DM_{0} + \beta_{1}DM_{1} + \beta_{2}DM_{2})P_{mji} \right] \right\}
\]

Note, as discussed above, that the intercept term, \( \alpha_{0m} \), in equation [6] captures the difference between intercept in the non-fishing and mode-\( m \) utility function, i.e. \( \alpha_{0m} = \alpha_{m} - \alpha_{0} \).

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12 The authors thank Daniel Hellerstein at ERS/U.S.D.A. for his generous assistance in obtaining that.

13 Results of the hedonic wage regression models and other details are available on request of the authors, however, because there are 38 specific destinations used to set the seven sites for each angler, summary statistics are not easily presented.
Estimation results for the participation and site/mode choice model are presented in Table 2. Table 2 indicates the explanatory variables that are significantly different from zero with expected signs: the constant terms for modes and the catch rate are positive, and the travel cost parameters are negative because of the fact that the likelihood function equation specifies the negative of the parameter in estimation. Because of the presence of 21 site/mode choice alternatives and the additional choice of not fishing for over 3,000 anglers, the model is not trivial to estimate, and most attempts to include other variables were unsuccessful. Note that the largest mode-specific constant term is for charter boat trips, which might indicate some unobserved, but non-random influence of such trips is attributable to the experience of being taken out fishing by a knowledgeable boat captain.

Of particular interest are the varying coefficients on the marginal utility of income. Comparing these across income levels, e.g., \( \beta_0, \beta_1, \) and \( \beta_2 \), we find some difference, with the smallest MU of income for the highest income group, consistent with economic theory: the value of a fishing dollar declines as income increases. As we discuss in more detail below, these differences across incomes indicate that anglers in the low-income group, who largely participate in shore fishing, are more responsive to fee changes than other fishermen.

In Table 3 we examine predicted trips, also breaking these up by income groups and modes. The expected number of trips over the period are equal to \( 61 \times \left( 1 - \pi_{m}^{FF} \right) \), and the expected trips for each mode are calculated by \( 61 \times \left( 1 - \pi_{m}^{FF} \right) \times \left( m_{mi}^{m} \right) \). First, it is interesting to note that after correcting for selection bias, the average number of predicted trips is significantly reduced as compared to a model with no such correction. With no selectivity correction, the reported and average predicted trips are well over six trips in the period. The corrected average in Table 3, is just over half that number: about 3.2 trips predicted for the high income groups. It can easily be seen that the private boat mode is preferred for all income categories. There is important variation across incomes for the other modes. First, only 0.006 charter trips per two-month period are predicted to be taken by low-income anglers, while high-income anglers are predicted to take 0.25 trips using that mode. Shore fishing is enjoyed almost equally by all income groups with high-income anglers predicted to take only 5% more shore trips than low-income anglers. Overall, the model finds that fishing is a normal good with high income group taking 47% more trips on average than the low-income group.

### V. Fee Effects on Trips and Welfare of Anglers in Different Income Groups for Fees and Catch-Rate Declines

Next, we explore the impacts of various fee policies that might be used to reduce fishing pressure in the Gulf. We can easily simulate the consequences of these on the low-, middle-, and high-income groups because of our allowance for income effects. Specifically, we first examine the impact on trips of several flat daily fees ($5, $10, $20) imposed on all modes, and on selected modes. A $5 per day fee is likely within the realm of any policy change that might
accompany a program to recover revenue today, or rising costs of managing facilities. A $20 per day fee, on the other hand, would represent a substantial increase in the daily cost of fishing, particularly in the low cost mode of shore fishing. Second, we report the WTP to prevent a 20% decline in catch. Though we were unable to uncover catch rates that vary by species, we hypothesize that there may well be quite different welfare impacts from catch rate declines on income groups that use different modes.

**Trip Impacts**

Table 4 reports the impact on trips of the fees equally imposed on all modes across the income groups, as well as a weighted average of these (far right-hand column). Note that the percentage loss in trips over the period is highest among low-income groups, as one might expect. In fact, a $20 daily fee imposed on all modes is predicted to reduce by three-fourths the number of trips taken by low-income anglers. High-income anglers also reduce their trips substantially, (about 66%), though their response is not as pronounced as for the low-income group.

Imposing a fee across all modes of fishing is likely not an effective way to reduce overfishing, particularly when the species targeted by different modes varies greatly. The boating anglers (private and charter boat) are able to catch species in deep water that are not accessible to shore anglers. If these types of fish are of more concern than those caught from shore, then it may make the most sense to impose the fee on these modes, together or separately. Table 5

**TABLE 4**

<table>
<thead>
<tr>
<th>Daily Fee</th>
<th>Low-Income</th>
<th>Middle-Income</th>
<th>High-Income</th>
<th>Weighted Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0</td>
<td>2.179 (0%)</td>
<td>2.580 (0%)</td>
<td>3.197 (0%)</td>
<td>2.417 (0%)</td>
</tr>
<tr>
<td>$5</td>
<td>1.544 (-29.2%)</td>
<td>1.895 (-26.6%)</td>
<td>2.452 (-23.3%)</td>
<td>1.752 (-27.5%)</td>
</tr>
<tr>
<td>$10</td>
<td>1.091 (-49.9%)</td>
<td>1.389 (-46.2%)</td>
<td>1.877 (-41.3%)</td>
<td>1.269 (-47.5%)</td>
</tr>
<tr>
<td>$20</td>
<td>0.543 (-75.1%)</td>
<td>0.743 (-71.2%)</td>
<td>1.095 (-65.8%)</td>
<td>0.664 (-72.5%)</td>
</tr>
</tbody>
</table>

*Note: Percentage declines are in parentheses.*

**TABLE 5**

<table>
<thead>
<tr>
<th>Daily Fee</th>
<th>Low-Income</th>
<th>Middle-Income</th>
<th>High-Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0 (Base)</td>
<td>2.179 (0%)</td>
<td>1.520 (0%)</td>
<td>1.890 (0%)</td>
</tr>
<tr>
<td>$5</td>
<td>2.164 (-0.7%)</td>
<td>1.339 (-11.9%)</td>
<td>1.707 (-9.7%)</td>
</tr>
<tr>
<td>$10</td>
<td>2.154 (-1.2%)</td>
<td>1.148 (-24.5%)</td>
<td>1.511 (-20.1%)</td>
</tr>
<tr>
<td>$20</td>
<td>2.141 (-1.7%)</td>
<td>0.773 (-49.1%)</td>
<td>1.105 (-41.6%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Daily Fee</th>
<th>Low-Income</th>
<th>Middle-Income</th>
<th>High-Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0 (Base)</td>
<td>2.179 (0%)</td>
<td>0.659 (91.9%)</td>
<td>0.690 (90%)</td>
</tr>
<tr>
<td>$5</td>
<td>1.539 (-28.5%)</td>
<td>0.364 (-44.7%)</td>
<td>0.402 (-41.7%)</td>
</tr>
<tr>
<td>$10</td>
<td>1.117 (-48.7%)</td>
<td>0.197 (-70.0%)</td>
<td>0.231 (-66.3%)</td>
</tr>
<tr>
<td>$20</td>
<td>0.582 (-73.3%)</td>
<td>0.056 (-91.5%)</td>
<td>0.074 (-89.2%)</td>
</tr>
</tbody>
</table>

*Note: Percentage declines are in parentheses.*
considers the loss in offshore boat trips and the corresponding total number of trips by imposing the same daily fees as considered in Table 4, but only on the offshore private and charter boat modes. Notice that when the fee is imposed on only these modes, the percentage reduction in total number of trips is much smaller than it is when the fee is on all modes. Differences across groups are small at low fees, but rise as the fee increases to $20 per day. As a percentage of the base number of trips, a $20 fee causes a 32% reduction in charter and private trips taken by the high-income anglers, but a much greater reduction, 49%, by the low-income group. It appears that high-income anglers are more likely to stick with expensive offshore boat modes, while low-income anglers who might sometimes use a boat (offshore) mode tend to shift their fishing to inexpensive shore fishing.

For the purpose of contrast, Table 5 also considers the impact of a flat fee imposed only on shore fishing. While probably not plausible in any political sense, it is interesting to note the much higher loss in all shore trips that would accompany a $20 fee on shore trips. Nearly every shore trip (92%) that would be taken over the period is lost to low-income groups. This policy will also decrease the total number of trips taken by the low-income group more than it would affect the behavior of higher income groups. Even though anglers can substitute away from the shore fishing into the other modes, our empirical results indicate that a fee on shore fishing increases the probability of not fishing so much that even fishing in other modes is predicted to decline.

**Welfare Estimates**

Welfare losses with income effects can be computed by examining the usual log-sum formula in the repeated choice version of the random utility model (see Morey 1999). We consider the per-period compensating variation (PPCV), which can be interpreted as the maximum willingness to pay on each choice occasion (or per day, in our case) to avoid the fee increase. Expected CV’s for a $5 fee imposed on two separate modes (offshore boats only and shore only), and for a catch rate decline of 20% are reported in Table 6. We also calculate CV as percentage of per period income to yield a better picture of the relative impact on the various income groups.

### Table 6

<table>
<thead>
<tr>
<th>Table 6</th>
<th>Expected Compensating Variation Associated with Policy Scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td>E(CV) by Income When A $5 Daily Fee is Imposed for Only Offshore Boats</td>
<td></td>
</tr>
<tr>
<td>Income Group</td>
<td>E(CV) per Day</td>
</tr>
<tr>
<td>Low</td>
<td>−3.29</td>
</tr>
<tr>
<td>Middle</td>
<td>−3.50</td>
</tr>
<tr>
<td>High</td>
<td>−3.80</td>
</tr>
<tr>
<td>E(CV) by Income When A $5 Daily Fee is Imposed for Only Shore Fishing</td>
<td></td>
</tr>
<tr>
<td>Income Group</td>
<td>E(CV) per Day</td>
</tr>
<tr>
<td>Low</td>
<td>−1.34</td>
</tr>
<tr>
<td>Middle</td>
<td>−1.19</td>
</tr>
<tr>
<td>High</td>
<td>−0.97</td>
</tr>
<tr>
<td>E(CV) by Income When Catch Rate Decreases by 20%</td>
<td></td>
</tr>
<tr>
<td>Income Group</td>
<td>E(CV) per day</td>
</tr>
<tr>
<td>Low</td>
<td>−0.57</td>
</tr>
<tr>
<td>Middle</td>
<td>−0.65</td>
</tr>
<tr>
<td>High</td>
<td>−0.80</td>
</tr>
</tbody>
</table>

Notes: The mean levels of specific 11 income categories with the highest category of $175,000 are used. The mean income levels for each income group are $23,109, $48,433, and $109,229, respectively.
When a $5 fee is imposed for each day of offshore fishing, the daily impact on the high income group is predicted to average about a $3.8, with a smaller loss of $3.29 on the low-income anglers, as might be expected. However, the welfare impact on low-income anglers as a percentage of daily income (0.87%) is bigger than that on high income group (0.21%). In contrast, if a $5 fee were levied for each day of shore fishing, the impact on low-income anglers would be greatest in both absolute and relative terms. Clearly, fee can have markedly different impacts on anglers of differing incomes and low-income anglers appear to always be affected more by a fee in terms of welfare loss relative to their income.

If nothing is done to solve over-fishing in the Gulf marine fishery, catch rates may fall. We do not know by how much they would fall, so we consider the case of a 20% decline and examine the accompanying welfare measures. In the bottom of Table 6 the per-day WTP to prevent this decline is reported. We estimate WTP values ranging from about $0.57 to $0.8, with higher income anglers benefiting the most. As percentage of daily income, however, the CV of low-income anglers is the greatest, 0.15% versus 0.04% for high-income anglers. This relative distribution of impacts across income groups is the same as the distribution of costs if a $5 fee is imposed on off-shore fishing. In contrast, if a fee is imposed only on shore fishing, the low-income anglers would pay the highest cost in both absolute and relative terms.

VI. SUMMARY AND CONCLUSIONS

There is increasing recognition that recreational fisheries as well as commercial fishing must be involved in solutions to overfishing. Standard economics dictates that limiting catch by using a price mechanism would be more efficient than seasonal closures or other forms of quantity rationing. However, a flat-pricing policy, such as an access fee for all anglers may have more significance to those on the lower end of the income distribution than to those on the upper end. Certainly if a fee is imposed on inexpensive onshore trips, the percentage burden on low-income anglers will be higher than for other anglers because they use this mode of fishing.

To obtain our results we used a model geared to the type of data we have. It is based on the approach taken by MSR (1991), which is appropriate when complete trip data are not available. Our model here extends that estimated by MSR (1991) in that it allows for a correction to intercept bias, as well as letting the price coefficient/marginal utility of income to vary across three income groups. We note, as a caveat, that many modern versions of the random utility model relax the assumption of the independence of irrelevant alternatives (IIA), while our model here does not. We therefore caution against any reading of the welfare impacts as being exact in our analysis, while noting the importance of relative orders of magnitude across the income groups, which is our focus.14

Although economists regularly wash their hands of equity-based analysis, there are two reasons why equity implications of fishery policies should be considered. First, the political viability of a policy is affected by its fairness or the perception of fairness. Some policies are just going to be dead on arrival, if they hit some groups too hard. Second, equity remains one of the fundamental normative principles accepted by most economists and, although we may not

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14 We add that we estimated a simplified version of the model using a random parameters logit (Train 1998), which is in theory, possible to do with our likelihood function and which would also relax the IIA. We specified the model with only one travel cost coefficient, assumed to be normally distributed, and one catch rate coefficient. The model converged after over six hours, resulting in a mean travel cost coefficient that is about the same as the one obtained using a similar flat conditional multinomial logit, and a significant standard deviation on this parameter. Were this true in the complex case, it would suggest little difference, on average, in welfare measures, at least if the normal distribution is the best one to use. Attempts to let the travel cost coefficient be log-normally distributed failed to achieve convergence, as is apparently typical (personal communication with Kenneth Train). Estimation of the more complex likelihood function with over 3,000 anglers will be quite a challenge that lies ahead.
be able to provide definitive recommendations based on this principle, it is informative to all if an analyst is able to present the distributional consequences of a policy (Arrow et al. 1996). The analytical tools that are used must be capable of providing information on distributional consequences. We cannot think of a way to do this unless income effects are allowed in the model.

REFERENCES


Morey, E. R., V. R. Sharma, and A. Mills. 2003. “Willingness to Pay and Determinants of Choice for Improved Malaria Treatment in...


