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An Estimable Dynamic Model of Recreation Behavior with an Application to Great Lakes Angling[1]

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This paper develops an estimable model of recreation behavior in which the recreation decision is cast as a dynamic programming problem. The model is illustrated with an application to salmon and trout fishing on Lake Michigan. The application considers various factors affecting the trip decision, including the expected catch, the weather, the opportunity to participate in a fishing derby, and the time elapsed since the last fishing trip. Catch is modeled as a Poisson-distributed random variable. Estimation results are promising, but a number of practical obstacles must be surmounted for the model to be regularly applied in recreation demand analysis. © 1997 Academic Press

1. INTRODUCTION

The travel cost method (TCM) is now widely used to estimate the economic benefit of nonmarket resources for site-specific recreational activities. Recent applications of the method use nested logit (NL) estimation and are motivated by appeals to the sequential nature of the recreation decision; for instance, an angler first chooses a particular species to fish and then chooses a site from the subset of sites known to have high populations of the species [6, 7, 14, 16, 17, 22]. Yet none of the recent studies formally considers that outcomes on earlier trips affect the decisions about when and where to take later trips. Also absent is the possibility that recreation decisions are forward-looking; *because* anglers know early in the fishing season that plenty of opportunities to fish lie ahead, they may postpone trips that they would not postpone later in the season. In other words, the *dynamic* nature of the decision process is absent from these models.[2]

Structural estimation of the dynamic decision process of anglers would allow the analyst to attain an empirical esthetic not found in the usual static models; the analyst may be able to formulate a decision problem that most observers would agree looks more like ‘‘the real thing’’ than what is currently found in the literature. This pursuit of ‘‘the real thing’’ would provide the opportunity not only

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[2] An exception to the use of static models in recreation demand analysis is the habit formation model examined in Adamowicz [1], in which utility is cast as a function of stock variables, the evolution of which depends on depreciation parameters.

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to derive estimates of economic values as in the usual static models, but also to approximate the structural parameters important to understanding the dynamic relationships between fish stocks and angler effort. In their study of the Green Bay, Lake Michigan yellow perch fishery, Johnson *et al*. [10] observe that "The prospect exists for managing variability in harvest and stock size and for maximizing economic returns in the fishery, but more information is required, *primarily on sportfishing dynamics and angler preferences*. Stock-recruitment relations, density dependence of growth, *and dynamics of sportfishing effort* are the primary sources of uncertainty limiting the precision of our predictions" (Abstract, emphasis added). Swallow [21] demonstrates the importance of intraseasonal management of a fishery to maximize angler welfare. Like Johnson *et al*., he concludes that additional research is required to understand angler behavior: "Evaluation of how different types of recreationists might switch days between subseasons in response to quality and regulations may prove critical. *The extant literature does not address the potential demand or equity implications for such intertemporal behavioral choices. Research on behavioral choices could enrich policy assessments based on recreational consumer's surplus*" [p. 933, emphasis added].

The fundamentally dynamic structure of the trip decision is certainly understood by TCM practitioners; for instance, Morey *et al*. [16] observe that, "In general, one might expect that the decision to fish at site j mode m in period t would affect the participation probability and site/mode probabilities in subsequent periods." Yet such relationships have not yet been modelled, most likely for two reasons. First, estimation of dynamic models would require fairly detailed data. And second, developing a conceptually coherent dynamic model of behavior that is also tractable in estimation is a daunting task. Arguably the first reason is simply an effect of the second; if dynamic structural models were easily estimated, data to estimate them would be gathered.

In this paper we describe a dynamic structural model of the decision to visit a recreation site. The estimation approach as described in the first part of the paper is the same as that first used by Rust [19] in his study of the dynamics of the bus engine replacement decision, and Miranda and Schnitkey [15] in their investigation of the dairy cow replacement problem. The model is best described as a dynamic multinomial logit model. By virtue of its dynamic nature, the model avoids the problem of the independence of irrelevant alternatives that afflicts static multinomial logit models. On the other hand, because the model has a multinomial logit form, the calculation of likelihoods can be done relatively cheaply. Welfare effects of changes in site quality are easily calculated via dynamic programming.

The second part of the paper illustrates the model with an empirical investigation of the decisions of fishing club members on the Wisconsin shore of Lake Michigan. As it turned out, most club members rarely ventured from a few launches close to home, and so for these anglers the fishing decision on any given day is reasonably cast as the simple binary choice of whether or not to fish for salmonids (salmon and trout) from local ramps on Lake Michigan. The application accounts for various factors influencing the decision to fish, such as the expected catch, the weather, the time-cost of fishing, and the time elapsed since the last trip. Estimation results are used to calculate the (conditional) probability of fishing on any given day of the season, the expected seasonal value of fishing, and the welfare effect of an increase in the quality of fishing, as measured by an increase in the site-wide average catch. The paper concludes with remarks on some of the methodological issues raised by the application.

2. THE BASIC MODEL

Over the past 10 years a literature concerning the estimation of stochastic dynamic behavioral models has emerged and no doubt will continue to grow in the years ahead. Reviews of this literature are contained in Rust [19], Eckstein and Wolpin [8], and Rust and Pakes [20]. Because the estimation technique is new in the nonmarket valuation literature, in the discussion here we present it in considerable detail. As with all previous attempts to estimate stochastic decision problems, we assume preferences are time-separable and state-separable. Time separability implies that total utility for the season can be expressed as the expected discounted sum of the utility generated on each day of the season. State separability implies that preferences in the current period depend only on the current state of nature, though this is not as restrictive as it might seem at first glance—it is a trivial matter in practice to include in the "current" state of nature past state values, or past outcomes. Rust and Pakes [20] argue that the assumptions of time and state separability still leave the analyst with enough flexibility to develop a good model of behavior. They conclude that, "While it is unlikely that human decision makers are literally solving time separable Markovian decision problems (either consciously or unconsciously), it turns out that this class is sufficiently rich and flexible to enable one to construct detailed models of most types of behavior" (p. 7).

We present the model in the context of recreational fishing, though it is certainly applicable to other recreational activities with a clear dynamic component. Let T denote the total number of days in the fishing season, and let $t = 1, \dots T$ denote an arbitrary day during the season. On day t an angler decides among various fishing alternatives, including not fishing at all. Ultimately the angler's decision depends on the state of nature at time t, as defined by state variables concerning the quality of fishing, the time elapsed since the last day fished, the weather, and so on. If the analyst knows all the variables that enter the angler's decision process, then in theory he or she can solve the appropriate dynamic decision problem to obtain an optimal "trip policy" that perfectly forecasts the fishing alternative chosen by the angler. Of course, knowing enough about the decision process to perfectly forecast trips is impossible, and so the analyst must concede the existence of random state variables entering the decision process that are observed contemporaneously by the angler but never observed by the analyst.

Suppose there are I trip destinations, and let y_t denote the angler's trip decision on day t, with $y_t = i$ if on day t alternative i is chosen, $i = 0 \dots I$. $y_t = 0$ denotes the decision not to fish on day t. The vector of observable state variables affecting utility on day t is denoted by $\mathbf{x}_t$; by *observable* we mean that both the angler *and* the analyst observe the value of the state variable. Included in this vector are such determinants of the trip decision as weather variables, trip costs, and catch rates at the various fishing sites. Along with the observable state variables the model includes decision-specific unobservable state variables $\tilde{\varepsilon}_t = (\tilde{\varepsilon}_{0t}, \dots \tilde{\varepsilon}_{It})$. These are random variables observed contemporaneously by the angler but *not* by the analyst.

For the purpose of understanding the angler's decision problem it is necessary to distinguish among various subvectors of $\mathbf{x}_t$. Let $\mathbf{x}_{at}$ denote the subvector of state variables with values observed by the angler at the time the fishing decision is made (where the subscript a denotes "anterior"), and let $\mathbf{x}_{pt}$ denote the subvector of state variables observed by the angler after the fishing decision is made (where the subscript p denotes "posterior"). In a model of recreational fishing the distinction between anterior and posterior state variables bears on the role of catch expectations in the trip decision; when anglers make trip decisions they know the probability distribution for catch at each site, but not the actual catch, which is revealed only after the trip is taken. Those anterior state variables that evolve over time independently of the fishing decision are denoted by $\mathbf{x}_{rt}$. Those anterior state variables influencing the utility associated with alternative i are denoted by $\mathbf{x}_{ait}$. Finally, those posterior variables influencing the utility associated with alternative i are denoted by $\mathbf{x}_{pit}$.

Each day the angler solves a complex dynamic decision problem involving, among other things, the consumption of income and the fishing decision. Here we assume that the allocation of income for day t is independent of the decision to fish; this allows the separation of the income allocation and fishing decisions. Specifically, the consumption of income on day t is denoted by $b_t(B_t(\mathbf{x}_{rt}), \mathbf{x}_{rt})$, where B_t is the angler's budget for the fishing season on day t. The budget evolves according to

$$B_t = \begin{cases} \bar{B}(\mathbf{x}_{rt}) & \text{if } t = 1 \\ B_{t-1} - b_{t-1} + \omega_t(\mathbf{x}_{rt}) & \text{if } t = 2, \dots T \end{cases}, \tag{1}$$

where $\bar{B}(\cdot)$ is the initial budget for the season, and $\omega_t(\mathbf{x}_{rt})$ is income added to the seasonal budget on day t. So, for instance, the model allows the possibility that the angler consumes more income on a warm, sunny weekend in July than on a cold rainy weekday in May, but it does not allow the possibility that more income is allocated to day t when the angler chooses fishing alternative i.

Let c_i denote the cost (price) of alternative i on day t.[3] The cost of making no trip is zero, and so $c_0 = 0$. The utility associated with decision $y_t = i$ is generally denoted by

$$\tilde{u}_i\Big(\mathbf{x}_{ait}, \mathbf{x}_{pit}, b_t\big(B_t(\mathbf{x}_{rt}), \mathbf{x}_{rt}\big) - c_i\Big) + \tilde{\varepsilon}_{it},$$

where the last argument in $\tilde{u}_i(\cdot)$ denotes consumption of the numeraire on day t.

In static random utility models of the recreation decision, utility is often represented as linear in the budget. This implies zero income effects, and so when the disturbance term $\tilde{\varepsilon}_{it}$ has a certain structure, closed-form solutions for compensating and equivalent variation are possible. In this regard the linear specification is therefore convenient but not necessary. Note, however, that this conclusion presumes the budget (income) is observed. In our dynamic model the budget of interest is the *daily* budget, which is at best extraordinarily difficult to observe. As

[3] An alternative expression of trip cost is $c_i(\cdot) = mcost_i + tcost(\mathbf{x}_{ait}; \delta)$, where $mcost_i$ is the money cost of alternative i, $tcost(\cdot)$ is the time cost of alternative i, measured in units of money, and δ is a set of estimable parameters. In this case the time cost of a trip is estimated (for a related discussion, see McConnell and Strand [12]). This is the approach used in the empirical investigation. In the discussion here it is for simplicity that trip costs are denoted by the constant c_i.

it turns out, a linear or quasi-linear specification allows this empirical problem to be circumvented. In light of the small differences in the daily budget over time, a linear specification may provide a reasonably good first-order approximation of the "true" model of indirect utility.

Suppose that utility takes the linear form

$$\tilde{u}_i = \tilde{\gamma}_{pi}\mathbf{x}_{pit} + \tilde{\gamma}_{ai}\mathbf{x}_{ait} + \lambda(b_t - c_i) + \tilde{\varepsilon}_{it}, \tag{2}$$

where $\tilde{\gamma}_{ai}$ and $\tilde{\gamma}_{pi}$ are conformable vectors of parameters and λ is the marginal utility of income. Dividing (2) by the marginal utility of income yields the money metric expression of utility u_i,

$$\begin{aligned} u_i &= \frac{\tilde{\gamma}_{pi}\mathbf{x}_{pit}}{\lambda} + \frac{\tilde{\gamma}_{ai}\mathbf{x}_{ait}}{\lambda} + b_t - c_i + \frac{\tilde{\varepsilon}_{it}}{\lambda} \\ &= \gamma_{pi}\mathbf{x}_{pit} + \gamma_{ai}\mathbf{x}_{ait} + b_t - c_i + \varepsilon_{it}. \end{aligned} \tag{3}$$

On day t the angler's dynamic decision problem is to maximize the sum of expected current and future utility, where future utility is discounted by an "impatience" factor β. Formally, the angler's problem is

$$\max E\left[\sum_{s=t}^{T} \beta^{s-t}\{\gamma_{pi}\mathbf{x}_{pis} + \gamma_{ai}\mathbf{x}_{ais} + b_s - c_i + \varepsilon_{is}\}_{i=0}^{I}\right]. \tag{4}$$

The expectation in (4) is taken over the three categories of random state variables, $\mathbf{x}_{ps}$, $\mathbf{x}_{as}$, and ε_s. At the time of the fishing decision on day t, the value of the posterior state vector $\mathbf{x}_{pt}$ is unknown and conditional on the state vector $\mathbf{x}_{at}$ and the decision y_t. We denote by θ_p the parameters associated with the (conditional) probability distribution of $\mathbf{x}_{pt}$. Similarly, the anterior state vector on day $t+1$ is unknown on day t and conditional on $\mathbf{x}_{at}$ and y_t. We denote by θ_a the set of parameters associated with the (conditional) probability distribution of $\mathbf{x}_{a,t+1}$. Finally, the elements of ε_t are independently and identically distributed over time according to a known multivariate probability distribution. We denote by μ the parameters of this distribution. It bears repeating that at the time the fishing decision is made, ε_t is known by the angler, but is never observed by the analyst.

Now define $\Gamma = (\theta_a, \theta_p, \beta, \mu, \gamma)$ and $\mathbf{c} = (c_0, \ldots c_1)$, and let $\nu_{t+1}(\mathbf{x}_{a,t+1}, \varepsilon_{t+1}, \mathbf{c}; \Gamma)$ denote the value of (4) on day $t+1$. Note that this function takes as arguments the state variables observed by the angler at the time the trip decision on day $t+1$ is made. Also, let $E_{\mathbf{x}_{pi}|\mathbf{x}_{ait}, i}$ denote the expectation over current (day t's) realizations of the state vector $\mathbf{x}_{pi}$, conditional on the current state vector $\mathbf{x}_{ait}$ and the current decision $y_t = i$; and let $E_{\mathbf{x}_a, \varepsilon|\mathbf{x}_{at}, i}$ denote the expectation over *tomorrow's* realizations of the state vector $\mathbf{x}_a$ and the random variable ε, conditional on $\mathbf{x}_{at}$ and the current decision i. Then by Bellman's principle of optimality, the angler's problem can be restated,

$$\begin{aligned} \nu_t(\mathbf{x}_{at}, \varepsilon_t, \mathbf{c}; \Gamma) = \max_i \Big[&\gamma_{pi} E_{\mathbf{x}_{pi}|\mathbf{x}_{ait}, i}\{\mathbf{x}_{pit}\} + \gamma_{ai}\mathbf{x}_{ait} - c_i + \varepsilon_{it} \\ &+ \beta E_{\mathbf{x}_a, \varepsilon|\mathbf{x}_{at}, i}\{\nu_{t+1}(\mathbf{x}_{a,t+1}, \varepsilon_{t+1}, \mathbf{c}; \Gamma)\}\Big]. \end{aligned} \tag{5}$$

The daily budget b_t is eliminated from the decision problem because it is the same for all alternatives.

For expositional reasons define

$$V_{t+1}(\mathbf{x}_{at}, i, \mathbf{c}; \Gamma) = E_{\mathbf{x}_a, \varepsilon|\mathbf{x}_{at}, i}\{\nu_{t+1}(\mathbf{x}_{a,t+1}, \varepsilon_{t+1}, \mathbf{c}; \Gamma)\}, \tag{6}$$

and

$$U_i(\mathbf{x}_{ait}, i; \gamma, \theta_{pi}) = \gamma_{pi} E_{\mathbf{x}_{pi}|\mathbf{x}_{ait}, i}\{\mathbf{x}_{pit}\} + \gamma_{ai}\mathbf{x}_{ait}. \tag{7}$$

Equation (5) now can be restated as

$$\nu_t(\mathbf{x}_{at}, \varepsilon_t, \mathbf{c}; \Gamma) = \max_i \{U_i(\mathbf{x}_{ait}, i; \gamma, \theta_{pi}) - c_i + \varepsilon_{it} + \beta V_{t+1}(\mathbf{x}_{at}, i, \mathbf{c}; \Gamma)\}. \tag{8}$$

With the parameter vector Γ known, and the vector ε_t observed, the decision problem (8) can be solved via backward recursion (see Bellman [3]). In general this is not a trivial problem. For instance, deriving $V_{t+1}(\cdot)$ involves I-dimensional integration over the state vector ε_{t+1} at each stage of the recursion. The problem is greatly simplified, however, by assuming that the variables ε_{it} are mutually independent Gumbel-distributed random variables with location parameters $\mu_0 \ldots \mu_I$ and scale parameter σ; in our notation, $\mu = (\mu_0, \ldots \mu_I, \sigma)$. From the standard properties of Gumbel-distributed random variables (see Ben-Akiva and Lerman [4]), integrating both sides of (8) with respect to ε at day $t+1$ yields

$$E_\varepsilon \nu_{t+1}(\mathbf{x}_{a,t+1}, \varepsilon_{t+1}, \mathbf{c}; \Gamma) = \frac{1}{\sigma} \ln\left\{ \sum_{j=0}^{I} \exp \sigma\left[U_j(\mathbf{x}_{aj,t+1}, j; \gamma_j, \theta_{pj}) - c_j + \mu_j + \beta V_{t+2}(\mathbf{x}_{a,t+1}, j, \mathbf{c}; \Gamma)\right]\right\}. \tag{9}$$

Substituting (9) into (6),

$$V_{t+1}(\mathbf{x}_{at}, i, \mathbf{c}; \Gamma) = E_{\mathbf{x}_a|\mathbf{x}_{at}, i} \frac{1}{\sigma} \ln\left\{ \sum_{j=0}^{L} \exp \sigma\left[U_j(\mathbf{x}_{aj,t+1}, j; \gamma_j, \theta_{pj}) - c_j + \mu_j + \beta V_{t+2}(\mathbf{x}_{a,t+1}, j, \mathbf{c}; \Gamma)\right]\right\}, \tag{10}$$

and so with $V_{t+2}(\cdot)$ known from the previous stage in the recursion, calculation of $V_{t+1}(\cdot)$ is a relatively simple affair involving integration over the random elements in the observable state vector.

Solution of the DP problem (8)–(10) is the defining characteristic of the estimation problem. With V_t known, maximum likelihood estimation of the dynamic problem is similar to that of its static counterpart. In particular, in the static case ($\beta = 0$) the probability of observing decision i given the observable state vector $\mathbf{x}_{at}$ and the parameter vector Γ has the form (see Ben-Akiva and Lerman [4]):

$$\Pr(i|\mathbf{x}_{at}, \mathbf{c}; \Gamma) = \frac{\exp \sigma\left[U_i(\mathbf{x}_{ait}, i; \gamma_i, \theta_{pi}) - c_i + \mu_i\right]}{\sum_{j=0}^{I} \exp \sigma\left[U_j(\mathbf{x}_{ajt}, j; \gamma_j, \theta_{pj}) - c_j + \mu_j\right]}, \tag{11}$$

whereas in the dynamic case the probability of observing decision i is

$$\Pr(i|\mathbf{x}_{at}, \mathbf{c}; \Gamma) = \frac{\exp \sigma\left[U_i(\mathbf{x}_{ait}, i; \gamma_i, \theta_{pi}) - c_i + \mu_i + \beta V_{t+1}(\mathbf{x}_{at}, i, \mathbf{c}; \Gamma)\right]}{\sum_{j=0}^{I} \exp \sigma\left[U_j(\mathbf{x}_{ajt}, j; \gamma_j, \theta_{pj}) - c_j + \mu_j + \beta V_{t+1}(\mathbf{x}_{at}, j, \mathbf{c}; \Gamma)\right]}.$$

Now suppose that the trip behavior of N anglers is observed for all T days of the fishing season. Letting y_{nt} denote the decision of angler n on day t, the likelihood of the sample is[4]

$$L(\Gamma) = \prod_N \prod_T \Pr(y_{nt}|\mathbf{x}_{a,nt}, \mathbf{c}; \Gamma). \tag{13}$$

Maximum likelihood estimation of the dynamic structural model thus involves a nested inner algorithm in which a dynamic programming (DP) algorithm derives $V_t(\cdot)$, $t = 1, \dots T$, for the specified vector Γ, and an outer hill-climbing algorithm that searches for the value of Γ yielding the highest value of $L(\Gamma)$. This nested structure places a premium on parsimony, both in the state vector $\mathbf{x}_t$ and in the parameter vector Γ; each time a new value of Γ is examined in the maximization routine, a DP problem must be solved.

2*a*. *The Issue of the Independence of Irrelevant Alternatives*

A well-known weakness of static multinomial logit models is the property of *independence of irrelevant alternatives* (IIA): the odds of choosing one alternative over another depends only on the attributes of the two alternatives. So, for instance, in the example offered by Bockstael [5], the IIA property implies the unlikely result that the odds of visiting a saltwater beach instead of a freshwater lake does not depend on whether a third beach is itself a saltwater or freshwater site. The IIA property does not extend to our dynamic model. The log odds ratio can be stated

$$\log\left\{\frac{\Pr(y_t = i|\mathbf{x}_{at})}{\Pr(y_t = j|\mathbf{x}_{at})}\right\} = \left[U_i(\mathbf{x}_{ait}, i; \gamma_i, \theta_{pi}) - c_i + \beta V_{t+1}(\mathbf{x}_{at}, i, \mathbf{c}; \Gamma)\right] - \left[U_j(\mathbf{x}_{ajt}, j; \gamma_j, \theta_{pj}) - c_j + \beta V_{t+1}(\mathbf{x}_{at}, j, \mathbf{c}; \Gamma)\right] \tag{14}$$

and so by virtue of the presence of $\mathbf{x}_{at}$ and $\mathbf{c}$ in $V_{t+1}(\cdot)$, the odds of choosing to fish at site i instead of site j depends on the attributes (state of nature) at all possible sites.

2*b*. *Welfare Analysis Using the Model*

On the last day of the season, day T, the angler's dynamic decision problem reduces to a static one. Consider now the welfare effect of a change in $\mathbf{c}$ and $\mathbf{x}_{aT}$ on the last day of the season. Let $\mathbf{c}^0$ denote the set of original prices of the various decision alternatives, and let $\mathbf{c}^1$ denote an alternative set. Similarly, let $\mathbf{x}_{aT}^0$ and $\mathbf{x}_{aT}^1$ denote the original and alternative vectors of anterior state variables. From (3)–(5) it is apparent that $v_T + b_T$ is a money measure of conditional indirect utility on the last day of the season, and so assuming nonsatiation ($b_T = B_T$), compensating

[4] The subscript indexing the angler (n) is generally suppressed to reduce notational clutter. It is used only when necessary to clarify the presentation.

variation (CV_T) and equivalent variation (EV_T) are defined by

$$CV_T = EV_T = \nu_T(\mathbf{x}^1_{aT}, \varepsilon_T, \mathbf{c}^1; \Gamma) - \nu_T(\mathbf{x}^0_{aT}, \varepsilon_T, \mathbf{c}^0; \Gamma) + B^1_T - B^0_T;$$

and with B_T unchanged,

$$CV_T = EV_T = \nu_T(\mathbf{x}^1_{aT}, \varepsilon_T, \mathbf{c}^1; \Gamma) - \nu_T(\mathbf{x}^0_{aT}, \varepsilon_T, \mathbf{c}^0; \Gamma).$$

Backward induction reveals that $\nu_t + B_t$ is a money measure of welfare for the remainder of the season on day t. Yet clearly welfare analysis is notably richer than on the last day of the season, because now such analysis involves a temporal aspect; the issue is not only *whether* a change takes place, but how the change is carried forward through time. Suppose, for instance, that exogenous processes governing site quality are altered. In our model, this is represented by a change in Γ (specifically, by a change in θ_a and θ_p). Let Γ^0 and Γ^1 denote the values of Γ under the original and alternative settings. Then for $B^0_t = B^1_t$, in this more general setting compensating and equivalent variation are defined by

$$CV_t = EV_t = \nu_t(\mathbf{x}^1_{at}, \varepsilon_t, \mathbf{c}^1; \Gamma^1) - \nu_t(\mathbf{x}^0_{at}, \varepsilon_t, \mathbf{c}^0; \Gamma^0).$$

Here both compensating and equivalent variation equal the one-time payment required on day t to make the angler indifferent to the proposed change in prices, exogenous processes, and the initial state. This value is readily obtained by solving two DP problems. In principle the estimated model is amenable to a rich variety of welfare analyses of intraseasonal management programs, such as those which shift the fish catch from one part of the season to another.

The definitions of compensating and equivalent variation offered above are *conditional* on the state of nature ($\mathbf{x}_{at}, \varepsilon_t$). Insofar as ε_t is not observable by the analyst, we can define an alternative notion of compensating and equivalent variation as the expected value of CV_t, where the expectation is taken over ε_t:

$$\overline{CV}_t = \overline{EV}_t = E_\varepsilon \nu_t(\mathbf{x}^1_{at}, \varepsilon_t, \mathbf{c}^1; \Gamma^1) - E_\varepsilon \nu_t(\mathbf{x}^0_{at}, \varepsilon_t, \mathbf{c}^0; \Gamma^0).$$

For policy analysis there remains the issue of presenting welfare measures as conditional on the observable state variables $\mathbf{x}_{at}$. Two points about this are relevant. First, for policy analysis interest most likely lies in seasonal welfare measures, and with $\beta = 1$ such welfare measures are unlikely to be much affected by the initial state $\mathbf{x}_{a0}$. This proposition can be examined via sensitivity analysis. Second, in the event $\mathbf{x}_{a0}$ does have a substantial impact on the value of $\overline{CV}_0$, historical data may be used to estimate the (unconditional) distribution of $\mathbf{x}_{a0}$, and a measure of compensating and equivalent variation for the season is then

$$\overline{\overline{CV}}_0 = \overline{\overline{EV}}_0 = E_{\varepsilon, \mathbf{x}_a} \nu_0(\mathbf{x}_{a0}, \varepsilon_0, c^1; \Gamma^1) - E_{\varepsilon, \mathbf{x}_a} \nu_0(\mathbf{x}_{a0}, \varepsilon_0, c^0; \Gamma^0).$$

3. AN APPLICATION OF THE MODEL

To illustrate the model we enlisted the support of two fishing clubs on the southwest shore of Lake Michigan. Members of the Lakeridge Boat Club fish primarily from launch sites along Lake Michigan from South Milwaukee to Racine, Wisconsin. Members of Salmon Unlimited-Kenosha fish from launches around Kenosha, Wisconsin. Each club supplied us with a list of club members. In late April and early May 1995 a letter was sent to club members describing our interest in recording their fishing activity throughout the 1995 season. This was followed by telephone contacts to confirm participation in the study. The survey of fishing activity was administered via telephone calls at 2-week intervals from mid-May to mid-October. Because only a handful of trips were taken before May 1 and after September 10, these dates were designated the beginning and end of the fishing season. Survey questions concerned dates, launch sites, and catch on the fishing trips taken during the interval between calls. A separate mail survey administered late in the season concerned angler characteristics such as age, employment status, boat size, and income.

Constructing the sample from club anglers served the primary purpose of developing a relatively simple model to illustrate the methodological issues in estimation. A total of 45 club members were included in the analysis. All anglers fished exclusively from boats towed to the launch site. Almost all of the fishing trips taken by these anglers were salmonid (salmon and trout) trips on Lake Michigan. Of the 813 fishing trips taken by these anglers, only 45 (5.5%) were not salmonid trips on Lake Michigan. Moreover, anglers rarely ventured from a few favorite launch sites close to one another on the southwest shore of Lake Michigan. For only 28 of the 768 Lake Michigan salmonid trips (3.6%) was the driving distance to the launch site more than 10 miles greater than the distance to the angler's primary site. Taken together, these data suggest that the fishing decision for these anglers is reasonably modeled as the simple binary decision of whether to take a salmonid trip on Lake Michigan. In the context of our model, we let y_t denote an angler's trip decision on day t, with $y_t = 1$ if a Lake Michigan salmonid trip is made, and $y_t = 0$ otherwise. Then setting $U_0(\cdot)$ equal to the zero function, the expected net gain from fishing on any given day is denoted by $U_1(\cdot) - c_1(\cdot)$, and so the value function $v_t(\cdot)$ measures the expected net gain from salmonid fishing for the remainder of the season.

3*a*. *Variables Used in Estimation*

Preliminary analyses with a logit model, and with various restricted structural models in which the number of estimable parameters varied between 5 and 9, were used to identify variables to include in the model.[5] This was done to limit to the extent deemed reasonable the size of the problem, in particular the size of the nested DP algorithm. The importance of such an exercise cannot be overstated. The model presented here required a little over 5 days to estimate on a Gateway Pentium-166 personal computer. Had the final model included all variables expected at the outset to have an impact on the fishing decision, but judged in pre-testing to have no significant effect (angler income is a prominent example), the solution time would have increased at least 10-fold, and thus the problem would have required solution on a supercomputer.

In the model, trip cost is represented as the sum of the money cost per trip, *mcost*, and the expected time cost of a trip, measured in dollars, $tcost_t$. The observed money cost varies across anglers but not over time and is calculated as the sum of the cost of driving to the launch site and operating the boat, minus the

[5] In the logit analysis, a dependent variable taking a value of 1 if a trip was taken, and 0 otherwise, was regressed on a set of explanatory variables including temperature, wind speed, angler income, money costs, site-wide average catch, the angler's previous catch, the time elapsed since the last trip, and the trip distance. The sample size for the analysis was the product of the length of the season in days and the number of anglers in the sample, $133 \cdot 45 = 5985$.

contribution toward expenses made by other trip participants.[6] The expected time cost of a trip is represented by

$$tcost_t = \delta_1 + \delta_2 job + \delta_3 job \cdot day_t + \delta_4 job \cdot day_t \cdot regday, \tag{15}$$

where *job* is a binary variable taking the value of one if the angler is employed full time during the season and zero otherwise; day_t is a binary variable taking the value of one if the day is a weekday (Monday to Friday) and zero otherwise; and *regday* is a third binary variable taking the value of one if the angler works a regular 40-hour work week (Monday to Friday) and zero otherwise. The expected time cost of a trip is thus a *relative* measure. The baseline cost is that of a retired person. For a retired person, $job = 0$, so $tcost_t = \delta_1$. For an angler who regularly works Monday to Friday, the expected time cost on a Saturday or Sunday is greater than that of a retiree by δ_2. Otherwise it is greater than that of a retiree by $\delta_2 + \delta_3 + \delta_4$.[7]

Ideally the trip cost would include a term for the time cost of the distance traveled to the launch site, $\delta_5 \cdot distance$, where δ_5 is an estimable parameter denoting the unit time cost of travel, as well as interaction terms like $\delta_6 \cdot distance \cdot job$, to distinguish the time cost of travel under different circumstances. Here such terms are not included because the benefit of doing so probably would be small and the cost of doing so certainly would be great. In the preliminary analyses used to identify variables to include in the model, *distance* was not a significant predictor of trip-taking behavior when *mcost* was included as an explanatory variable. So on the benefit side, terms involving *distance* probably would not prove statistically significant in modeling the dynamic trip-taking decision of anglers. On the cost side, including the distance traveled as an explicit state variable would involve the addition of yet another continuous state variable to the model, thereby increasing the computation time by at least an order of magnitude. It is well-established in the travel cost literature that welfare estimates are biased downward when the time cost of travel is not included in estimation. For the present application this bias is probably small. Most anglers in the sample live within 15 miles of the launch site, and so travel times are generally trivial in comparison to the total time spent on the water.

Two weather variables are included in the model. $wind_t$ is the average wind speed on day t, measured in miles per hour, and $temp_t$ is the maximum temperature, measured in degrees Fahrenheit. These weather data were obtained from

[6] The driving distance was calculated as the trip-weighted average distance to the angler's primary and secondary launch sites. Distances to primary and secondary launch sites are generally within 10 miles of one another. The driving cost was calculated as this distance multiplied by the operating cost per mile for the vehicle type most often used by the angler, as reported in 1995 by the American Automobile Association (AAA). This cost considers fuel and oil costs, and wear-and-tear on tires. The cost of boat operation was estimated via a regression equation in which the angler's estimate of the fuel and oil cost of operating a boat was treated as a quadratic function of boat length. Surprisingly, estimation of a model in which the day of the season ($t = 1, \ldots 133$) was included as an independent variable found that operating costs remain constant through the season. Anglers reported for each trip the contribution toward trip expenses made by other trip participants. An angler-specific average contribution was calculated from these reports.

[7] The time spent on a trip (including the time spent on the water) is a choice variable, so that the time cost of a trip is itself a matter of choice. Yet at the time the trip decision is made the angler makes the decision based on the expected length of the trip and by extension the expected time cost of the trip. See McConnell [11] and McConnell and Strand [12] for related discussions.

climatology data for Mitchell Field in Milwaukee, posted electronically by the National Weather Service.[8]

The variable $catch_t$ is the trip catch on day t of salmonids meeting size limits, as reported in the telephone interviews. Total (boat) catch on the trip is considered instead of the angler's individual catch, because salmonid fishing by boat on Lake Michigan usually involves trolling with at least several lines per angler, and landing a fish is a team effort. This variable is a posterior state variable, unobserved at the time the trip decision is made, so its role in estimation is strictly conceptual, as described in the next section. The variable $excatch_t$ is an anterior state variable denoting the trip catch on the previous outing. Its relationship to the variable $catch_t$ is obvious; for instance, if the angler fishes on day t, $excatch_{t+1} = catch_t$. The variable $catch2_t$ is the site-wide average catch of salmonids per boat on day t. It is an anterior state variable constructed from the 1995 creel census conducted by the Wisconsin Department of Natural Resources at launch sites in Milwaukee and Racine counties.[9] The census included a total of 458 salmonid trips, with an average of 24.1 trips per week. Trips were grouped into weeks to derive weekly averages of catch per trip. Quadratic splines were then fit to these data, yielding the average catch estimates shown in Fig. 1. For the most part the figure matches the informal feedback we received from anglers. In late June the fishing was relatively poor. It was best from mid-July to early August, and then fell off sharply. The fishing was probably worse in early May and September than indicated in Fig. 1. For these intervals very few salmonid trips are in the creel census, and so at the chronological "tails" our estimates of site-wide catch per trip may be high.

Three other observable state variables are included in the model. The variable $elapsed_t$ equals the number of days elapsed since the last fishing trip, up to 20 days; when the days elapsed exceeds 20, the value of $elapsed_t$ remains at 20 until a trip is taken. The upper bound is arbitrary and is imposed to constrain the size of the DP algorithm. This variable is included to provide a dynamic analog to the static concept of diminishing marginal utility. We hypothesize that the utility from a trip increases as the time elapsed since the last trip increases. The variable *age* is a dummy variable taking a value of one if the angler is older than age 75 and zero otherwise. Older anglers in the sample indicated they are somewhat restricted in the decision to fish due to health and safety concerns. The final observable variable concerns participation in Salmon-A-Rama, a popular fishing derby that in 1995 lasted from Saturday July 15 to Sunday July 23. The total value of prizes in the contest is approximately $100,000, far more than any other fishing tournament in the Great Lakes, and the entry fee is a total of $20 per person for the full 9 days of the tournament. In principle, during Salmon-A-Rama an angler faces three alternatives in the fishing decision: to stay home, to participate in the derby, or to fish without participating in the derby. To simplify matters, we assumed that anglers who reported that they fished in the derby *always* preferred entering the derby when they fished, and that anglers who did not fish in the derby *never* preferred entering the derby when they fished. The effect of Salmon-A-Rama on the fishing decision is then adequately represented by including in $U_1(\cdot)$ the dummy variable

[8] As of June 1996, climate data are available at ftp://ftp.ncdu.noaa.gov/pub/data/fsod/fsod_ascii.14839.

[9] A separate approximation for the Kenosha ramp was not possible because of the small number of trips in the Kenosha census. In the model we assume average catch for Kenosha is the same as that for Milwaukee–Racine.

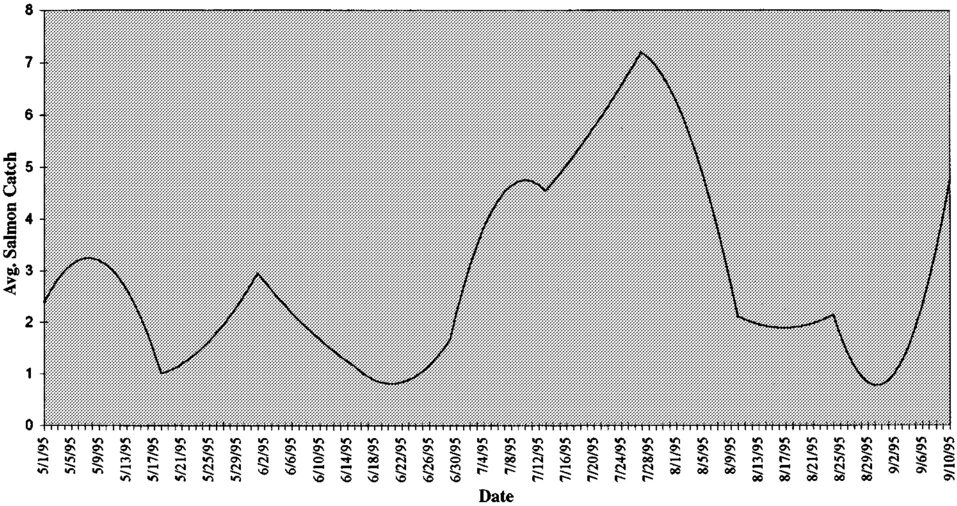

FIG. 1. Average salmonid catch at Milwaukee–Racine ramps, 1995.

$derby_t$, taking the value 1 for the dates July 15 to July 23 *if* the angler reported participating in Salmon-A-Rama, and 0 otherwise.[10]

The unobservable variable ε_t is assumed to be an identically and independently Gumbel-distributed random variable with location parameter $\mu = 0$ and scale parameter σ. It captures variation in the financial contributions of other trip participants, variation in the expected time cost of the trip, and so on.

3*b*. *Statement of the Estimable Model*

With the simple binary decision process considered here, the money measure of the expected net gain from salmonid fishing on a given day is simply $U_1(\cdot) - c_1(\cdot)$, where to remain consistent with the theoretical discussion in Section 2, the subscripts on these functions index the decision to take a trip. Letting z_t denote the angler's expected catch on day t, these functions take the form

$$U_1 = \gamma_1 temp_t + \gamma_2 wind_t + \gamma_3 elapsed_t + \gamma_4 derby_t + \gamma_5 z_t + \gamma_6 age, \qquad (16)$$

and

$$\begin{aligned} c_1 &= mcost + tcost_t \\ &= mcost + \delta_1 + \delta_2 job + \delta_3 job \cdot day_t + \delta_4 job \cdot day_t \cdot regday. \qquad (17) \end{aligned}$$

The dynamics of the model are as follows. On day t the angler knows the weather (maximum temperature and average wind speed) for days t and $t+1$. The angler assumes that for all days following day $t+1$ the weather is seasonal (typical).

[10] We did not anticipate the significance of Salmon-A-Rama in the fishing decision of anglers in the sample, so we determined participation via the mail survey sent at the end of the season. Consequently, we did not check for violations of the behavioral assumption underlying treatment of the derby in estimation. That is, we did not check for cases where anglers both entered the derby *and* fished during the period July 15–July 23 without entering the derby. Nonetheless, informal conversations with anglers in the sample left us with the impression that the assumption used here is a reasonable simplification.

Given the present quality of weather forecasting, assuming the angler knows the weather for a 2-day horizon seems reasonable. Setting the weather for days $t+2, t+3$, at their seasonal values implies that the future *variability* in the weather has no impact on the angler's current fishing decision, though the "typical" weather does. In the estimated model the seasonal weather for any day is the average weather for the 2-week period centered on the day. For instance, the seasonal wind speed for July 1 is the average wind speed over the 15 days centered on July 1.

The state process governing the evolution of day_t is straightforward. Because the start of the season (May 1) was a Monday, day_t evolves according to

$$day_t = \begin{cases} 0 & \text{if } t = 6, 7, 13, 14, 20, 21, \dots \\ 1 & \text{otherwise} \end{cases} \tag{18}$$

The time elapsed between fishing trips ($elapsed_t$) evolves in the obvious way. If a trip is taken on day t, then $elapsed_{t+1} = 1$. If no trip is taken, then $elapsed_{t+1} = elapsed_t + 1$, unless $elapsed_t = 20$, in which case $elapsed_{t+1} = 20$. Note that the upper limit on this variable implies that, all else equal, the expected utility for a trip taken 20 days after the previous trip is the same as a that for a trip taken, say, 30 days after the previous trip.

The angler's catch on a trip, $catch_t$, is a random variable unobserved by the angler at the start of the trip. The expected catch for a trip is a linear combination of the catch on the previous trip and the sitewide catch on day t. Formally, the angler's expected catch on day t is

$$z_t = \alpha_1 excatch_t + \alpha_2 catch2_t. \tag{19}$$

Certainly other, more complex and perhaps more intuitive expressions of the expected catch are possible, but indications from pre-testing are that models with more complex expressions for expected catch do no better, and may do worse, than a model using (19). Because the value of $excatch_t$ is not observed until after the first trip of 1995, estimation involves only those observations following the first trip of the season. Importantly, the estimated model nonetheless applies to the entire season—in particular, to the start of the season before the first trip is made—*if* the expression of catch expectations in (19) applies throughout the season. In this case, before the first trip is made $excatch_t$ is the catch on the last trip of the previous season.

Because utility is linear in catch, the expected utility is linear in expected catch, as presented in (16). Higher moments of the catch distribution do not affect the money measure of the net gain from fishing on the current day (day t). Unfortunately, matters are not so simple in the calculation of the expected gain from *future* fishing, $V_{t+1}(\mathbf{x}_{at}, i; \mathbf{c}, \Gamma)$, a calculation which is part of the angler's decision process (see expressions (5) and (6)). Recall that in general calculation of this value involves integrating on day t over the random elements of $\mathbf{x}_{a,t+1}$, given the anterior state vector $\mathbf{x}_{at}$ and the decision y_t. In the present application the only problematic variable is $excatch_{t+1}$. Given the decision *not* to fish on day t, $excatch_{t+1}$ is equal to $excatch_t$, and so calculation of $V_{t+1}(\cdot)$ is a deterministic exercise.[11] On the other hand, given the decision to fish on day t, $excatch_{t+1}$ is

[11] $excatch_t$ is an anterior state variable that affects expected utility on day t via its influence on expected fish catch z_t.

equal to $catch_t$, and so because $v_{t+1}(\cdot)$ is not known to be linear, calculation of $V_{t+1}(\cdot)$ necessarily involves integrating over the distribution of $catch_t$.

In estimation $catch_t$ is modeled as Poisson-distributed with mean z_t. A significant theoretical advantage of using the Poisson distribution is that it applies to random events taking positive integers, obviously the case for fish catch. A significant empirical advantage is that the recursive equation in (10)—the equation used to calculate the money measure of the expected *future* gain from fishing—can be solved for the case where the angler chooses to fish on day t, without resorting to numerical quadrature. Suppressing for the sake of clarity those anterior state variables governed by deterministic processes, and noting again that for $y_t = 1$, $excatch_{t+1} = catch_t$, Eq. (10) can be stated,

$$\begin{aligned} V_{t+1}(z_t(excatch_t), y_t = 1) &= \sum_{catch_t} \Bigg[\bigg(\frac{1}{\sigma} \ln \big\{ \exp \sigma \big[U_1(z_{t+1}(catch_t)) - c_t \\ &\qquad + \beta V_{t+2}(z_{t+1}(catch_t), y_{t+1} = 1) \big] \big\} \bigg) \cdot \left(e^{-z_t} \frac{z_t^{catch_t}}{catch_t!} \right) \Bigg] \\ &\quad + \sum_{catch_t} \big[\beta V_{t+2}(z_{t+1}(catch_t), y_{t+1} = 0) \big] \cdot \left(e^{-z_t} \frac{z_t^{catch_t}}{catch_t!} \right). \end{aligned} \tag{20}$$

A few final notes about the mechanics of the estimation are worth reporting. $Elapsed_t$ and $catch_t$ are integer variables and were treated as such in the estimation algorithm. $Mcost_t$ is a continuous real variable. In the dimension of this variable, $V_t(\cdot)$ was approximated as a fifth-order Chebyshev polynomial. Upper bounds on all three of these variables were imposed to constrain the size of the dynamic programming problem. The upper bound on $elapsed_t$ is already discussed. The upper bound on $mcost_t$ is \$50, which is greater than the maximum value (\$32) calculated for the sample. The upper bound on $catch_t$ is 25, which is greater than the maximum catch observed in the sample. To assure a good approximation to the distribution of $catch_t$ despite this upper bound—that is, to avoid significant truncation of the distribution—an upper bound of 15 was set for expected catch, z_t.[12]

4. ESTIMATION RESULTS

The DFP algorithm in Goldfeld and Quandt's GQOPT was used to obtain maximum likelihood estimates of the parameter set Γ. Estimation results were confirmed with NPSOL, a solver created at the Department of Operations Research, Standford University [9]. A copy of the FORTRAN subroutine used to calculate likelihood values is available from the authors.

[12] The Poisson distribution has an upper limit of infinity and is completely defined by its mean z_t (recall that for the Poisson distribution, the mean and variance are the same). For $z_t = 15$, the lower tail of the Poisson at $catch_t = 25$ is 0.9938. At the solution the constraint on expected catch was not binding for any observation. In fact, at the solution the expected catch for the vast majority of observations was *far* less than 15, indicating that in estimation the approximation to the Poisson distribution was excellent.

Fourteen parameters were included in Γ: the scale parameter σ, the two catch expectation parameters α, the four cost parameters δ, and the six parameters γ of the expected utility function. The impatience factor β was not estimated. In theory this factor is equal to the discount factor for money. In a daily model, this implies $\beta \approx 1$, and so to reduce the size of the estimation problem we set $\beta = 1$.

Results of the estimation are presented in Table 1. A 1° Fahrenheit increase in the air temperature raises the net value of a fishing trip by $1.67. A 1 mile per hour increase in the wind speed reduces the net value of a trip by $3.52. The coefficient on $elapsed_t$ is statistically significant, but its sign is opposite that expected. It indicates that as the time elapsed increases the expected net gain from fishing falls at the rate of $15.16 per day. Whether this is a legitimate expression of the dynamics of preferences over time—the value an angler places on fishing falls as the time spent away from fishing increases—or instead reflects a misspecification bias arising because anglers who rarely fish are not adequately differentiated from those who do, is a difficult question that we do not address here.

The coefficient on $derby_t$ testifies to the significance of Salmon-A-Rama to the anglers in the sample. For participants, the derby raises the expected net value of a trip by $162.63. The increase may be due to the competitive and social aspects of the contest, as well as the opportunity to win substantial prizes.

The expected fish catch is nearly a convex combination of the catch on the last trip and the site-wide catch on the current day, with a greater weight on the angler's catch on the last trip (0.730) than on the current site-wide catch (0.476). The large standard error on the latter estimate indicates it is imprecise. The increase in the expected value of a trip from a marginal increase in the expected fish catch is only $1.04 (the value of the parameter γ_5). This is lower than we anticipated and may be due to the linear form used to represent the utility of anglers, combined with the high average catch rate (five salmonids per trip) for anglers in the sample. The estimate may simply indicate that for highly successful anglers, catching one more fish has a low payoff. Alternatively, together with the large standard error on the expectation parameter α_2, the low value of γ_5 may indicate that catch expectations are not well specified for the sample. Anglers in

TABLE 1

Parameter Estimates of the Model

Parameter	Associated variable	Estimate	Standard error
γ_1	$Temp_t$	1.67	.243
γ_2	$Wind_t$	−3.52	1.458
γ_3	$Elapsed_t$	−15.16	1.621
γ_4	$Derby_t$	162.63	9.499
γ_5	z_t	1.04	.653
γ_6	*Age*	−68.93	9.359
δ_1	(Constant)	220.83	47.185
δ_2	*Job*	−70.66	7.565
δ_3	$Job \cdot day_t$	154.29	8.291
δ_4	$Job \cdot day_t \cdot regday$	2.73	3.110
α_1	$Excatch_t$	0.730	0.363
α_2	$Catch2_t$	0.476	0.952
σ	(Scale parameter)	0.00988	0.0047

the sample may form their catch expectations in a complicated way, often expecting to catch fish despite low values for the current site-wide catch, and regardless of their catch on the last trip. In this case the decision to fish on a given day would not be particularly sensitive to the expected catch variable constructed in (19), engendering a low value for γ_5.

As expected, the coefficient on the binary variable *age* is negative and indicates that probably due to health and safety concerns, the expected net value of a fishing trip is \$68.93 lower for an angler over age 75 than for one who is not.

Keeping in mind that costs are *subtracted* to obtain the net value of fishing, positive signs on the coefficients δ_i indicate a *reduction* in the net value of fishing. The values of δ_2, δ_3, and δ_4 indicate the following about the time cost of fishing. First, as indicated by the value of δ_4 and its associated standard error, there is little difference in the time cost of fishing for anglers who work a regular week (Monday–Friday) and working anglers whose schedule is not regular. Second, as indicated by the sum of δ_3 and δ_4, for an angler who works a regular week the opportunity cost of a fishing trip is \$157.02 greater on a weekday than on a weekend. And third, as indicated by the value of δ_2, the cost of fishing on a weekend is actually \$70.66 *greater* for a retired angler than for an angler who works. On the other hand, on a weekday the time cost of fishing is \$86.56 lower for a retired angler than for an angler who works a regular week ($\delta_2 + \delta_3 + \delta_4$). Possibly retired anglers choose to fish on weekdays to avoid the crowds and save the weekends for other activities.

Figures 2–4 illustrate the sort of analysis possible with the model. Figures 2 and 3 map the probability of fishing against the money cost of a fishing trip and the day of the season. In both figures, probabilities for each day are calculated for the case where the previous catch was five ($excatch_t = 5$, the season average catch); the last trip was 8 days before ($elapsed_t = 8$); and the angler participates in Salmon-A-

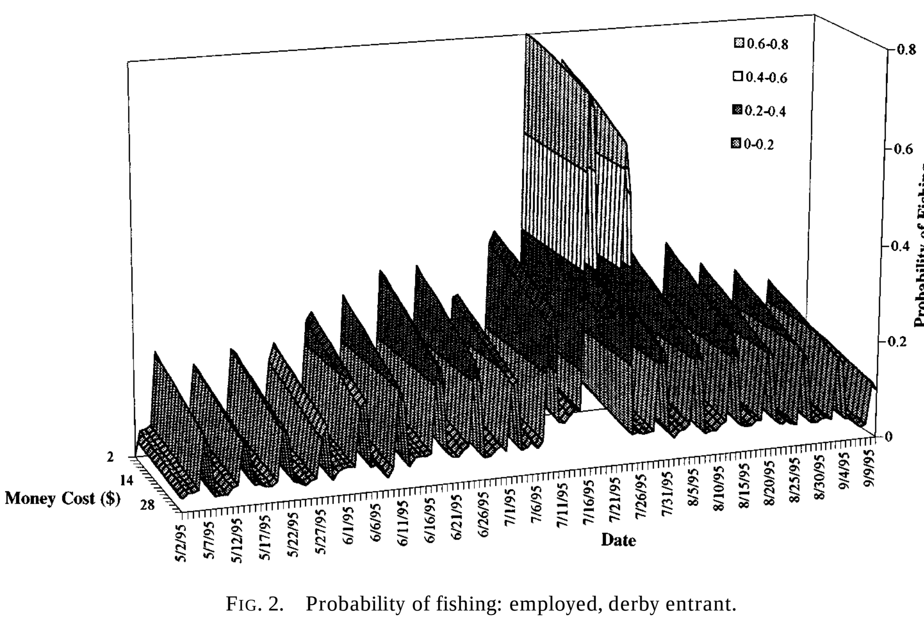

FIG. 2. Probability of fishing: employed, derby entrant.

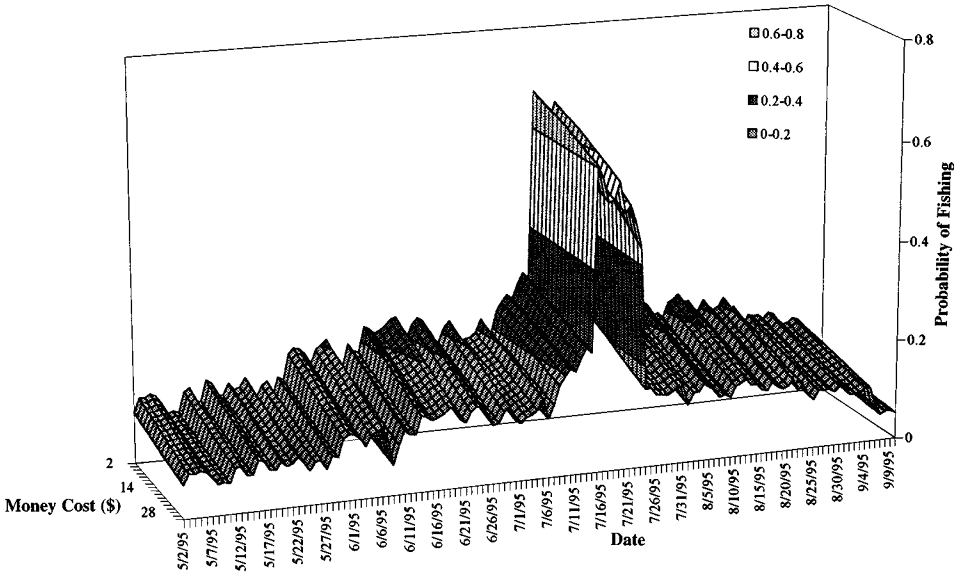

FIG. 3. Probability of fishing: retired, derby entrant.

Rama. Figure 2 applies to employed anglers with a regular (Monday–Friday) work week. Figure 3 applies to retired anglers (but with $age = 0$). The distinctive accordion-like structure of Fig. 2 arises because employed anglers are much more likely to fish on a weekend than on a weekday. The otherwise corrugated appearance of the figures—especially prominent in Fig. 3—arises because of changes in

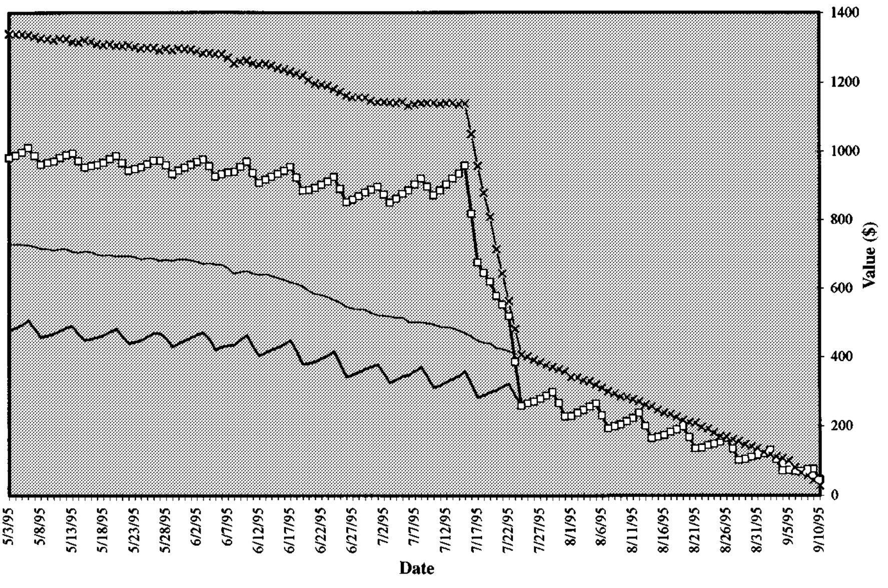

FIG. 4. Expected net seasonal value of salmon fishing (V_r). □, employed angler, derby entrant; ×, retired angler, derby entrant; —, employed angler, no derby; — retired angler, no derby.

the daily wind and temperature. The figures illustrate several results. First, Salmon-A-Rama has a significant effect on the fishing decision. For employed anglers this effect is most prominent on the two weekends of the derby. Second, the money cost of fishing reduces the probability of fishing on any given day; generally the probability of fishing falls by about one-third as the money cost of a trip increases from $2 to $32 (the maximum value in the sample). And third, quite apart from the effects of Salmon-A-Rama, the probability of fishing is greatest from the end of June to the beginning of August (this is most apparent by comparing the height of the ''peaks'' in Fig. 2), probably because catch rates were high in this period and the weather was relatively pleasant.

Figure 4 presents the values $V_t(\cdot)$ for particular states of nature. Values are presented for four categories of anglers, each distinguished by whether the angler is employed or retired (but with $age = 0$), and whether the angler fished in Salmon-A-Rama. Values are for the remainder of the season, as evident by the definition of $V_t(\cdot)$ in (10), and are derived for the case where the money cost of a trip is the sample median ($7.50), and the angler last fished 8 days before, catching five salmonids (the season average catch). Importantly, then, Fig. 4 does not display the expected *time paths* of the value of salmonid fishing; instead it is correctly understood to present *conditional* expected values for the remainder of the season.

Several insights are apparent from Fig. 4. Seasonal values appear plausible. The value of the season is highest for a retired angler who participates in Salmon-A-Rama ($1340) and lowest for an employed angler who does not ($480). For participants in Salmon-A-Rama the conditional expected value of salmonid fishing is much higher just before the derby than just after it, suggesting that most of the season's value is contained in the 9 days of the derby. As expected, after the derby the conditional expected value of the season is the same for derby participants as for nonparticipants: for both types of anglers, on the day after the derby (July 24) the future looks exactly the same. For employed anglers the conditional expected value of salmonid fishing cycles on a weekly basis, rising during the work week and peaking on Saturday. The explanation for this result is straightforward. Because employed anglers are unlikely to fish during the work week, and the time elapsed since the last trip has a negative effect on the net value of a trip, employed anglers are worse off on a Monday than they are on the following Saturday in the same circumstance. To elaborate in the context of Fig. 4, on any given Monday it is not until the following Saturday—at which time 13 days will have passed since the last fishing trip—that there is any reasonable chance that the angler will fish. So, all else equal, the angler is worse off on a Monday having last fished 8 days before than he is on the following Saturday having last fished 8 days before.

A good approximation of the unconditional value of salmonid fishing at the start of the season is obtained by setting the time elapsed since the last trip at 20 days (the maximum), and setting the previous catch at 5 (the season average catch). At the median trip cost of $7.50, values are close to those shown in Fig. 4: $1340 and $730 for retired derby entrants and nonentrants, and $980 and $480 for employed derby entrants and nonentrants. For our particular sample of dedicated anglers these values seem reasonable. An approximation of daily values for trips in and out of the derby can be calculated as follows. The difference between the two seasonal values for retired anglers is $610, which we take as an estimate of the value that retired derby anglers place on fishing in the derby. These anglers took an average of 5.3 derby trips, yielding a value per derby trip of $610/5.3 ≈ $115/trip. Note that this is an *average* value per derby trip, compared to the coefficient on $derby_t$, \$162.63, which gives the *marginal* effect of the derby on the expected value of a trip.

Retired anglers took an average of 18.8 non-derby trips per season. Dividing the seasonal value of retired non-contestants by this figure yields \$39 as an approximation of the value placed by retired anglers on non-derby trips. Similar calculations for employed anglers yield \$88 for a derby trip and \$37 for a non-derby trip. Note that the value of a non-derby trip is virtually the same for retired and employed anglers.

Finally, to examine the effect of an increase in site quality on the value of the season, the average site-wide catch of salmonids on each day of the season was raised by one fish. Keeping all other variables at the levels used in Fig. 4, the value of the season rises by about \$20 and \$14 for retired and employed anglers who fish in Salmon-A-Rama. It rises by \$21 and \$12 for retired and employed anglers who do not fish in Salmon-A-Rama. These values are low and may reflect the low marginal value of a fish for anglers who typically catch close to 100 salmonids per year.

5. CONCLUSION

This paper presents an estimable dynamic model of recreation behavior that avoids a number of consistency issues arising in static random utility models, while permitting standard welfare analysis. In an illustrative application of the model to the behavior of Lake Michigan salmonid anglers, results are mixed. The signs for all estimated coefficients but one are as expected, and most are statistically significant. Seasonal values for salmonid fishing are plausible. Moreover, the application demonstrates the model's potential to estimate economic variables not readily calculated in static analyses, such as the relative time cost of fishing on a weekend. Still, it is questionable whether the model well approximates the dynamics of catch expectations in the decision to take a trip.

The application highlights a number of methodological issues, and we conclude by commenting on some of these. First, in the valuation of nonmarket goods, dynamic structural models require either observation of the daily (or periodic) budget b_t, or assumptions concerning both the state equation governing the budget *and* the utility function that effectively eliminate the budget from the estimable model. As it is extraordinary to obtain data with daily (periodic) budgets, future empirical work will be limited to simple and often unsatisfying treatments of budget state equations.

Second, dynamic structural models assume that the basic structure of the relevant decision problem is the same for all agents. Of course, the same fundamental assumption of homogeneity underlies static models, but the extensive nature of a structural dynamic model, especially the formal statement of state equations, engenders the sense that the model overreaches. For instance, in the model presented here expected catch is cast as a linear combination of two variables, when it seems reasonable that catch expectations vary considerably across anglers, and perhaps over time.

On the matter of the formation of catch expectations, three observations are relevant. First, in static analyses there is no formal statement of catch expectations, and consequently in the calculation of seasonal welfare values such expectations are implicit and fundamentally *ad hoc*. Second, when an agent's judgment of the nature of a stochastic process is not disciplined by the marketplace, there are no apparent theoretical grounds for asserting one form for expectations over another. So, for instance, whereas it is possible to construct an argument that the catch expectations of commercial anglers are fairly homogenous and thus adequately represented by a particular structure—essentially, those anglers who badly underperform their competitors in forecasting catch do not stay in business for long—similar arguments appear somewhat problematic when applied to recreational anglers.[13] And third, the assumption of homogeneity can be relaxed by estimating a separate structural problem for each angler or each subset of anglers. This is simply a limiting case in which the number of estimable parameters grows large. It requires a large number of observations for each angler and is not computationally practical.

Finally, estimation of dynamic structural models requires surmounting several notable obstacles. Obtaining the requisite data is generally quite expensive, as it involves fairly detailed panel data. Developing the estimation algorithm requires considerable effort by a programmer experienced in writing dynamic programming algorithms. Moreover, because a dynamic program must be solved at each iteration in the search for parameter estimates, it is critical to computational feasibility that the model capture the essential features of the decision problem with relatively few state variables. The best way to distill the set of potential state variables to the essential few is by preliminary analyses using standard regression techniques (e.g., logit or multinomial logit regressions), though this comes at the cost of compromising the usual statistical tests. Even after such preliminary analysis, decision problems larger than the simple binary choice problem presented here will probably require processor time on a supercomputer.

With these obstacles in mind, future work should focus on determining when it is appropriate to use a static estimation framework—when, in other words, the *forward-looking* element of the decision process (the value function $V_{t+1}(\cdot)$) is weak or nonexistent or is suitably approximated with a simple functional form. Static estimation of this sort abandons the effort to develop insights to the dynamic processes governing behavior, but it may yield welfare estimates close to those obtained via its dynamic counterpart. This is an empirical question that awaits investigation.

REFERENCES

1. W. L. Adamowicz, Habit formation and variety seeking in a discrete choice model of recreation demand, *J. Agric. Res. Econom.* **19**, 19–31.
2. American Automobile Association, "Your Driving Costs," 1995 ed., Automotive costs booklet prepared by AAA and Runzheimer International, Rochester, WI.
3. R. Bellman, "Dynamic Programming," Princeton Univ. Press, Princeton (1957).
4. M. Ben-Akiva and S. R. Lerman, "Discrete Choice Analysis: Theory and Application to Travel Demand," MIT Press, Cambridge, MA (1985).

[13] An anonymous referee points out that those anglers who badly underperform others will consistently obtain less utility in fishing than will their counterparts, and therefore will, on average, fish less often. This reasoning may serve as the basis for making assumptions about the homogeneity of catch rate expectations.

5. N. E. Bockstael, Travel cost models, *in* "The Handbook of Environmental Economics" (Daniel W. Bromley, Ed.), Blackwell, Cambridge, MA (1995).
6. N. E. Bockstael, W. M. Hanemann, and C. L. Kling, Modeling recreational demand in a multiple site framework, *Water Res. Res.* **23**, 951–960 (1987).
7. N. E. Bockstael, K. E. McConnell, and I. E. Strand, A random utility model for sportfishing: some preliminary results for Florida, *Mar. Resource Econom.* **6**, 245–260 (1989).
8. Z. Eckstein, and K. Wolpin, The specification and estimation of dynamic discrete choice models: A survey, *J. Human Resources* **29**, 562–598 (1989).
9. P. E. Gill, W. Murray, M. A. Saunders, and M. H. Wright, "User's Guide for NPSOL (Version 4.0): A FORTRAN Package for Nonlinear Programming," Technical Report SOL 86-2, Systems Optimization Laboratory, Department of Operations Research, Stanford University, (1986).
10. B. L. Johnson, S. R. Milliman, R. C. Bishop, and J. F. Kitchell, Evaluating fishery rehabilitation under uncertainty: A bioeconomic analysis of quota management for the Green Bay Yellow Perch fishery, *North Amer. J. Fish. Management* **12**, 703–720 (1992).
11. K. E. McConnell, On-site time in the demand for recreation, *Amer. J. Agric. Econom.* **74**, 918–925 (1992).
12. K. E. McConnell and I. E. Strand, Measuring the cost of time in recreational demand analysis: an application to sport fishing, *Amer. J. Agric. Econom.* **63**, 153–156 (1981).
13. S. R. Milliman, R. C. Bishop, and B. L. Johnson, Economic analysis of fishery rehabilitation under biological uncertainty: A conceptual framework and application, *Can. J. Fish. Aquat. Sci.* **44**, 289–297 (1987).
14. J. W. Milon, Travel cost methods for estiating the recreational use benefits of artificial marine habitat, *South. J. Agric. Econom.* **20**, 87–101 (1988).
15. M. Miranda and G. Schnitkey, An empirical model of asset replacement in dairy production, *J. Appl. Econom.* **10**, 541–556 (1995).
16. E. Morey, W. D. Shaw, and R. Rowe, A discrete-choice model of recreational participation, site choice, and activity valuation when complete trip data are not available, *J. Environ. Econom. Management* **22**, 181–201 (1991).
17. E. Morey, W. D. Shaw, and M. Watson, A repeated nested-logit model of Atlantic salmon fishing, *Amer. J. Agric. Econom.* **75**, 578–592 (1993).
18. J. Rust, Optimal replacement of GMC bus engines: A dynamic model of Harold Zurcher, *Econometrica* **55**, 999–1033 (1987).
19. J. Rust, "A Backwards Solution Algorithm for Structural Estimation of Discrete Control Processes," unpublished manuscript, University of Wisconsin, Madison (1988).
20. J. Rust and A. Pakes, "Estimation of Dynamic Structural Models: Problems and Prospects. I. Discrete Decision Processes," unpublished manuscript, University of Wisconsin, Madison (1990).
21. S. K. Swallow, Intraseason harvest regulation for fish and wildlife recreation: An application to fishery policy, *Amer. J. Agric. Econom.* **76**, 924–935 (1994).
22. T. C. Wegge, R. T. Carson, and W. M. Hanemann, "Site Quality and the Demand for Sportfishing in Southcentral Alaska," paper presented at the Sportfishing Institute Symposium, Charleston, SC, March 14–15, 1988.