VALUING A CHANGE IN A FISHING SITE WITHOUT COLLECTING CHARACTERISTICS DATA ON ALL FISHING SITES: A COMPLETE BUT MINIMAL MODEL

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Resource economists are often asked to value a proposed change at one, and only one, recreational site; the model we develop and estimate is applicable for those cases. The application is valuing the elimination of fish consumption advisories on a large bay on Lake Michigan. The model is minimal but complete: complete in that the choice set is not restricted, minimal in that only two conditional indirect utility functions are estimated. It is utility-theoretic and one does not have to collect characteristic data on all of the other fishing sites in the region. Data include the number of trips each individual currently takes to Green Bay, answers to "would you prefer to fish Green Bay under conditions A or B?" and how often each angler says they would fish Green Bay under different sets of conditions.

Key words: intentions, single-site, RP data, SP choice data, SP frequency data.

While there are many exceptions, resource economists are often asked to value a change at only a single recreational site; the model we develop and estimate is applicable for those cases. Many Natural Resource Damage Assessments (NRDA) are in this category.

The original travel cost models were each just single-site, single-equation: the demand for trips to the site as a function of only travel costs to that site. While these models often committed theoretical and statistical sins, attention was appropriately directed at the site of policy interest and one did not need to collect characteristics data on other sites, or even data on the site in question quality, and everything else, got embedded in the constant term.

Hanemann (1991) showed that with suitable functional forms these single-site equations were utility-theoretic. Since these models excluded site characteristics, they were unable to make any predictions about what would happen if the characteristics of the site were improved or deteriorated, and so were unable to estimate the expected compensating variation, $E[cv]$, associated with such changes. One could derive the $E[cv]$ for a price change or the elimination of the site.

Now recreational demand modelers estimate multiple-site utility-theoretic demand models that require characteristics data for all of the sites in the choice set; the reasons for this practice include the ability to model changes in a site's characteristics, the ability to predict how the demand for other sites will be affected by such a change, and the ability to value simultaneous changes in multiple sites. For discrete choice models, this means at least J-conditional indirect utility functions where J is the number of sites in the choice set. These multisite models, however, come at a high cost: one needs characteristic data on all of the sites in the choice set. If the model has only J-conditional indirect utility functions, the researcher is able to estimate only per trip $E[cv]$, not $E[cv]$.[1]

The latter deficiency can be overcome by including an additional alternative in the choice set, *doing something else*. In the discrete choice context, one divides the year into a finite number of "choice occasions," such that if one does not recreate on a choice occasion (visit one of the sites in the choice set), one has chosen the

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[1] Per trip $E[cv]$ is our expectation of the angler's compensating variation for the policy subject to the constraint that the angler must take a trip to one of the sites in the choice set. That is, it is how much the angler would pay (or have to be compensated) per fishing trip.

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something else alternative. Morey, Rowe, and Watson (1993) are an early example. Other examples include Lupi et al. (1998); Breffle and Morey (2000); Morey, Breffle and Greene (2001); Morey et al. (2002); and Haab (1996). In this class of models, there are $J + 1$ alternatives. Note that no researcher considers collecting characteristic data on every other activity in the world.[2] From such models one can derive $E[cv]$ per choice occasion, which multiplied by the number of choice occasions in the year is $E[cv]$. One still needs characteristics data for all of the sites in the choice set. We will refer to this type of model as *complete* and *detailed:* complete in the sense that all alternatives are included in the choice set and detailed in the sense that at least some of the other alternatives are presented as distinct alternatives rather than all being aggregated into a generic activity called *Other*.[3] No one will ever estimate a model that is both complete and completely detailed in the sense that every alternative in the individual's choice set is included and modeled as a distinct alternative.

Assume the task (the task we were asked to perform) was to estimate the $E[cv]$ for a change in the characteristics of one site and one site only: in our case, a quite unique site, Green Bay, a large bay on Lake Michigan. This required that we estimate a complete model; that is, a model that did not restrict the individual to fish Green Bay or even restrict the individual to fish. At a minimum, this requires a conditional indirect utility function for fishing Green Bay that is a function of the fishing characteristics of Green Bay and a conditional indirect utility for doing something else. In such a *minimal model*, fishing at other sites is simply combined with all the non-fishing alternatives.[4] Substitutes are not being excluded from the model.

Estimation of such a minimal model is not common practice, but can be a reasonable and productive modeling choice. One still needs to collect site data for the site of interest but not characteristic data on all of the other fishing sites in the region. Our experience is that in a region with many fishing sites, collecting legally defensible data on all of the sites can cost hundreds of thousands of dollars, or more. The goal of this article is to develop and estimate a minimal model and demonstrate that it is reasonable, utility-theoretic, and cost-effective.

Only two conditional indirect utility functions are specified: one for using a choice occasion to take a trip to Green Bay and one for doing something else on a choice occasion, *Other*. As is common practice in discrete choice models that incorporate participation, a fixed number of choice occasions is assumed.

Estimation requires SP data on fishing Green Bay under different conditions. The model will be estimated with SP choice pairs—"would you prefer to fish Green Bay under conditions A or B?"—RP (revealed preference) data on the actual number of trips to Green Bay under current conditions, and an SP (stated preference) frequency question that asks how often the respondent would fish Green Bay under other described conditions.[5]

Lumping all of the alternative activities into one aggregate is always theoretic, but doing so will make some uncomfortable: close and distant fishing sites are being combined with all other potential substitute activities. Our comfort with this minimalist approach was originally enhanced by the uniqueness of Green Bay: one alternative is Lake Michigan (an ocean in comparison); the other alternatives are the hundreds of small lakes, rivers, and streams in the region (puddles in comparison).

When the site of interest is unique in its category (fishing, climbing, skiing, etc.), a completely different type of activity may be a closer substitute for recreation at the site of interest than is recreation at an alternative fishing site with fundamentally different characteristics. For the first author, mountain biking out of doors is a closer substitute for fishing the local stream than is fishing in the local lake. Those who argue for the inclusion of close substitutes as distinct alternatives would have to include mountain biking as a distinct alternative before they considered including lake fishing as a distinct alternative. Of course, which activities are

[2] Of course, one could expand this type of model disaggregating *Other* into categories such as bowling, watching TV, and other pastimes. But why?

[3] Note that models with only J-conditional indirect utility functions (one for each site in the choice set) are detailed but not complete. They do not allow the individual to do something other than fish.

[4] Of course, such a model will not suffice if one wants to value changes at multiple fishing sites (e.g., the effects of acid rain over a wide region) or how much demand at another site will drop when one site is improved, but that is not the charge here.

[5] SP frequency questions are also called "contingent behavior" (CB) questions. Few environmental applications have used only SP frequency data. Most of the applications that have used SP frequency data have combined it with RP frequency data, as we do. Examples include Adamowicz, Louviere, and Williams (1994); Englin and Cameron (1996); Nester (1998); Rosenberger and Loomis (1993); Eiswerth et al. (2000); and Grijalva et al. (2002).

close substitutes for the site-specific activity in question are likely to vary across individuals, making the issue of which to include as distinct substitute activities even more of a morass.

However, our minimal model can be a wise choice even if the single site of policy interest is not unique in terms of the alternatives in this category. Both it and the *complete detailed* models are utility-theoretic and complete: all alternatives are included in the choice set. The advantage of our minimal model is that one does not need to identify and collect data on all of the substitutes in the site's category, a difficult and expensive process.[6]

One cannot estimate a minimal model with just RP data, SP data are required: one cannot use the observed choices among sites to estimate the parameters on site characteristics using the cross-sectional variation in the observed characteristics. Estimation of the parameters on the site's characteristics requires that one ask SP choice or frequency questions, varying the characteristics of the site. For this reason, those who disdain SP data will not choose the minimalist approach; we are not in this category, arguing that SP data are often to be preferred.

The Policy Issue

Green Bay is contaminated with high levels of PCBs (polychlorinated biphenyls); Lake Michigan is PCB contaminated to a lesser degree; inland lakes and rivers are not PCB contaminated. Through the food chain, PCBs bio-accumulate in fish and wildlife. As a result of elevated PCB concentrations in fish, in 1976 the Wisconsin Department of Health and Human Services first issued fish consumption advisories (FCAs) for sport-caught fish in the Wisconsin waters of Green Bay. These FCAs for the waters of Green Bay continue today, although the specifics of the FCAs have varied through time. The research task was to estimate, in a reasonable and cost-effective manner, the $E[cv]$s Green Bay anglers would associate with eliminating or reducing the need for the FCAs.[7]

FCAs vary by species. To value the changes in FCA levels that would result in different levels of contamination, we defined nine FCA levels/configurations, each specifying the FCA for each of our four species of interest (yellow perch, trout/salmon, walleye, and smallmouth bass). Level 1 indicates PCB levels are sufficiently low such that all species may be eaten in unlimited quantities; there is no health risk from consumption. Level 9 is the most restrictive: trout/salmon, walleye, and bass should not be eaten, and a perch meal should be consumed once a month at most. Level 4 corresponds to current conditions. The FCAs by species for all levels are listed in table 1.

With one exception, as one moves up through the nine levels, the FCA becomes more severe: the FCA for each species either stays the same or becomes more severe.[8] $E[cv]$s are reported below for a reduction from level 4 to level 1.

Population, Sampling, and Response Rates

The target population is current Green Bay anglers who live in the area: anglers who purchased licenses in eight counties near Green Bay and who fished in Green Bay in 1998. A three-step procedure was used in 1998 to collect data from a random sample of the targeted anglers. First, a random sample of anglers was drawn from the 1997 license holders in the county courthouses in the eight targeted counties. Second, using the license holder list, a telephone survey was conducted to identify and recruit Green Bay anglers for a follow-up mail survey. The telephone survey collected some attitudinal data and data on the number of fishing days at Green Bay. The overall response rate to the telephone survey by Green Bay anglers was 69.4%. Third, a mail survey with the SP questions was conducted with the current Green Bay anglers. The response rate to the mail survey was 78.9%, yielding a data set of 647 individual anglers used in the model and an overall response rate of 54.8%.

The RP data consist of the number of days the angler fished Green Bay under current conditions. In the sample, the number of Green Bay days varies from one to over fifty with a mean of 9.3 and a median of 5. The RP data also include Green Bay per day costs for each

[6] Deciding which sites to include in the category choice set, and the implications of the decision, is a literature in itself.

[7] The complete Report of Assessment for this NRDA is Breffle et al. (1999), that contains many study details not presented or explained in this article. As of November 2005, this report can be downloaded at http://midwest.fws.gov/nrda/index.html. Breffle et al. (forthcoming) is a nontechnical overview of all stages of the damage assessment.

[8] The exception is in moving from level 4 to level 5 and from level 5 to level 6 with the consumption of some species becoming more restricted and others less restricted. This anomaly is reflected in the parameter estimates.

Table 1. Possible Green Bay FCA Levels

	Species	Fish Meals Advised
FCA level 1	Yellow perch	"Unlimited"
	Trout/salmon	"Unlimited"
	Walleye	"Unlimited"
	Smallmouth bass	"Unlimited"
FCA level 2	Yellow perch	"Unlimited"
	Trout/salmon	"Eat no more than 1 meal a week"
	Walleye	"Eat no more than 1 meal a week"
	Smallmouth bass	"Unlimited"
FCA level 3	Yellow perch	"Unlimited"
	Trout/salmon	"Eat no more than 1 meal a month"
	Walleye	"Eat no more than 1 meal a month"
	Smallmouth bass	"Eat no more than 1 meal a week"
FCA level 4	Yellow perch	"Eat no more than 1 meal a week"
	Trout/salmon	"Eat no more than 1 meal a month"
	Walleye	"Eat no more than 1 meal a month"
	Smallmouth bass	"Eat no more than 1 meal a month"
FCA level 5	Yellow perch	"Unlimited"
	Trout/salmon	"Eat no more than 1 meal a month"
	Walleye	"Do not eat"
	Smallmouth bass	"Eat no more than 1 meal a month"
FCA level 6	Yellow perch	"Unlimited"
	Trout/salmon	"Do not eat"
	Walleye	"Eat no more than 1 meal a month"
	Smallmouth bass	"Eat no more than 1 meal a month"
FCA level 7	Yellow perch	"Unlimited"
	Trout/salmon	"Do not eat"
	Walleye	"Do not eat"
	Smallmouth bass	"Eat no more than 1 meal a month"
FCA level 8	Yellow perch	"Eat no more than 1 meal a week"
	Trout/salmon	"Do not eat"
	Walleye	"Do not eat"
	Smallmouth bass	"Eat no more than 1 meal a month"
FCA level 9	Yellow perch	"Eat no more than 1 meal a month"
	Trout/salmon	"Do not eat"
	Walleye	"Do not eat"
	Smallmouth bass	"Do not eat"

angler. Costs include vehicle operating costs and the opportunity cost of anglers' time. While the inclusion of the RP data has no effect on the estimation of the FCA parameters relative to each other (because the FCA level is the same for all observed Green Bay fishing days), visitation varies significantly with fishing costs, and the RP data play an important role in the estimation of the marginal utility of money.

Each angler was presented with eight SP choice pairs: Green Bay under conditions A or conditions B. Each Green Bay alternative was described in terms of six characteristics: a launch fee; the average amount of time necessary to catch a fish (catch time) for each of the four species; and the FCA level. Green Bay is characterized in terms of catch rates and FCA levels, and an angler's share of the daily launch fee. Figure 1 is an example of a choice pair from the survey. The levels for each characteristic were chosen so as to include current conditions.

After each choice pair, a follow-up question about the expected number of days the angler would visit the preferred site was asked:

> How often would you fish the waters of Green Bay if it had the conditions described by the alternative you just chose (A or B)? Your answer could depend on a number of factors:
>
> – How many days you typically fish in a year and how many of those days are spent fishing the waters of Green Bay.
> – How much you enjoy fishing the waters of Green Bay compared to other places you might fish.
> – How far you live from Green Bay compared to other places you might fish.
> – The cost of fishing the waters of Green Bay compared to other places you might fish.
> – Whether you think the conditions for the waters of Green Bay in the alternative you just chose are better, worse, or about the same as current conditions.
> – The more you fish the waters of Green Bay the less time you will have for fishing elsewhere.
>
> Excluding ice fishing, how many days, on average, would you fish the waters of Green Bay in a typical year if the conditions on the waters of Green Bay were those described in the alternative you chose? Fill in the blank.

If you were going to fish the waters of Green Bay, would you prefer to fish the waters of Green Bay under Alternative A or Alternative B? *Check one box in the last row*

	Alternative A ▼	Alternative B ▼
Yellow Perch		
Average catch rate for a typical angler......................	40 minutes per perch	30 minutes per perch
Fish consumption advisory.......	No more than one meal per week	No more than one meal per week
Trout and Salmon		
Average catch rate for a typical angler......................	2 hours per trout/salmon	2 hours per trout/salmon
Fish consumption advisory.......	Do not eat	No more than one meal per month
Walleye		
Average catch rate for a typical angler......................	8 hours per walleye	4 hours per walleye
Fish consumption advisory.......	Do not eat	No more than one meal per month
Smallmouth bass		
Average catch rate for a typical angler......................	2 hours per bass	2 hours per bass
Fish consumption advisory.......	No more than one meal per month	Unlimited consumption
Your share of the daily launch fee............................	Free	$3
Check the box for the alternative you prefer...	❑	❑

Figure 1. Example choice question

___days fishing the waters of Green Bay in a typical year.

This is an SP frequency question. Answers to this question vary from zero to over fifty with a mean of 15.64 and a median of 10. That 15.64 is greater than 9.3 (the actual average under current conditions) is expected and reasonable. Most choice pairs contain at least one alternative that is preferred to current conditions. The preferred alternative in each pair is the one chosen, and the individual is indicating the number of trips he would likely take to fish Green Bay (i.e., his intentions) under these preferred conditions.[9]

[9] Manski (1999) considers the problem of individuals having to choose an action before the choice environment and choice set are completely disclosed. He refers to these cases as incomplete scenarios. In such cases, "coherent and cooperative individuals"

However, the magnitude of the difference is an indication that the respondents are overly optimistic in terms of how often they would fish Green Bay in improved conditions—they report their good intentions. Looking ahead, this suspicion is borne out by the parameter estimates that predict that under current conditions anglers will average 14.29 trips, an estimate much closer to 15.64 than to how often they currently fish Green Bay. $E[cv]$s are therefore presented with and without an adjustment for this optimism.

We proceed by assuming the responses to the SP frequency questions are proportionately correct with respect to one another. Our hypothesis is that when answering SP frequency data respondents tell us what they intend to do, assuming everything else in their future is running according to plan.[10]

For the SP choice data, income and fishing costs cancel out the likelihood function, because they are constant across the two alternatives. However, for the SP frequency data and the RP data, fishing costs do not drop out of the likelihood function; fishing costs significantly affect how often an angler fishes (RP data), and how often the angler expects he will fish under varying conditions (SP frequency data).

The Basic Model

Assume that there are N opportunities to fish Green Bay during the season.[11] On each choice occasion, the angler decides either to fish Green Bay or do something else. If angler i chooses to fish Green Bay, utility is

$$U_{GBi} = V_{GBi} + \varepsilon_i \quad i = 1, \ldots, M \tag{1}$$

where the random term, ε_i, is assumed to be a random draw from one dimension of a joint normal distribution. The dimension depends on whether the choice is real (RP data) or hypothetical (SP data).

Further assume

$$V_{GBi} = \sum_{l=p,s,w,b} \beta_l c_l + \sum_{q=2}^{9} \beta_{FCAq} FCA_q + \beta_m (y_i - TC_i - fee) + \varepsilon_i \tag{2}$$

where c_l is the time (in hours) it takes, on average, to catch one fish of species l (perch, salmon/trout, walleye, and bass). For example, the current perch catch time is approximately 0.75 hours. The nine possible configurations of FCA's (discussed above) are represented by a set of eight dummy variables.

The variables y_i and TC_i are choice-occasion income and the cost of fishing Green Bay, excluding any fees. The variable *fee* is a charge imposed to fish Green Bay. The marginal utility of money, β_m, is assumed to be a constant. Income not spent on fishing Green Bay, $(y_i - TC_i - fee)$, is spent on the *numéraire*.

If the angler chooses to do something else

$$U_{Oi} = V_{Oi} + \mu_i \tag{3}$$

where μ_i is a random draw from a different dimension of the above-mentioned joint normal distribution. Further assume

$$V_{Oi} = \alpha_0 + \beta_m y_i + \alpha_g G_i + \alpha_a Age_i + \alpha_r R_i + \alpha_b B_i + \alpha_L L_i + \alpha_{LG} LG_i \tag{4}$$

where $G_i = 1$ if individual i is male, $R_i = 1$ if the individual is retired, $B_i = 1$ if the individual owns a boat, $L_i = 1$ if the individual resides in a county that borders Lake Michigan but not Green Bay, and $LG_i = 1$ if the individual resides in a county that borders both Lake Michigan and Green Bay. Looking ahead, these are the individual characteristics found to be significant determinants of how often the individual fishes Green Bay. The region dummies, L_i and LG_i, were included to reflect, in part, differing choice sets across counties. For example, individuals who reside in Door County, the only county bordering both the lake and the bay have fewer small site alternatives than those in other areas. However, the significance of these two dummies cannot be attributed solely to the difference in fishing alternatives across counties, but that does not really matter.

base their answers on their "intentions." See also Manski (1990). What individuals state they would do in a survey context can be different from what they would actually do on some actual choice occasion, and that what they do on actual occasions might differ across occasions. See McFadden (1986, 1999) for a discussion of decision protocols and why different decision protocols for stated intentions and actual choices might be assumed.

[10] Supporting this, Grijalva et al. (2002) test the validity of SP frequency questions and find that responses to SP frequency questions are responsive to scope (the extent and direction of the quality change). Their data set is unique in the sense that they collected SP frequency data for a proposed site change and RP frequency data after the change was made policy.

[11] We set N to 50. Only a few individuals in the sample fished more than fifty times, and some of these were extreme outliers. Setting N equal to or larger than the maximum number of trips in the sample (120 in our case) would cause the per choice-occasion probability of fishing Green Bay to be very small for most anglers, making accurate estimation difficult.

The Likelihood Function

The data are of three types: the SP choice data (Green Bay under conditions A or B), the SP frequency data (how many times the angler would choose to fish Green Bay if it had the characteristic levels described in the chosen alternative) and the RP frequency data (how many times the angler fished Green Bay under current conditions).

The Component of the Likelihood Function Corresponding to the SP Choice Data

Anglers answered J Green Bay choice pairs. For simplicity, initially suppress the i and j notation and denote the angler's utility from choosing alternative K as U_{GB}^{K}, $K = A, B$ with its random term denoted ε^{K}.

The probability of the angler choosing alternative A is therefore

$$(5) \qquad \Pr(A) = \Pr\left(U_{GB}^{A} > U_{GB}^{B}\right).$$

Assume each ε^{K} is an independent random draw (across both individuals and pairs) from a normal distribution with zero mean and variance σ_{ε}^{2}.

Given these normality assumptions, the probability of choosing alternative A is

$$(6) \qquad \begin{aligned} \Pr(A) &= \Pr\left[V_{GB}^{A} + \varepsilon^{A} > V_{GB}^{B} + \varepsilon^{B}\right] \\ &= \Pr\left[\varepsilon^{B} - \varepsilon^{A} < V_{GB}^{A} - V_{GB}^{B}\right] \\ &= \Phi\left(V_{GB}^{A} - V_{GB}^{B}\big/\sqrt{2}\sigma_{\varepsilon}\right) \end{aligned}$$

where $\sqrt{2}\sigma_{\varepsilon}$ is the standard deviation of $\varepsilon^{B} - \varepsilon^{A}$ and $\Phi(\cdot)$ is the CDF (cumulative distribution function) of the standard normal.

Reintroducing the i and j notation, the likelihood function for these data alone is

$$(7) \qquad \prod_{i=1}^{M}\prod_{j=1}^{J} \Pr{}_{ij}(A)^{a_{ij}}\left[1 - \Pr{}_{ij}(A)\right]^{1-a_{ij}}$$

where $a_{ij} = 1$ if individual i chooses alternative A in pair j and zero otherwise. With these data alone, one could estimate the parameters in the conditional indirect utility function for Green Bay (equation 2) but not the parameters in the conditional indirect utility function for choosing *Other* (equation 4), so one can estimate $E[cv]$ per Green Bay fishing trip but not $E[cv]$ per choice occasion, which is what we want; estimation of that requires frequency data. So, we add SP and RP frequency data.

The Component of the Likelihood Function Corresponding to the SP Frequency Data

After each SP choice question, the angler indicated how many times he or she would choose to fish Green Bay if it had the characteristic levels described in the chosen alternative. Let n_{ij} be the number of times angler i indicates he would fish Green Bay if it had the characteristic levels in the alternative he chose in pair j and $k_{ij} = 1$ if alternative k was chosen and zero otherwise, $k = a, b$.[12]

What is needed for the likelihood function is the probability, on each choice occasion, of choosing the chosen Green Bay alternative over doing something else, conditional on the fact that the utility from the chosen Green Bay alternative is greater than the utility from the Green Bay alternative not chosen. For example, the probability of choosing Green Bay over something else, conditional on alternative A being chosen over B is

$$(8) \qquad \Pr(GB \mid A) = \Pr\left[U_{GB}^{A} > U_{O} \,\middle|\, U_{GB}^{A} > U_{GB}^{B}\right].$$

For each individual and pair, n has a binomial distribution. That is, for an individual who chose alternative A in the pair

$$(9) \qquad \Pr(n \mid A) = \binom{N}{n}\Pr(GB \mid A)^{n} \times [1 - \Pr(GB \mid A)]^{N-n}$$

and for an individual who chose B

$$(10) \qquad \Pr(n \mid B) = \binom{N}{n}\Pr(GB \mid B)^{n} \times [1 - \Pr(GB \mid B)]^{N-n}.$$

Consider now the distribution of the μ, the random term in equation (3). Assume each μ is an independent (across individuals and pairs) random draw from a normal distribution with zero mean and variance σ_{μ}^{2}. We allow a nonzero covariance, $E(\varepsilon\ \mu) \equiv \sigma_{\varepsilon\mu}$; that is, the random component in the utility from doing something else covaries with the random component in the chosen SP Green Bay alternative.

[12] With enough variation in this SP frequency data, it alone is sufficient to estimate the parameter in both conditional indirect utility functions.

Given these normality assumptions

(11)

$$\begin{aligned}\Pr(GB \mid A) &= \Pr\left[U_{GB}^{A} > U_O \mid U_{GB}^{A} > U_{GB}^{B}\right] \\ &= \Pr\left[\mu - \varepsilon^A < V_{GB}^{A} - V_O \mid \varepsilon^B - \varepsilon^A < V_{GB}^{A} - V_{GB}^{B}\right] \\ &= \frac{\Phi_2\left[\left(V_{GB}^{A} - V_O\right)/\sigma_{\mu-\varepsilon}, \left(V_{GB}^{A} - V_{GB}^{B}\right)/\sqrt{2}\sigma_\varepsilon, \rho\right]}{\Pr(A)}\end{aligned}$$

where Φ_2 is the the CDF of the standard bivariate normal, $\sigma_{\mu-\varepsilon}^2 \equiv Var(\mu - \varepsilon) = \sigma_\mu^2 + \sigma_\varepsilon^2 - 2\sigma_{\varepsilon\mu}$, and ρ is the correlation between $(\mu - \varepsilon^A)$ and $(\varepsilon^B - \varepsilon^A)$.

$$(12) \qquad \rho = \frac{\sigma_\varepsilon^2}{\sqrt{2\sigma_\varepsilon^2 \sigma_{\mu-\varepsilon}^2}}.$$

The parameter σ_ε^2 is fixed at 0.5 to identify the model. The value of $\sigma_{\mu-\varepsilon}^2$ is estimated; ρ is a function of σ_ε^2 and $\sigma_{\mu-\varepsilon}^2$.

The joint likelihood function for the SP frequency data and the SP choice data is therefore

$$(13) \qquad \prod_{i=1}^{M}\prod_{j=1}^{J}\binom{N}{n_{ij}}\Pr(GB \mid a_{ij})^{n_{ij}} \times [1 - \Pr(GB \mid a_{ij})]^{N-n_{ij}} \times \Pr{}_{ij}(A)^{a_{ij}}[1 - \Pr{}_{ij}(A)]^{1-a_{ij}}$$

where $\Pr(GB|1) = \Pr(GB|A)$ and $\Pr(GB|0) = \Pr(GB \mid B)$.

The Component of the Likelihood Function Corresponding to the RP Frequency Data

In addition to the SP data, we have for each individual the number of times they fished Green Bay under current conditions, gb_i.[13] Let $\Pr(gb_i \mid C)$ be the probability of gb_i given the current conditions of Green Bay. This is a function of $\Pr(GB \mid C)$, the probability of choosing Green Bay over something else on a choice occasion.

$$\begin{aligned}(14) \qquad \Pr(GB \mid C) &= \Pr\left[U_{GB}^{C} > U_O\right] \\ &= \Pr\left[V_{GB}^{C} + \varepsilon_C > V_O + \mu\right] \\ &= \Pr\left[\mu - \varepsilon_C < V_{GB}^{C} - V_O\right]\end{aligned}$$

where ε_C is the random component on the utility from actually fishing Green Bay under current conditions.[14]

Assume the ε_C are independently distributed random draws across individuals from a normal distribution with zero mean and variance $\sigma_{\varepsilon_C}^2$; that is, the variance on the ε from the actual choices, $\sigma_{\varepsilon_C}^2$, is allowed to differ from the variance on the ε from the A,B hypothetical choices, σ_ε^2. In other words, the amount of noise in the utility from a hypothetical Green Bay is allowed to differ from the amount of noise in the utility from the actual Green Bay. In addition, we allow a nonzero covariance between the μ and the ε_C; that is, $E(\mu\varepsilon_C) = \sigma_{\mu\varepsilon_C}$; the random components in the real alternatives are allowed to be correlated.

Given these normality assumptions

$$\begin{aligned}(15) \qquad \Pr(GB \mid C) &= \Pr\left[\mu - \varepsilon_C < V_{GB}^{C} - V_O\right] \\ &= \Phi\left[\left(V_{GB}^{C} - V_O\right)/\sigma_{\mu-\varepsilon_C}\right]\end{aligned}$$

where $\sigma_{\mu-\varepsilon_C}^2 = Var(\mu - \varepsilon_C) = \sigma_\mu^2 + \sigma_{\varepsilon_C}^2 - 2\sigma_{\mu\varepsilon_C}$.

Therefore,

$$(16) \qquad \Pr(gb \mid C) = \binom{N}{gb}\Pr(GB \mid C)^{gb} \times [1 - \Pr(GB \mid C)]^{N-gb}$$

and the likelihood function for the RP only component of the data is

(17)

$$\prod_{i=1}^{M}\binom{N}{gb_i}\Pr(GB \mid C_i)^{gb_i}[1 - \Pr(GB \mid C_i)]^{N-gb_i}.$$

The joint likelihood function for the three types of data is

[13] Note that with this RP frequency data alone, one could estimate the probability of fishing Green Bay on each choice occasion as a function of cost; however, without additional data, the parameters on the characteristics of Green Bay are not identified but rather embedded in a constant term. Such a model would be a complete demand system but have little detail.

[14] The current conditions at Green Bay are as follows. Average catch times for perch, salmon, walleye, and bass are 0.75 hours, 19.4 hours, 7.4 hours, and 15.0 hours, respectively. The FCA level is level 4 (see table 1), and the average fee is $3.

(18)

$$\prod_{i=1}^{M}\left[\begin{array}{c}\binom{N}{gb_i}\Pr(GB \mid C_i)^{gb_i}[1-\Pr(GB \mid C_i)]^{N-gb_i}\\ \prod_{j=1}^{J}\binom{N}{n_{ij}}\Pr(GB \mid a_{ij})^{n_{ij}}[1-\Pr(GB \mid a_{ij})]^{N-n_{ij}}\\ \Pr_{ij}(A)^{a_{ij}}[1-\Pr_{ij}(A)]^{1-a_{ij}}\end{array}\right].$$

A few words about identification are in order. As noted above, the parameter σ_ε is fixed to identify the model. The following parameters then can be identified and estimated: $\boldsymbol{\beta}, \boldsymbol{\alpha}, \sigma_{\mu-\varepsilon_C}$, and $\sigma_{\mu-\varepsilon}$. The individual components, σ_{ε_C} and σ_μ cannot be separately identified since we have allowed for the nonzero covariances $\sigma_{\mu\varepsilon_C}$ and $\sigma_{\varepsilon\mu}$, but looking ahead we get a hint of their relative magnitudes.

Parameter Estimates and Results

Table 2 reports the maximum likelihood estimates and *t*-statistics.

In summary, the utility from fishing Green Bay is decreasing in catch time for each species with the perch catch-time parameter being the largest of the catch parameters in absolute value. With one exception, the FCA parameters become larger negative values as one increases from level 1 (the least stringent) to level 9 (the most stringent). The exception is, as expected, level 5; see footnote 8. Men, boat owners and the retired, are more likely to fish Green Bay; the probability of fishing Green Bay decreases with age. The constant term for *Other* is large because most anglers do not fish Green Bay on most choice occasions. The included parameters are all significant, but given that the variance–covariance matrix of the parameter estimates is approximated, we do not put great stock in the magnitudes of the reported *t*-statistics: likelihood ratio tests corroborate the significance of all the included parameters.

The estimated variances of both $\mu - \varepsilon(Var(\mu-\varepsilon) = \sigma_\mu^2 + \sigma_\varepsilon^2 - 2\sigma_{\varepsilon\mu})$ and $\mu - \varepsilon_C(Var(\mu-\varepsilon_C) = \sigma_\mu^2 + \sigma_{\varepsilon_C}^2 - 2\sigma_{\mu\varepsilon_C})$ are large. This is probably because their common element, σ_μ^2, is large; that is, the random, unexplained component in the conditional indirect utility function for *Other* is large relative to the variances of the Green Bay random terms (σ_ε^2 and $\sigma_{\varepsilon_C}^2$)–not surprising since *Other* includes everything possible but fishing Green Bay.

The model predicts that, under current conditions, trips to Green Bay will vary from 0.21 to 17.3 with a mean of 14.29 and a median of 14.84; these are too high (the actual average is 9.3). They are being pulled up by the responses to the SP frequency questions that indicate intentions.

One can adjust for this divergence between intent and outcome by scaling upward the parameters in the conditional indirect utility function for *Other*. The scale that causes the predicted number of Green Bay trips under current conditions to effectively equal the actual number is 1.7, suggesting optimism averages 70%; someone who says that he will likely take three trips is more likely to actually take two trips. With this adjustment, the predicted number of trips to Green Bay varies from 0.1 to 12.9 with a mean of 9.5 and a median of 9.8. With the calibration the model predicts that the average number of Green Bay days will increase to 9.7 (a 2% increase) if the need for the FCAs is eliminated (level 4 to level 1).[15] We feel the calibration is appropriate.[16]

Table 2. Maximum Likelihood Estimates and t-Statistics

Parameter	Estimate	*t*-Statistic
β_p	−.36691	−64.00
β_s	−.00736	−4.486
β_w	−.02661	−16.938
β_b	−.01517	−21.439
β_{FCA2}	−0.1442	−7.149
β_{FCA3}	−0.2566	−7.641
β_{FCA4}	−0.4261	−12.704
β_{FCA5}	−0.6476	−29.632
β_{FCA6}	−0.4424	−15.925
β_{FCA7}	−0.7840	−34.043
β_{FCA8}	−1.0411	−38.540
β_{FCA9}	−1.2068	−46.825
β_y	.055289	−216.921
α_0	12.6896	138.666
α_g	−2.0886	−166.822
α_a	5.2056	56.224
α_r	−2.3618	−13.699
α_b	−2.2482	−71.295
α_L	0.5153	12.862
α_{LG}	1.9510	48.437[a]
$\sigma_{\mu-\varepsilon}$	27.112	426.780[a]
$\sigma_{\mu-\varepsilon c}$	25.78	160.143[a]

[a]This *t*-statistic applies to the square root of the parameter logged.

[15] Without the calibration, the model predicts a 2% increase in the number of Green Bay trips.

[16] When the contingent behavior questions were answered, they were answered under varying sets of described characteristics. Our use of the phrase "in a typical year" in the contingent behavior questions refers to a typical year with those characteristics.

The $E[cv_i]$s for Reducing FCA Levels from Current Conditions (Level 4) to Unlimited Consumption of All Species (Level 1)

Estimated $E[cv]$ is calculated for each angler in the sample by calculating $E[cv]$ per choice occasion and then multiplying by fifty, the assumed number of choice occasions.

Individual *i*'s $E[cv]$ per choice occasion is

$$(19)\quad E\left[cv_i^{occ}\right] = \frac{1}{\beta_y}\left[E(\max\left(U_i^{G^1}, U_i^O\right)) - E\left(\max(U_i^{G^0}, U_i^O)\right)\right]$$

where U_i^O is the choice-occasion utility from doing something else and U_i^G is the choice-occasion utility from fishing Green Bay. Given that U_i^G and U_i^O are bivariate normal (Maddala, 1983):

$$(20)\quad E\left(\max\left(U_i^G, U_i^O\right)\right) = V_{oi} + (V_{GB_i} - V_{oi})\Phi\left(\frac{V_{GB_i} - V_{oi}}{\sigma_{\mu-\varepsilon_C}}\right) + \sigma_{\mu-\varepsilon_C}\phi\left(\frac{V_{GB_i} - V_{oi}}{\sigma_{\mu-\varepsilon_C}}\right)$$

where $\Phi(\cdot)$ is the CDF of the univariate, standard normal, and $\phi(\cdot)$ is the univariate, standard normal density function.

Calibrating V_{oi} (multiplying it by 1.7) so that the model correctly predicts the current average number of trips to Green Bay, the $E[cv_i]$ for eliminating the need for the FCAs vary from \$0.55 to \$100.35 with a mean of \$74.10 (95% confidence interval \$64 to \$84) and a median of \$76.42.[17] These are annual values. The \$0.55 is for an angler who lives far from Green Bay; the calibrated model predicts that this individual would take only 0.07 trips to Green Bay if it had no FCAs. The \$100.35 is for a male angler who owns a boat and lives on Green Bay; the calibrated model predicts that this angler would fish thirteen times per year if there were no FCAs. Table 3 reports the frequency of the $E[cv_i]$ in \$10 increments; the distribution has a long left tail toward \$0.

Given that the $E[cv_i]$ estimates are substantively determined by SP responses, the skeptic might question their reasonableness, and so the appropriateness of our minimalist approach. We do not. The $E[cv_i]$ are highly sensitive to the extent of the improvement in the FCA levels (the scope test). For example, the mean $E[cv_i]$ for reducing the FCA levels from level 4 to 2 are \$48.82 and from level 4 to level 3 are \$29.26. For halving the perch catch time the mean $E[cv_i]$ is \$23.74.

These damage estimates are reasonable. The $E[cv_i]$ are only a small fraction of current expenditures on Green Bay fishing trips. The estimates for the removal of FCAs fall within the range of other values in the literature. See, for example, Herriges, Kling, and Phaneuf (1999); Chen and Cosslett (1998); Jakus, Dadakas, and Fly (1998); and Parsons, Jakus, and Tomasi (1999).

The estimates are also consistent with the anglers' answers to the attitudinal questions; those answers reflect a serious concern for PCB levels in fish. Many anglers indicate that they have changed their behaviors in response to the FCAs (e.g., they changed where they fish, how much they eat, how they prepare the fish).

Table 3. Individual Per-Year *E[cv]* for Eliminating FCAs

$E[cv]$	Frequency	Percent (%)
<\$10	5	0.773
\$10–19.99	3	0.464
\$20–29.99	2	0.309
\$30–39.99	13	2.01
\$40–49.99	21	3.25
\$\$30–39.99	62	9.58
\$60–69.99	110	17.0
\$70–79.99	148	22.9
\$80–89.99	205	31.7
\$90–99.99	77	11.9
\$100–110	1	0.155

Summary and Extensions

The task was to develop and estimate a model capable of valuing a proposed change in the characteristics of one, and only one, recreational site. While not all valuation exercises are of this nature, many are. The task was accomplished in a repeated, discrete choice, random utility model with only two conditional indirect utility functions: one for visiting the site in question and one for everything else. That is, everything other than visiting the site on a choice occasion is lumped together in one generic alternative. The model is therefore

[17] For comparison, without the calibration, the $E[cv_i]$ for eliminating the need for the FCAs are higher; they vary from \$1.66 to \$133.14 with a mean of \$111.17 (95% confidence interval \$96 to \$128) and a median of \$115.51.

complete in that all alternatives are included in the choice set. The big advantage of such a minimal model is that one does not need to explicitly define the set of explicit substitute sites for the site of interest (e.g., all of the other fishing sites in the choice set) or the characteristics of each of those sites. Collecting characteristics data for all of the other sites in the choice set is typically difficult, expensive, and hard to defend.

At a minimum, estimation of the model requires SP frequency data for the site of interest (data on how many times each recreator would visit the site under different sets of site characteristics). In our case, the efficiency of the parameter estimates is increased by also including SP choice data ("would you prefer to visit the site under conditions A or B?") and RP frequency data (how often does each recreator visit the site under current conditions). The RP frequency data are also used to calibrate the model so that it accurately predicts the current number of trips to the site. Our model harks back to earlier times when environmental economists often estimated a single-site demand. Our model is a complete and utility-theoretic demand model that explicitly includes the characteristics of the site and the estimation of the parameters on those characteristics.

The $E[cv_i]$ are estimated for changes in the levels of FCAs in the bay of Green Bay, which was the primary objective of the Green Bay application. The estimates are reasonable in magnitude and scope.

The model is easily extended in numerous ways without increasing the number of conditional indirect utility functions. For example, income effects could be included or some of the parameters could be made random parameters.

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