Static Modeling of Dynamic Recreation Behavior: Implications for Prediction and Welfare Estimation

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Abstract

This paper examines the consequences of using a static model of recreation trip-taking behavior when the underlying decision problem is dynamic. In particular, we examine the implications for trip forecasting and welfare estimation using a panel dataset of Lake Michigan salmon anglers for the 1996 and 1997 fishing seasons. We derive and estimate both a structural dynamic model using Bellman's equation, and a reduced-form static model with trip probability expressions closely mimicking those of the dynamic model. We illustrate an inherent identification problem in the reduced-form model that creates biased welfare estimates, and we discuss the general implications of this for the interpretation of preference parameters in static models. We then use both models to simulate trip taking behavior and show that although their in-sample trip forecasts are similar, their welfare estimates and out-of-sample forecasts are quite different.

1. Introduction

Two of the more practical applications of recreation demand modeling are forecasting the effects of site quality changes on both behavior and welfare. This is particularly true for resource managers who must allocate limited budgets across multiple management activities, including investments in site quality improvements. In a recent paper that focuses on the role of preference heterogeneity in out-of-sample prediction, Provencher and Bishop (2003) demonstrate for recreational angling that static random utility models (RUMs) tend to overstate the impact of inter-seasonal changes in site quality on trip frequency. This implies the actual number of trips taken during a season is less elastic than the predicted number of trips and therefore any welfare estimates based on those predictions may be exaggerated.

Although several explanations for this result are possible, perhaps the most reasonable is that angler behavior is constrained on a seasonal basis in a way not considered by static RUMs. One approach that addresses this possibility is the Kuhn-Tucker (KT) model which imposes a seasonal budget constraint on each agent, as in Phaneuf, Kling and Herriges (2000). However, although appealing for its utility-theoretic basis, KT models do not account for the temporal allocation of trips throughout a season and therefore overlook useful information that might be gleaned from observing the impact of intra-seasonal variability on recreation behavior.

An integrated utility-theoretic model linking a seasonal recreation budget with a dynamic (forward-looking) RUM therefore would seem to be appropriate, but empirical estimation of structural dynamic models is both complicated and time consuming. As evidence of this, one need look no further than the existing literature on recreation demand which contains a preponderance of static RUMs (see Herriges and Kling, 1999, for an overview) despite the fact that the recreation decision clearly involves the evolution of predictable state variables and the expenditure of limited resources through time, thus making the decision appropriate for modeling in a dynamic framework.

With this in mind, the purpose of this paper is to examine the consequences of using a much simpler static model of trip-taking behavior when a more complicated dynamic one is appropriate. In particular, we examine the implications for trip prediction and welfare estimation using Lake Michigan salmon angling data for the 1996 and 1997 fishing seasons. Our results suggest that although a static model can forecast in-sample trip-taking behavior quite well, the out-of-sample forecasts are not as good and the welfare estimates are significantly different from those produced by a fully dynamic model.

2. Derivation of the Behavioral Model

We model the trip decision as a simple binary process in which the angler decides on each day of the season whether to fish for salmon, or instead spend the day doing other things. This is a reasonable representation of the decision faced by our Lake Michigan salmon anglers: on any given day the variability in catch rates along the Lake Michigan shore is difficult to detect and, because fishing is most often done far from shore, aesthetic differences among launch sites are few. Thus the vast majority of anglers in the study took the bulk of his (all anglers are male) trips from one or two favorite launch sites. Moreover, the vast majority of fishing trips taken by anglers in the sample were salmon trips on Lake Michigan. For example, of the 1504 total trips taken by sample anglers in 1996, 92 (6.1%) were non-Lake Michigan (usually inland lake) fishing trips; 56 (3.7%) were non-salmonid trips on Lake Michigan; and the remaining 1356 (90.2%) were salmonid trips on Lake Michigan. Of these salmonid trips, 1258 (83.6% of all trips, 92.8% of Lake Michigan salmonid trips) were from boat launches along the Milwaukee-Racine waters of Lake Michigan.

We present the basic model first. Letting $\mathbf{x}_{nt}$ denote a vector of state variables affecting the trip utility of angler (n) on day (t), the net utility from a fishing trip on day (t) can be expressed as:

$$u_{nt} \equiv \beta \mathbf{x}_{nt} + \varepsilon^{*}_{nt} \tag{1}$$

where β is a conformable vector of preference parameters. The vector of state variables $\mathbf{x}_{nt}$ is observable in the sense that both the angler and the analyst observe the value of these variables at the start of day (t). The random state variable ε^{*}_{nt} is assumed to be iid standard logistic (arising from the difference between two iid standard Gumbel-distributed random variables $\boldsymbol{\varepsilon}_{nt} \equiv \left\{\varepsilon^{1}_{nt}, \varepsilon^{0}_{nt}\right\}$, the first representing the unobserved utility from taking a trip, the second representing the unobserved utility from not taking a trip) and is observed contemporaneously by the angler but never observed by the analyst.

In the analysis, the vector $\mathbf{x}_{\mathrm{nt}}$ includes an intercept and the following variables: the average (expected) money cost of a trip, $cost_n$, taken as the sum of driving costs, ramp fees, and boat operation costs and food costs, less the donations made by other anglers on the trip to defray trip costs; a variable denoting whether the angler is employed full-time during the fishing season, job_{n}; a variable denoting the average site-wide catch on day (t), $catch_{\mathrm{t}}$; the weather variables $temp_{\mathrm{t}}$, denoting the high temperature on day (t), and $wind_{\mathrm{t}}$, denoting average wind speed on day (t); the time cost variable $weekday_{\mathrm{t}}$, a dummy variable taking a value of one if the day is Monday through Friday; the time cost interaction term $job_n \cdot workday_{nt}$ taking a value of one on days when a fully employed angler is scheduled to work; a dummy variable $derby_{\mathrm{t}}$ taking a value of one if day (t) falls within the run of a popular annual 9-day fishing derby based in Racine, called Salmon-O-Rama; and two variables that capture the effect of past behavior on current trip decisions: $elapsed_{\mathrm{nt}}$, recording the number of days elapsed since the last salmon trip taken by angler (n), and $elapsed_{nt}^2$. Previous models by Provencher and Bishop (1997) and Provencher, Baerenklau and Bishop (2002) each used only the linear term and derived results consistent with habit formation. The quadratic specification we use here (also used by Swait *et al*., 2004) is more flexible and may provide additional insights into the effect of lagged endogenous variables on trip taking behavior. Furthermore, we assume the *inter*seasonal elapse of time has a very different effect on utility than the *intra*seasonal elapse of time. This is captured by a dummy variable $first_{nt}$ taking a value of zero if no trip has yet been taken during the season and one otherwise. This variable enters the utility function directly as a component of $\mathbf{x}_{\mathrm{nt}}$ and through interactions with $elapsed_{nt}$ and $elapsed_{nt}^2$. If no trip has yet been taken the utility function is reduced by the coefficient on $first_{nt}$ and by the omission of the variables $elapsed_{nt}$ and $elapsed_{nt}^2$.

In a static model, the net utility function in (1) denotes the difference between the utility on day (t) with a trip and without a trip. The income allocated for consumption on day (t) nets out under the assumption that income not spent fishing is spent in the consumption of other goods. In the absence of this assumption, the model must accommodate income dynamics. However, the model nonetheless includes two variables with implications for dynamic decision-making: $elapsed_{\mathrm{nt}}$ and $elapsed_{nt}^{2}$. Arguably a forward-looking angler recognizes that a trip on day (t) affects utility in the future via these variables. Yet these variables do not provide a compelling case for dynamic analysis. For example, to argue that the presence of $elapsed_{\mathrm{nt}}$ in the utility function compels modeling the decision process as dynamic is to argue, given a positive marginal effect of elapsed on utility, that an angler on day (t) may choose to postpone a trip because he understands that postponement increases the utility of future trips; this is akin to postponing opening a gift in the knowledge that the joy of consumption will be greater for the wait. Though we do not doubt the existence of such effects, given the great difficulty of structural estimation of dynamic decision processes it strikes us as a relatively weak basis for dynamic modeling. By contrast, the dynamics introduced by a seasonal budget constraint pertain not to marginal changes in trip utility, but to the very opportunity to take a trip in the future. It seems eminently defensible to argue that an angler constrained to, say, eight trips during the season, performs forward calculations especially when only two or three trips remain.

2.1 The Seasonal Budget Constraint

An important question arises, though, regarding specification of this seasonal budget constraint. To be consistent with classical theory, the analyst should model the complete allocation of scarce resources across all activities in all time periods, including salmon fishing during the 1996 and 1997 seasons, in order to ensure the optimization condition that the marginal utility of each resource be equated across activities. But this approach clearly raises problems of empirical tractability and routinely is ignored by practitioners. An alternative approach that has gained currency in the behavioral economics and marketing literatures (Thaler, 1985 and 1990; Heath and Soll, 1996; Read, Lowenstein and Rabin, 1999; Moon and Casey, 1999) is that of “mental accounting.” Thaler (1999) observes,

> “A primary reason for studying mental accounting is to enhance our understanding of the psychology of choice. In general, understanding mental accounting processes helps us understand choice because mental accounting rules are not neutral. That is, accounting decisions such as to which category to assign a purchase, whether to combine an outcome with others in that category, and how often to balance the “books”, can affect the perceived attractiveness of choices. They do so because mental accounting violates the economic notion of fungibility. Money in one mental account is not a perfect substitute for money in another account. Because of violations of fungability, mental accounting matters” (p.185).

Mental accounting provides an explanation for behavior inconsistent with the life cycle hypothesis. Thaler (1990) observes that the life cycle hypothesis, in which current consumption is the outcome of an optimal allocation of consumption over time, does not fare well in real-world tests. For instance, the young tend to consume too little and the old tend to consume too much. In the context of recreation models, the life cycle hypothesis essentially argues that the decision to take a recreation trip is a dynamic problem in which a trip at time (t) subtracts from lifetime expected wealth, and the consumer determines whether this is a worthwhile tradeoff. Few people would argue that this is a useful or realistic conception of the trip decision. Yet what is the alternative?

The alternative is a model of mental accounting in which recreation trips fall within one of a consumer’s several mental accounts, with the account then allocated among a designated set of goods and services. This is the approach taken implicitly or explicitly by all published utility-consistent recreation studies that attempt to explain the demand for recreation trips over a specified horizon. Mental accounts are defined by their time frames, their sizes, and the set of goods that draw on them.

In the KT model, the lifetime dynamic budget is trimmed to an annual budget equal to annual income, which is then allocated across all consumption for the year. Provided relevant aspects of the trip decision are unchanging over the course of a year (for instance, there are no intraseasonal changes in site quality), this model seems quite reasonable and indeed it is to be favored for its simplicity and elegance. But it does make a particular assumption about the psychology of choice, one economists make willingly but psychologists caution against, namely mental accounts are quite broad in the set of goods that draws on them. Suppose, for instance, that hunting trips and food purchases are not perfectly fungible; that due to either household rules or norms, or perhaps due to the hunter's psychological bracketing, the hunter does not calculate, "If I take another hunting trip today, I'll have to cut back on gourmet foods". Far more likely is a narrow calculation suggestive of narrow bracketing, such as, "If I take a trip today, I won't be able to go next week", or a calculation consistent with narrow bracketing over goods, but broad bracketing over time, such as, "If I take a cruise this year, I won't be able to go next year".

The issue of mental accounting is especially apparent in trip occasion models attempting to examine the intraseasonal allocation of recreation trips. Such models have the potential to address economic issues which are of great concern to resource managers, but which have received relatively little attention from resource economists, such as season length, intraseasonal variation in site quality, and bag limits. In these models, the only way to avoid a model with a dynamic budget constraint is to assume that the time frame of mental accounts is the time frame of the choice occasion. In the repeated nested logit model of Morey, Rowe and Watson (1993), the relevant mental account allocates income to the consumption of all goods, but the duration of the account is the duration of a choice occasion (one week), and the size of the account is annual income divided by the number of choice occasions. Buchanan *et al*. (1998) assume that the relevant account is a daily budget defined by monthly disposable income divided by thirty. The account applies to all goods except those essential purchases (such as mortgage payments) already netted from monthly income. Provencher and Bishop (1997) and Provencher, Baerenklau and Bishop (2002) define the relevant budget as a daily budget that is conditional on a set of state variables and is random from the perspective of the analyst, though due to the linear form of the utility function, defining the exact value of the daily budget is not necessary for estimation of the choice model.

Misspecifying the budget constraint for recreation trips generates bad trip forecasts and bad welfare estimates impacting management decisions. Suppose, for instance, that managers of a fishery are interested in the economics of increasing catch rates at a number of sites, as would occur from habitat restoration and/or fish stocking programs. What would be the effect on angler welfare and trip behavior? In the presence of seasonal recreation budgets effectively constraining the number of trips taken in the season, the trip occasion models used in Morey, Rowe and Watson (1993) and Provencher, Baerenklau and Bishop (2002) would overstate angler trip response to the improvement, because these models do not impose the (true) constraint on the number of trips for the season.

This tendency for static trip occasion models to overstate the trip response of anglers to changes in catch rates was observed by Provencher and Bishop (2003) in a comparison of the forecasting performance of various static models of angler heterogeneity. The models compared included a number of finite mixture (latent class) and random parameters logit models. The application was to salmon fishing on Lake Michigan, and forecasts were compared for 1996 and 1997. Catch rates in 1997 averaged 31% greater in 1996 than in 1997. Generally the models estimated on the 1996 data overforecasted trips in 1997, and the models on the 1997 data underforecasted trips in 1996. Although several explanations for this result are possible, one of the most reasonable – arguably the most reasonable – is that angler behavior during the season is constrained in a way not considered by the static models. A dynamic budget constraint, in which trips are allocated from a seasonal trip budget, is a strong and reasonable candidate.

In the next sections we present two estimable models of trip taking behavior. The first model uses a common random utility specification for each choice occasion, but treats anglers as forward-looking decision-makers allocating a fixed seasonal trip budget. This budget is presumed to arise from an optimization problem we present later, analogous to that of KT model, solved by each angler at the start of the season. Specifically, we assume each angler allocates income between fishing and other consumption with the understanding that future decisions about when to fish will be made optimally. The model is utility-theoretic and yet addresses the trip occasion decision without the untenable assumption that all income allocated to the day in question must be consumed. The second model is a reduced-form static version of the first (an extension of that examined by Provencher and Bishop, 2003) in which anglers are treated as myopic, deciding on each day of the season whether to take a trip. As with other such models found in the literature, it is understood that if a trip is not taken then the budget allocated to the day is spent on other consumption that day.

Our goal is to evaluate the performance of both models, but we focus on the prediction and welfare estimation results for the static model assuming the true underlying decision problem is represented by the dynamic model. In reality, the assumption of a fixed seasonal budget may be too restrictive, and agents may instead update their mental accounts as they revise their expectations about the remainder of the season. But the static and dynamic models presented here may be considered as two extremes of a spectrum: continuous (daily) updating of the seasonal budget and no updating. With this interpretation, our results represent upper bounds on the discrepancies introduced by the reduced-form static model.

2.2 Statement of the Structural Dynamic Model

In the static model given by (1), the optimal decision on day (t) is to take a trip if $u_{nt} > 0$. Letting y_{nt} take a value of one if angler (n) takes a trip on day (t) and zero otherwise, and assuming iid standard Gumbel-distributed error terms, the probability of observing angler (n) taking a trip on day (t) is given by the usual logit expression:

$$P\left(y_{nt}=1\right)=\frac{\exp\left(\beta\mathbf{x}_{nt}\right)}{1+\exp\left(\beta\mathbf{x}_{nt}\right)}. \tag{2}$$

The likelihood of angler (n)'s trip sequence for the season follows as:

$$L_n^{static} \equiv \prod_t \left[P\left(y_{nt}=1\right)^{y_{nt}} \cdot P\left(y_{nt}=0\right)^{1-y_{nt}}\right]. \tag{3}$$

In the dynamic model, the decision problem is complicated by the state equations

$$\mathbf{x}_{n,t+1} \equiv \mathbf{f}\left(\mathbf{x}_{nt}, y_{nt}\right) \tag{4}$$

and

$$s_{n,t+1} \equiv s_{nt} - y_{nt}, \tag{5}$$

where s_{nt} is the stock of trips (i.e., the budget) remaining for the season. The state equation in (4) is strictly relevant for three variables in our model. The first is the dummy variable $first_{nt}$, tracking whether angler (n) has yet to take a trip during the season. Indexing the first day of the season by t=0, it evolves according to:

$$first_{nt} = \begin{cases} 0 \quad \text{if} & \left\{ \begin{array}{l} t = 0, \text{ or} \\ t > 0 \text{ and } \sum_{s=1}^{t-1} y_{ns} = 0 \end{array} \right\} . \\ 1 \quad \text{otherwise} \end{cases} \tag{6}$$

The other two state variables[1] are $elapsed_{nt}$ and $elapsed_{nt}^2$:

$$elapsed_{n,t+1} \equiv \begin{cases} 1 & \text{if } y_{nt} = 1 \\ elapsed_{nt} + 1 & \text{otherwise} \end{cases} \tag{7}$$

$$elapsed_{n,t+1}^2 \equiv \begin{cases} 1 & \text{if } y_{nt} = 1 \\ \left(elapsed_{nt} + 1\right)^2 & \text{otherwise} \end{cases} \tag{8}$$

For the sake of simplicity of notation, we use the general form presented in (4). Regarding (5), in this binary decision problem there is a one-to-one correspondence between the number of trips remaining in the season and the fishing budget available to angler (n) for fishing on day (t); so we express the budget constraint in terms of trips. Also, there is no justification for the presence of $cost_n$ in the utility function in (1) because, in contrast to the static model, it is not true that the opportunity cost of a trip on day (t) is $cost_n$ less consumption of other goods on day (t); rather, the opportunity cost is one fewer trip available to take in the future. Later we show how welfare estimation remains possible with this model even though we remove $cost_n$ from (1).

In the dynamic model the angler's decision problem is solved recursively. In the last period (T) angler (n)'s indirect utility may be written as:

$$\nu_{nT}\left(\mathbf{x}_{nT}, s_{nT}, \boldsymbol{\varepsilon}_{nT}\right) \equiv \begin{cases} \max\left[\beta \mathbf{x}_{nT} + \varepsilon_{nT}^1, \varepsilon_{nT}^0\right] & \text{if } s_{nT} \geq 1 \\ \varepsilon_{nT}^0 & \text{otherwise} \end{cases}, \tag{9}$$

where all right-hand side terms are as defined previously. This specification recognizes that the angler cannot fish if he has no income in his fishing account, and that any income left in the account at the end

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[1] To reduce the runtime of the dynamic model, we set the maximum allowable value of $elapsed_{nt}$ to 30 days. Relaxing this constraint does not appear to have any significant effect on the estimation results.

of the season is used in other activities. The properties of Gumbel-distributed random variables give the result (Ben-Akiva and Lerman):

$$V_{nT}\left(\mathbf{x}_{nT},s_{nT}\right)\equiv E_{\boldsymbol{\varepsilon}}\left[\nu_{nT}\left(\mathbf{x}_{nT},s_{nT},\boldsymbol{\varepsilon}_{nT}\right)\right]=\begin{cases}\ln\left(\exp\left(\beta\mathbf{x}_{nT}\right)+1\right)+\gamma & \text{if } s_{nT}\geq 1\\ \gamma & \text{otherwise}\end{cases}, \tag{10}$$

where γ is Euler's constant and represents the expected value of each Gumbel-distributed random variable. Furthermore, the probability of observing a trip is given by:

$$P\left(y_{nT}=1\right)=\begin{cases}\dfrac{\exp\left(\beta\mathbf{x}_{nT}\right)}{1+\exp\left(\beta\mathbf{x}_{nT}\right)} & \text{if } s_{nT}\geq 1\\ 0 & \text{otherwise}\end{cases}. \tag{11}$$

Stepping backwards, in period (T-1) each angler's indirect utility may be written as:

$$\begin{aligned}&\nu_{n,T-1}\left(\mathbf{x}_{n,T-1},s_{n,T-1},\boldsymbol{\varepsilon}_{n,T-1}\right)\\ &\equiv\begin{cases}\max\begin{bmatrix}\beta\mathbf{x}_{n,T-1}+\varepsilon^{1}_{n,T-1}+\rho V_{nT}\left(f\left(\mathbf{x}_{n,T-1},1\right),s_{n,T-1}-1\right),\\ \rho V_{nT}\left(f\left(\mathbf{x}_{n,T-1},0\right),s_{n,T-1}\right)+\varepsilon^{0}_{n,T-1}\end{bmatrix} & \text{if } s_{n,T-1}\geq 1\\ \rho V_{nT}\left(f\left(\mathbf{x}_{n,T-1},0\right),s_{n,T-1}\right)+\varepsilon^{0}_{n,T-1} & \text{otherwise}\end{cases},\end{aligned} \tag{12}$$

where ρ is the discount factor. Similarly to (10), taking the expectation of $\nu_{n,T-1}$ with respect to the random portion of utility at time (T-1) yields:

$$\begin{aligned}&V_{n,T-1}\left(\mathbf{x}_{n,T-1},s_{n,T-1}\right)\equiv E_{\boldsymbol{\varepsilon}}\left[\nu_{n,T-1}\left(\mathbf{x}_{nT},s_{nT},\boldsymbol{\varepsilon}_{nT}\right)\right]\\ &=\begin{cases}\ln\left\{\exp\left[\beta\mathbf{x}_{n,T-1}+\rho V_{nT}\left(f\left(\mathbf{x}_{n,T-1},1\right),s_{n,T-1}-1\right)\right]+\exp\left[\rho V_{nT}\left(f\left(\mathbf{x}_{n,T-1},0\right),s_{n,T-1}\right)\right]\right\}+\gamma & \text{if } s_{n,T-1}\geq 1\\ \rho V_{nT}\left(f\left(\mathbf{x}_{n,T-1},0\right),s_{n,T-1}\right)+\gamma & \text{otherwise}\end{cases}.\end{aligned} \tag{13}$$

And the probability of observing a trip (conditional on $s_{n,T-1}$) is given by:

$$\begin{aligned}&P\left(y_{n,T-1}=1\right)\\ &=\begin{cases}\dfrac{\exp\left(\beta\mathbf{x}_{n,T-1}+\rho V_{nT}\left(f\left(\mathbf{x}_{n,T-1},1\right),s_{n,T-1}-1\right)-\rho V_{nT}\left(f\left(\mathbf{x}_{n,T-1},0\right),s_{n,T-1}\right)\right)}{1+\exp\left(\beta\mathbf{x}_{n,T-1}+\rho V_{nT}\left(f\left(\mathbf{x}_{n,T-1},1\right),s_{n,T-1}-1\right)-\rho V_{nT}\left(f\left(\mathbf{x}_{n,T-1},0\right),s_{n,T-1}\right)\right)} & \text{if } s_{n,T-1}\geq 1\\ 0 & \text{otherwise}\end{cases}.\end{aligned} \tag{14}$$

Continuing with the recursion gives the indirect utility on any day (t):

$$\nu_{nt}\left(\mathbf{x}_{nt}, s_{nt}, \boldsymbol{\varepsilon}_{nt}\right) \equiv \begin{cases} \max\begin{bmatrix} \beta\mathbf{x}_{nt} + \varepsilon_{nt}^{1} + \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt},1\right), s_{nt}-1\right), \\ \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt},0\right), s_{nt}\right) + \varepsilon_{nt}^{0} \end{bmatrix} & \text{if } s_{nt} \geq 1 \\ \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt},0\right), s_{nt}\right) + \varepsilon_{nt}^{0} & \text{otherwise} \end{cases}, \tag{15}$$

with the probability of observing a trip on that day given by:

$$P\left(y_{nt}=1\right) = \begin{cases} \dfrac{\exp\left(\beta\mathbf{x}_{nt} + \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt},1\right), s_{nt}-1\right) - \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt},0\right), s_{nt}\right)\right)}{1+\exp\left(\beta\mathbf{x}_{nt} + \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt},1\right), s_{nt}-1\right) - \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt},0\right), s_{nt}\right)\right)} & \text{if } s_{nt} \geq 1 \\ 0 & \text{otherwise} \end{cases}. \tag{16}$$

Conditional on s_{n0}, the likelihood of angler (n)'s trip behavior is then given by:

$$L_n^{dynamic}\left(\cdot \mid s_{n0}\right) \equiv \prod_t \left[P\left(y_{nt}=1 \mid s_{n0}\right)^{y_{nt}} \cdot P\left(y_{nt}=0 \mid s_{n0}\right)^{1-y_{nt}} \right], \tag{17}$$

where $P\left(y_{nt} \mid s_{n0}\right)$ is calculated as shown in (11) and (16).

As mentioned previously, we assume each angler selects s_{n0} as the solution to an optimization problem solved at the start of the season, with the understanding that future decisions about when to fish will be made optimally. In this sense, our approach is analogous to the KT model. Specifically, each angler chooses s_{n0} to maximize the difference between the expected seasonal utility of fishing and the opportunity cost of taking fishing trips:

$$s_{n0} \equiv \max_{0 \leq s \leq \bar{s}} \left\{ V_{n0}\left(\mathbf{x}_{n0}, s\right) - \left(\mu \cdot cost_n + \eta\right) \cdot s \right\}, \tag{18}$$

where μ is the marginal utility of income; $cost_n$ is the trip cost variable described previously; η is an additional component of trip cost that is separate from per-trip cash expenses; and $\bar{s}$ is an upper bound on the number of trips. This approach is consistent with other utility-theoretic models of recreation demand which assume decisions regarding the total number of trips to take during a season are made at the start of the season. It reflects a type of mental accounting in which annual income is allocated across different categories of consumption, but here this budget allocation is made while explicitly acknowledging the dynamics of trip allocation throughout the season. The model readily generalizes to the case where the choice occasion involves multiple sites, heretofore the province of KT models.

Treating the unobserved component of each seasonal budget in (18) as iid standard Gumbel-distributed random variables, the probability that an angler chooses any particular budget s^* is given by the familiar multinomial logit expression:

$$P\left(s_{n0} = s^*\right) = \frac{\exp\left(V_{n0}\left(\mathbf{x}_{n0}, s^*\right) - \left(\mu \cdot cost_n + \eta\right) \cdot s^*\right)}{\sum_{s=0}^{\bar{s}} \exp\left(V_{n0}\left(\mathbf{x}_{n0}, s\right) - \left(\mu \cdot cost_n + \eta\right) \cdot s\right)}. \tag{19}$$

The likelihood of observing angler (n)'s behavior is then given by:

$$L_n^{dynamic} \equiv \sum_s \left\{ P\left(s_{n0} = s\right) \cdot \prod_t \left[P\left(y_{nt} = 1 \mid s\right)^{y_{nt}} \cdot P\left(y_{nt} = 0 \mid s\right)^{1-y_{nt}} \right] \right\} \tag{20}$$

and the sample log likelihood is the sum across all anglers of the logs of (20).

2.3 Statement of the Reduced-Form Static Model

With the structural dynamic model fully specified, we now address the task of determining a simpler reduced-form static model that we believe has the potential to closely mimic the results of the dynamic model but with far less modeling effort. To begin, we first revisit equation (16) for the case of $s_{nt} \geq 1$ (because there is no seasonal budget to exhaust in the static model):

$$P\left(y_{nt} = 1\right) = \frac{\exp\left(\beta \mathbf{x}_{nt} + \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt}, 1\right), s_{nt} - 1\right) - \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt}, 0\right), s_{nt}\right)\right)}{1 + \exp\left(\beta \mathbf{x}_{nt} + \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt}, 1\right), s_{nt} - 1\right) - \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt}, 0\right), s_{nt}\right)\right)}. \tag{21}$$

Defining:

$$A_{nt} \equiv \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt}, 1\right), s_{nt} - 1\right) - \rho V_{n,t+1}\left(f\left(\mathbf{x}_{nt}, 0\right), s_{nt}\right), \tag{22}$$

we can rewrite (21) as follows:

$$P\left(y_{nt} = 1\right) = \frac{\exp\left(\beta \mathbf{x}_{nt} + A_{nt}\right)}{1 + \exp\left(\beta \mathbf{x}_{nt} + A_{nt}\right)}. \tag{23}$$

Notice that equation (23) takes the form of a standard logit model with $u_{nt} \equiv \beta \mathbf{x}_{nt} + A_{nt} + \varepsilon^*_{nt}$, where A_{nt} can be interpreted as an intercept term that varies across individuals and through time. We therefore propose to substitute a reduced form for A_{nt}, denoted by A^*_{nt}, which we will specify later. If A^*_{nt} can be made arbitrarily close to A_{nt}, then when $s_{nt} \geq 1$ the much simpler static model in (23) will be empirically indistinguishable from the more complicated dynamic model in (11), (16) and (18) and will yield identical predictions regarding trip-taking behavior. Only on days when the seasonal budget has been exhausted will the dynamic model yield superior predictions.

This is a promising result for the predictive ability of the reduced-form model, but unfortunately a similar result cannot be derived for its welfare estimates. To see why, first consider the differences in model structures. In the static model, the marginal utility of income (MUI) is given by the β coefficient on the variable $cost_n$ in equation (1) and the opportunity cost of a trip is $cost_n$ less consumption of other goods on the day of the trip. But in the dynamic model, the MUI is given by μ in equation (18) and the opportunity cost of a trip is one fewer trip available to take in the future. These differences alone suggest that the welfare estimates of the static model will differ from those of the dynamic model, but the problems with welfare calculations using the static model appear to be deeper than this.

To examine this issue further, recall that the first step in welfare estimation is to derive the money metric version of the per-period indirect utility function (ν_{nt}). Assuming as we do here that the per-period direct utility function (u_{nt}) is linear in income, this requires first dividing u_{nt} by the MUI. In the structural dynamic model, we then use the money metric version of ν_{nt} to calculate recursively V_{n0} as shown in the preceding equations. This quantity is, by definition, the expected present value of the fishing season – a theoretically consistent welfare measure.

In the reduced-form static model, our per-period direct utility function includes an extra term: A_{nt}. While it is tempting to simply treat A_{nt} as a variable intercept term and follow the same procedure for calculating welfare (i.e., divide u_{nt} by the MUI and calculate the discounted expected seasonal value), *this is not a theoretically consistent approach when the underlying decision problem is dynamic*. To understand why, note that A_{nt} is the reduced form of an expression involving *future* utility; in other words, it represents a function of utility derived from decisions made *after* period (t). Therefore in a static model this term should not be included in the calculation of utility derived from the decision made at time (t). Including this term will produce biased (and theoretically inconsistent) welfare calculations.

A possible alternative approach would be to omit A_{nt} from the per-period welfare calculation and proceed as before; but this, too, is problematic because the static estimation method necessarily sweeps the mean value for A_{nt} into the constant term of $\mathbf{x}_{nt}$ and expresses the results for A_{nt} as deviations from this (unknown) mean. In other words, we have an identification problem: the static model cannot simultaneously recover unbiased estimates of A_{nt} (as it is defined by the dynamic model) and of the constant term in $\mathbf{x}_{nt}$. It is the additional structure imposed on the problem by the dynamic model that permits simultaneous identification; but unfortunately this identification cannot be achieved without deriving and estimating the more complicated dynamic model or, perhaps, by imposing additional structure on the functional form of A_{nt} (but we do not examine this possibility here). Of course, when the underlying decision problem is static then $\rho = A_{nt} = 0$ and welfare estimation can proceed as usual.

These observation raise an important issue regarding the interpretation of variable intercept terms in static RUMs. Frequently, analysis of panel data employs a static model with some sort of variable intercept specification such as "fixed-effects" or "random-effects" in order to address unobserved heterogeneity in the sample population (Hsiao, 1986). When the underlying decision problem is static, these coefficients are appropriately interpreted as preference parameters that contribute to per-period utility and should be included in welfare calculations. But when the underlying decision problem is dynamic, our preceding discussion shows that this interpretation is theoretically inconsistent – behavioral prediction may be quite good, but welfare estimates will be biased; unfortunately, the literature has not previously recognized this.

To demonstrate these claims empirically, we estimate both the structural dynamic model and the reduced form static model presented above using Lake Michigan salmon angling data for the 1996 and 1997 fishing seasons. We then examine the trip forecasts and welfare estimates derived from each model. The exact functional specification we choose for A_{nt} in the static model is motivated by our results for the dynamic model which we present in the following section.

3. Estimation and Results

Our dataset is composed of 97 anglers surveyed over the two-year period from 1996 to 1997. Anglers were queried about their fishing activity by telephone approximately every two weeks from May through September. Although the season for salmon fishing on Lake Michigan typically begins around April 1 and continues until December 31, anglers rarely fish before May 1 or past October 1. For the 1996 season angler activity was charted from May 1 to September 15, and for the 1997 season from May 15 to October 1. These dates give the effective seasons used in the empirical analysis. A mail survey was conducted at the end of each season to collect additional demographic information from the study anglers.

We first use the data to estimate the dynamic model described in Section 2 for each season. The likelihood function for the dynamic model (equation 20) is maximized by applying FORTRAN optimization subroutines in the commercial package GQOPT to original code that calculates the likelihood. The coefficient estimates and standard errors are shown in Table 1 and are consistent with our intuition about salmon angling. Note that the variable $elapsed_{nt}$ produces strictly negative marginal utility within the relevant range, despite a positive coefficient on the quadratic term. With these estimates in hand, we now specify an appropriate reduced-form static model. To do this, we first use equation (22) to derive values of A_{nt} for each angler in the sample.

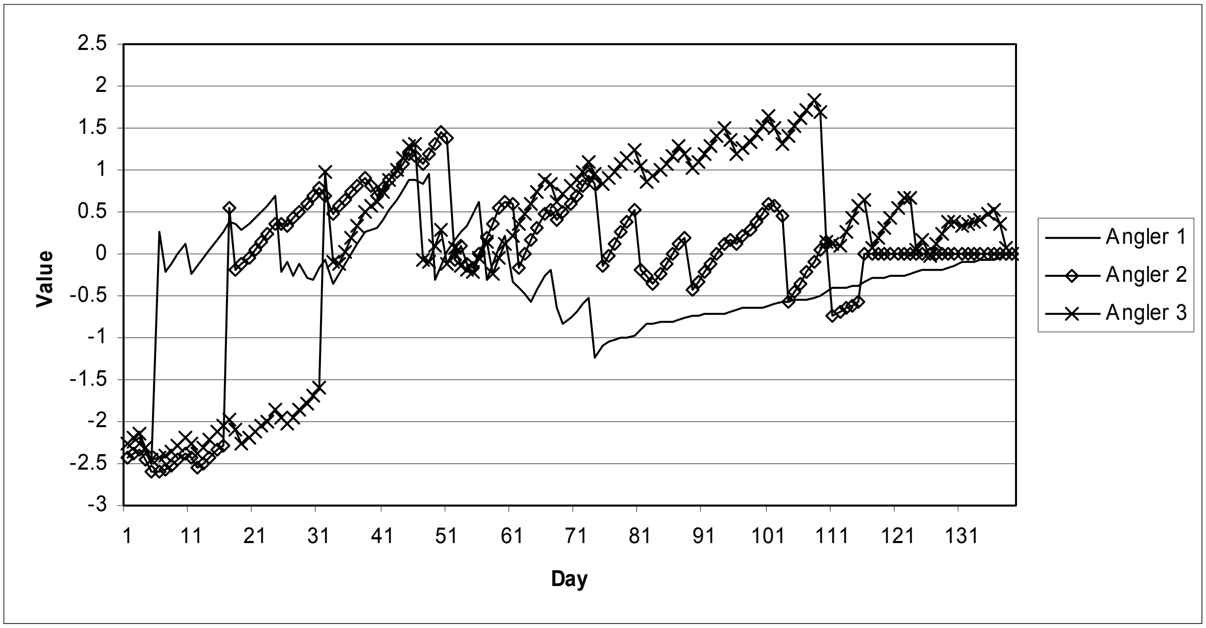
Figure 1 shows calculated values of A_{nt} for three sample anglers during the 1996 season. For each angler, A_{nt} initially is negative and increasing at the beginning of the season, then it becomes positive after each angler takes his first trip. At this point, A_{nt} follows a variety of paths depending on

Table 1: Coefficient Estimates and Standard Errors for the Dynamic Model

Per-Period Utility	1996 Season		1997 Season	
	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
constant	-1.2642	0.4858	-0.2459	0.3542
$catch_t$	0.2192	0.0921	0.1431	0.0470
$temp_t$	0.0149	0.0038	0.0136	0.0033
$wind_t$	-0.0471	0.0105	-0.1405	0.0141
$weekday_t$	-1.5228	0.0902	-1.2093	0.0744
$derby_t$	0.6737	0.0833	0.5665	0.0843
job_n	0.0022	0.0645	0.0272	0.0527
$job_n \cdot workday_{nt}$	-0.2188	0.1002	-0.4888	0.0831
$first_{nt}$	0.0354	0.1124	0.0271	0.1002
$first_{nt} \cdot elapsed_{nt}$	-0.2383	0.0142	-0.2990	0.0148
$first_{nt} \cdot elapsed_{nt}^2$	4.9290e-4	4.7436e-5	6.6609e-4	4.9011e-5
Other Coefficients	**Coefficient Estimate**	**Standard Error**	**Coefficient Estimate**	**Standard Error**
$budget_n$	0.1343	0.3716	0.1938	0.1900
$cost_n \cdot budget_n$	0.0131	0.0036	0.0118	0.0028

each angler's remaining trip budget and trip taking behavior. When an angler has trips remaining in his budget, A_{nt} tends to be positive and increasing during long periods when no trips are taken; it then decreases sharply and becomes negative immediately after a trip is taken. Primarily this is due to the effect of $elapsed_{nt}$. To see this, note that A_{nt} represents the difference in the expected value of the remainder of the season if a trip is taken at time (t) and the expected value if a trip is not taken. When an angler has not taken a trip for a long time, $elapsed_{nt}$ is large and (because the marginal effect of $elapsed_{nt}$ is negative) A_{nt} is positive – the expected value of the remainder of the season is larger if a trip is taken because $elapsed_{nt}$ will be reset from a large value to zero. When a trip has been taken recently, however, the more intuitive case emerges: A_{nt} is negative because the expected value of the remainder of the season tends to be smaller if a trip is taken due to the budget constraint and because the

Figure 1: Values of A_{nt} for Three Anglers in 1996



effect of resetting $elapsed_{nt}$ to zero is not as great when its current value is smaller. When an angler has only one trip remaining in his budget (e.g., Angler 1 after day 73 and Angler 2 after day 110), A_{nt} is strictly non-positive because the value of the remainder of the season if a trip is taken will be zero (e.g., Angler 2 after day 115) whereas the value will remain positive if no trip is taken.

Figure 1 suggests that it will be difficult to find a reduced form that will closely approximate A_{nt} in the static model. It is clear that on any day, A_{nt} takes different values for different anglers; and for any angler, A_{nt} takes different values on different days. To attempt to control for some of this heterogeneity, we specify two individual-specific constants for each angler: one before the first trip is taken and one afterwards. The remainder of the unexplained variability in A_{nt} for each angler is then captured by the error term. This type of individual-specific constant is commonly used by practitioners working with panel data (Hsiao, 1986) and provides a useful baseline from which to compare other more complicated specifications. We adopt it here and redefine A_{nt} for each angler as:

$$A^*_{nt} \equiv \begin{cases} A^0_n \text{ if } \mathit{first}_{nt} = 0 \\ A^1_n \text{ if } \mathit{first}_{nt} = 1 \end{cases}, \tag{24}$$

where first_{nt} is defined in equation (6). Furthermore, because our model includes a lagged endogenous variable ($\mathit{elapsed}_{nt}$) as a regressor, we employ a "random effects" specification for A^*_{nt}. In other words, we assume each A^0_n is drawn independently from a common distribution with mean and variance to be estimated, and similarly for A^1_n. If our model did not include this lagged endogenous variable, we also could examine a "fixed effects" specification using Chamberlain's (1980) conditional likelihood approach; but inclusion of this variable unfortunately renders this method invalid (Grether and Maddala, 1982; Card and Sullivan, 1988) and we are not aware of any other feasible estimation approach for a dataset as large as ours.

Again assuming iid standard Gumbel-distributed error terms, the probability of observing a trip by angler (n) on day (t) is now given by:

$$P(y_{nt} = 1) = \frac{\exp\left(\beta \mathbf{x}_{nt} + A^0_n + A^1_n \cdot \mathit{first}_{nt}\right)}{1 + \exp\left(\beta \mathbf{x}_{nt} + A^0_n + A^1_n \cdot \mathit{first}_{nt}\right)}. \tag{25}$$

And the likelihood of observing angler (n)'s trip sequence for the season is:

$$L^{static}_n \equiv \int_A \prod_t \left[P(y_{nt} = 1)^{y_{nt}} \cdot P(y_{nt} = 0)^{1-y_{nt}} \right] \cdot dF(A), \tag{26}$$

where $F(A)$ is the joint distribution of the individual-specific effects and is assumed to be $BVN\left(0, 0, \sigma^2_0, \sigma^2_1, \sigma_{01}\right)$.[2] The likelihood function in (26) is maximized using the CO optimization routine in the GAUSS programming language and employs Gaussian Quadrature to evaluate the integral. The coefficient estimates and standard errors are shown in Table 2.

[2] Note that means of this bivariate normal distribution are set equal to zero because $\mathbf{x}_{nt}$ already contains a constant term and the dummy variable first_{nt}. Therefore, our approach effectively randomizes these two coefficients.

Table 2: Coefficient Estimates and Standard Errors for the Static Model

Per-Period Utility	1996 Season		1997 Season	
	Coefficient Estimate	Standard Error	Coefficient Estimate	Standard Error
constant	-3.6444	0.3495	-3.5711	0.3728
$catch_{\mathrm{t}}$	0.4904	0.1170	0.3017	0.0757
$temp_{\mathrm{t}}$	0.0246	0.0041	0.0264	0.0043
$wind_{\mathrm{t}}$	-0.0681	0.0127	-0.1420	0.0142
$weekday_{\mathrm{t}}$	-1.3653	0.0990	-1.0800	0.0914
$derby_{\mathrm{t}}$	0.9938	0.0981	0.9066	0.1072
$cost_{n}$	-0.0182	0.0074	-0.0118	0.0101
job_{n}	-0.0200	0.1068	0.0466	0.1594
$job_{\mathrm{n}} \cdot workday_{\mathrm{nt}}$	-0.4996	0.1219	-0.7694	0.1259
$first_{\mathrm{nt}}$	1.3174	0.1498	1.4769	0.1543
$first_{\mathrm{nt}} \cdot elapsed_{\mathrm{nt}}$	-0.1136	0.0155	-0.1183	0.0159
$first_{\mathrm{nt}} \cdot elapsed^2_{\mathrm{nt}}$	0.0021	0.0005	0.0025	0.0005
Other Coefficients	**Coefficient Estimate**	**Standard Error**	**Coefficient Estimate**	**Standard Error**
σ_0^2	0.0354	0.0399	0.1035	0.0704
σ_1^2	0.2551	0.1405	0.2332	0.0627
σ_{01}	0.0046	0.0249	0.0905	0.0472

Generally the estimates are similar to those for the dynamic model, but there are some notable differences. Anglers in the static model generally appear to be more affected by the daily fishing conditions (i.e., the catch rate, temperature, wind speed), workdays and the fishing derby; and less affected by past trip-taking behavior. Our main focus here, though, is to compare the predictive ability and welfare estimates of this static model with those of the dynamic model. The following section presents these comparisons.

4. Prediction and Welfare Estimation

A total of 1216 trips were observed during the 1996 season and 1261 during the 1997 season. To obtain trip forecasts and welfare estimates, we conduct 1000 simulations for each model and each season and then compute the means of the simulations. Table 3 summarizes the trip forecasts on a seasonal basis and Figures 2 through 5 present them on a daily basis. Figures 2 and 3 show the cumulative prediction error for the 1996 season using the 1996 and 1997 model estimates, respectively; Figures 4 and 5 show analogous results for the 1997 season. Downward movements in these cumulative errors represent under-prediction and upward movements represent over-prediction. Perfect prediction throughout the season would be represented by a horizontal line at zero.

Table 3: Number of Trips Observed and Predicted, Entire Season

	Observed	Static Prediction	Dynamic Prediction
Forecasting 1996 trips with 1996 estimates	1216	1224	1216
Forecasting 1996 trips with 1997 estimates	1216	1101	1161
Forecasting 1997 trips with 1996 estimates	1261	1437	1313
Forecasting 1997 trips with 1997 estimates	1261	1211	1261

On a seasonal basis, both models forecast well in-sample (lines 1 and 4 in Table 3). On average, the static model over-predicts by 8 trips in 1996 and under-predicts by 50 trips in 1997. The dynamic model performs even better with an average aggregate prediction error of less than one trip in both seasons. The superior predictive ability of the dynamic model is also evident in the out-of-sample results (lines 2 and 3 in Table 3). Whereas the static model under-predicts by 115 trips in 1996 and over-predicts by 176 trips in 1997, the dynamic model under-predicts by only 55 trips in 1996 and over-predicts by only 52 trips in 1997. These results are consistent with those reported by Provencher and Bishop (2003) and suggest behavior may be constrained in a way the static model cannot address.

Examining the forecasting results on a daily basis provides additional insight into the predictive ability of each model. Figures 2 through 5 show the daily cumulative forecasting errors and demonstrate that these errors can be significantly larger during the season than at the end. Typically (Figures 2, 3 and 5), both models tend to under-predict early in the season and then compensate by over-predicting late in the season. This tendency is more pronounced in the static model, which can produce forecasts that are as good as or even better than the dynamic model early in the season, but which eventually produces larger

Figure 2: Cumulative Prediction Error for 1996 Season using 1996 Coefficient Estimates

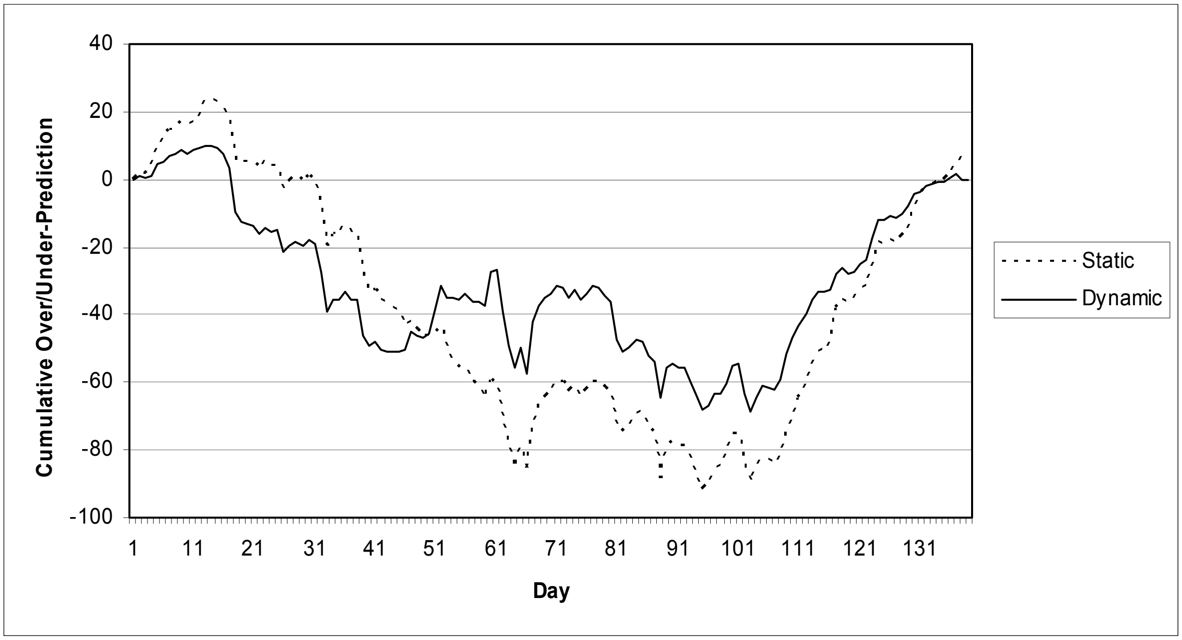


Figure 3: Cumulative Prediction Error for 1996 Season using 1997 Coefficient Estimates

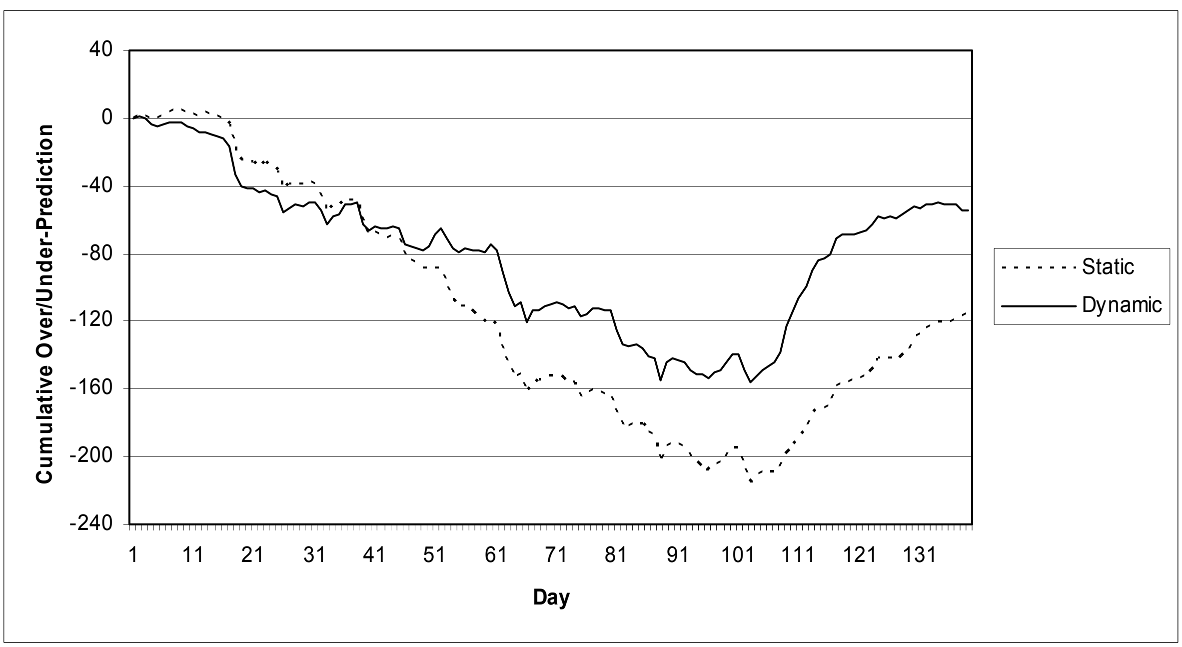


Figure 4: Cumulative Prediction Error for 1997 Season using 1996 Coefficient Estimates

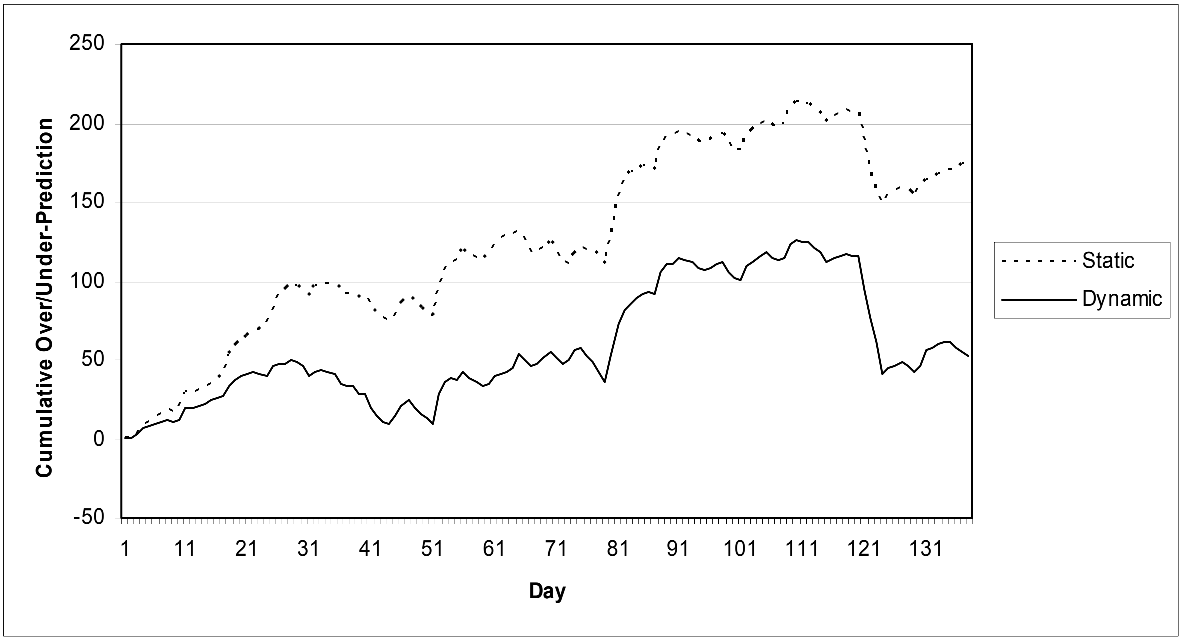
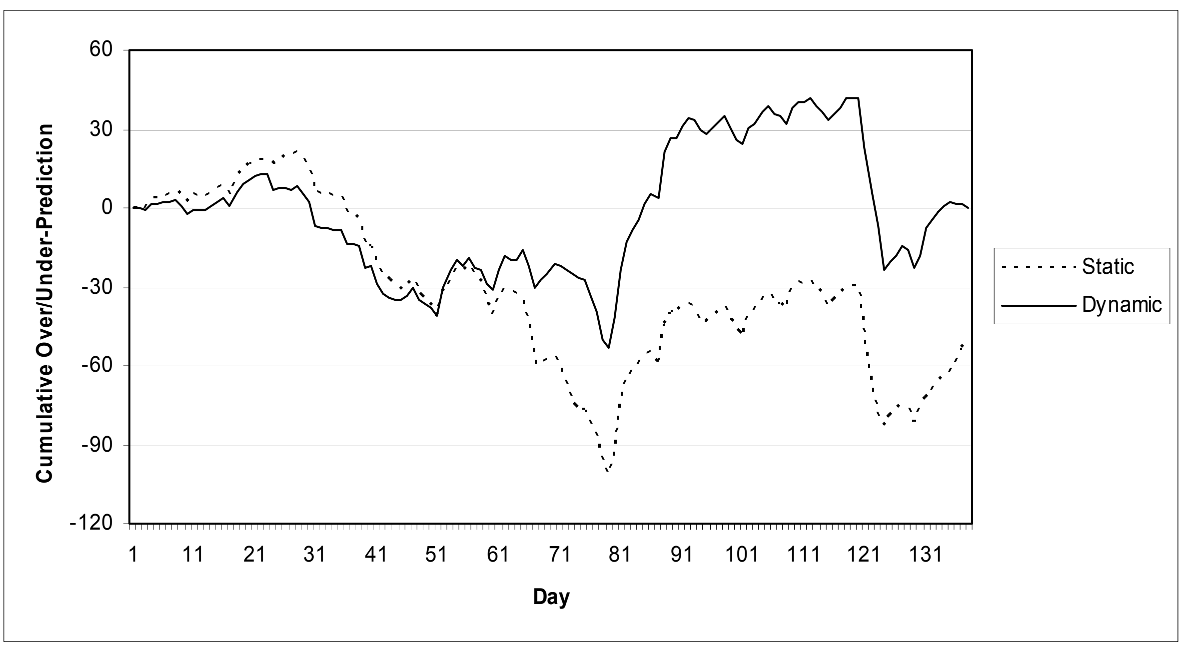


Figure 5: Cumulative Prediction Error for 1997 Season using 1997 Coefficient Estimates



prediction errors later in the season. These observations have two implications. First, they suggest a static model may be adequate early in the season when budgets remain relatively large; but eventually a dynamic model will produce better forecasts as budget constraints begin to loom. Second, the recurring pattern of under-prediction followed by over-prediction suggests that preference parameters may not remain constant throughout the season. In other words, good fishing conditions early in the season may be more valuable to anglers than the same conditions late in the season (e.g., anglers may be more responsive to good catch rates and/or nice weather in the spring than they are to the same conditions in late summer). This has obvious repercussions for welfare estimation, but we choose to leave an investigation of time-varying utility parameters for future work.

Table 4 presents each model's average (per-person) seasonal welfare estimates. As we argued previously, the welfare estimates for the static model are theoretically inconsistent under the assumption that the true behavioral model is dynamic, but we report these results to illustrate the potential error associated with using this reduced-form approach.[3] As the table shows, the static model significantly *underestimates* the value of the fishing season in each year: by 82% in 1996 (line 1) and by 72% in 1997 (line 4). The static model also tends to *overestimate* inter-seasonal changes in welfare. For example, using the 1996 estimates (lines 1 and 3), the static model would predict a change in seasonal value of $167 per person whereas the dynamic model would predict a change of only $74. Using the 1997

Table 4: Average Seasonal Welfare Estimates, Per-Angler

	Static Estimate	**Dynamic Estimate**
Calculating 1996 welfare with 1996 estimates	$809	$4424
Calculating 1996 welfare with 1997 estimates	$1130	$4389
Calculating 1997 welfare with 1996 estimates	$976	$4498
Calculating 1997 welfare with 1997 estimates	$1263	$4456

[3] Alternatively, the static and dynamic estimates demonstrate the range of possible seasonal values depending on the degree of dynamic behavior exhibited by the anglers.

estimates (lines 2 and 4), the static model predicts a change of $133 per person whereas the dynamic model predicts a change of only $67.

5. Conclusions

The dynamic nature of behavior, whether in recreation or otherwise, tends to be overlooked by most empirical studies in order to simplify the behavioral model and reduce the computational complexity of the estimation. We have demonstrated here that when the underlying structural model is truly dynamic, a reduced-form static model may fit the data fairly well but it cannot provide unbiased welfare estimates due to problems of identification. And furthermore, our empirical application suggests this bias can be significant. Additional research focusing on this identification problem would be useful to the extent it might produce an estimation approach capable of providing reliable welfare estimates without estimating a fully dynamic model of behavior.

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