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Choice and temporal welfare impacts: incorporating history into discrete choice models

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Abstract

Static, cross-sectional discrete choice models are often employed to calculate welfare measures in environmental valuation. These measures will be biased if the underlying preference function includes temporally related attributes and lagged dependent variables, nevertheless, static models continue to dominate the literature. In this paper we provide an approach to estimating discrete choice models that includes consideration of prior behavior and past attribute perceptions and allows for testing consistency with random utility maximization in a time-series context. We apply this model to the case of recreational fishing site choice and participation, comparing our time-series approach to static versions. We find that the time-series model provides a richer behavioral characterization of site choice. We also find significant differences between cross-section and time-series welfare measures. The time-series model raises several concerns about the specification of the policy impact and the subsequent welfare measurement that are not apparent in the static case.

> forward looking behaviour is not considered!

Keywords: Temporal dependence; Discrete choice; Random utility model; Welfare measurement; Time-series discrete choice

1. Introduction

Static discrete choice models of recreational site choice are often employed to calculate welfare measures in cases of damage assessment or environmental valuation. However, demand itself may be temporally variable, perhaps characterized by habits, learning, state dependence, consumption

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inertia, temporal preference heterogeneity and initial conditions effects. For example, it may be that the impact of a chemical spill on beach recreation will be to drive recreationists away from the affected site and change their visitation pattern so that they do not return to the affected site even long after the physical impact has disappeared.

Economic assessments of policy options that do not take these temporal behavioral factors into account will likely be biased. While casual observation suggests that such temporal effects occur, there has been relatively little empirical implementation of intertemporal welfare analysis in the environmental valuation literature, especially where demand involves discrete choices. To a large degree this arises because of the difficulty in estimation of utility-consistent dynamic discrete choice models of consumer choice and because of the limited availability of time-series data.

There is a continuum from pure cross-section models (assuming independence over time and usually across individuals or choice occasions) to fully dynamic models of discrete choice. In the latter the consumer is assumed to be dynamic in the sense that they recognize that decisions made today will affect future consumption or behavioral decisions. Fully dynamic choice models are relatively rare. The classic example is Rust's [15] choice model that describes how individuals make decisions about replacing capital equipment. This model supposes that the individual solves a dynamic program over the time period of interest. In recreation demand this model has been employed by Provencher and Bishop [14]. Given the mental processing costs, it is possible that fully dynamic behavior is only used by individuals in certain circumstances where there are high net returns to dynamic behavior. Thus, the situation examined by Rust [15] may correspond to one that is more likely to exhibit true dynamic behavior than is recreational fishing. Between the poles of the static↔dynamic modeling continuum are approaches which recognize temporal dependence, but do not assume full dynamic behavior. Models that allow for learning about preferences or attributes, memory errors, and updating of perceptions are temporally dependent. Models may incorporate expectations about attributes, and thus also include temporal dimensions.

In this paper we explore this middle ground between fully dynamic and static models. We assume that recreational site choice behavior is influenced by history of choice (i.e. past behavior) and of attributes, but that the behavior is not fully dynamic. Our approach provides a tractable method for identifying certain types of temporal dependence. We examine participation and site choice behavior by recreational anglers over a single season where the individual chooses between three alternative fishing sites and a 'stay at home' option in each of 19 weeks. The time period is characterized by changing fish abundance at the sites throughout the season. We specify the model with utility in a given period being determined by current and previous attribute levels (assuming that consumers weight current and previous period attribute levels to construct their measures of perceived attribute levels), as well as by previous choice (a lagged endogenous variable). We find significant evidence of temporal dependence that arises from the process of updating attribute perceptions and incorporating history into the explanation of current choices. Using simulations to evaluate the impacts of a number of policy scenarios we find that the time-series models illustrate the persistence of welfare impacts beyond the time period of the simulated "physical" impact and show a corresponding welfare loss that in our case is significantly larger than that generated from static models.

The paper is structured as follows: Section 2 introduces the proposed time-series choice model, after which we introduce the data utilized in the empirical study and discuss model estimation results; following, several typical policy scenarios are contrasted using a standard model and the richer time-series model derived from our approach; the paper concludes with a summary of our contribution and suggestions for future research.

2. Incorporating temporal dependence in discrete choice models

First, we formalize some definitions of factors affecting choice in time-series models. Time-series discrete choice responses can be characterized by *state dependence* (current preferences being affected by previous choices), *habit persistence* (current preferences being affected by previous preferences), *initial conditions* (lack of knowledge about preferences before the observation period available to the analyst), and *taste heterogeneity* (taste differences between individuals and over time). Current preferences could be affected by previous preferences and choices through learning, habit formation or variety seeking or general consumption inertia. Several researchers have explored these factors through the use of ''previous choice'' within static discrete choice model structures (among others, [1,13]). These approaches assume that unobserved components of utility are uncorrelated over time and that utility maximization includes the previous choices as components of the deterministic portion of utility. An alternative approach is to represent the decision maker as formally solving a dynamic programming problem and to embed the statistical estimation process within this dynamic programming framework. Applications include replacement of capital equipment [15], recreational fishing site choice [14], and brand choice in consumer packaged goods [7]. These approaches attempt to account for the impact of future choices on current choices (and commonly assume the unobserved effects are uncorrelated over time as well). While appealing in theoretical form, they are relatively difficult to estimate and at times produce results that appear counter-intuitive (e.g. [14]). In the literature on environmental valuation the applications of time series in choice models include Adamowicz [1], McConnell et al. [10] and Provencher and Bishop [14].

Smith [16], reviewing the literature in this area, discusses the importance of temporal dimensions in environmental valuation. The issues are perhaps best addressed by an example. Much of the recreation valuation literature focuses on developing welfare estimates associated with damages to the natural environment—with the use of these models aimed at natural resource damage assessment (see [4,6] for a discussion of one such case—the American Trader). In these cases the welfare impacts associated with the damages are usually assessed using static models, and then the impacts on aggregate visitation rates are examined in separate models that describe time series of recreational site use. However, if consumers are not ''perfect'' in their updating of attribute perceptions, then welfare estimates from the static models will be significantly biased. For this reason we turn our attention to the development of a time-series model of choice, and compare welfare measures from this model with those of a static model.

In this paper we incorporate the history of attributes into a random utility model of participation and site choice. The model includes time-varying covariance structures. Time-varying covariance structures, which include changes in both diagonal and off-diagonal elements, lead to temporal heteroscedasticity and temporally differentiated cross-substitution effects. These are both features that have received relatively little attention in the choice modeling literature. Though the general idea we present can be applied to other discrete choice model families, the most general model considered here includes these covariance structures and becomes a form of "nested logit" model, implying that we are also able to test temporal consistency with stochastic utility maximization [9, 11].

2.1. MNL panel data model

First we define our notation. Let $t = 1, \ldots, T$, be a discrete time point, j one of J alternatives, and I_t the information set at time t (as noted above, this includes past choices, past utilities, current and past attributes, etc.). Conditional indirect utilities in each period that rely only on current period attributes are represented as $V_t = (V_{1t}, \ldots, V_{Jt})$. We construct a meta-utility function that incorporates current and previous utilities as follows. Define the meta-utility of alternative j in time t as a function of the product of utilities in current and previous periods:

$$\hat{V}_{jt} = \prod_{s=0}^{t} \alpha_{js} \exp(V_{jt-s}). \tag{1a}$$

This expression relates previous "static" utilities to current utility; note that the static utilities are weighted by the α's, which are weights associated with previous periods. The unknown parameters are

$$\textit{Initial utilities}: \quad V_0 = (V_{10}, \ldots, V_{J0}) \tag{1b}$$

$$\textit{Past dependence}: \quad 0 \leqslant \alpha_{js} \leqslant 1, \; \alpha_{j0} \equiv 1, \; \forall s, \; j = 1, \ldots, J, \; 0 \leqslant s \leqslant t, \tag{1c}$$

This describes a set of meta-utilities linked through time by dependence on previous utilities and initial utilities. Instead of working with the product form of the meta-utility expression we redefine (1a) by taking logs, which generates

$$\ln \hat{V}_{it} = \sum_{s=0}^{t} (V_{it-s} + \ln \alpha_{is}), \quad i = 1, \ldots, J, \; t = 1, \ldots, T. \tag{2}$$

Addition of past and contemporaneous error terms to the RHS of (2) results in

$$\sum_{s=0}^{t} (V_{it-s} + \ln \alpha_{is}) + \sum_{s=0}^{t} \varepsilon_{it-s} = \tilde{V}_{it} + \sum_{s=0}^{t} \varepsilon_{it-s} = \tilde{V}_{it} + \tilde{\varepsilon}_{it}, \quad i = 1, \ldots, J, \; t = 1, \ldots, T. \tag{3}$$

Subsequently, for tractability, the error terms $\tilde{\varepsilon}_{it}$ are assumed to be independent over time for a given individual, despite the clear temporal dependence shown in (3). In this spirit, the assumption that these errors are IID Gumbel with scale factors $\mu_t \geqslant 0$, leads to choice probabilities of familiar form:[1]

$$P(i \mid I_t) = \frac{\exp(\mu_t \tilde{V}_{it})}{\sum_{j=1}^{J} \exp(\mu_t \tilde{V}_{jt})}. \tag{4}$$

The temporal variability of the scale factors, which are inversely related to variance, implies that the model exhibits the potential for temporal heteroscedasticity. Note that the model constructed

[1] The unobservable aspects associated with the meta-utility function are assumed to be independent over time. This assumption is less likely to hold to the extent that the errors themselves are composed of a weighted average of the unobservables associated with each time period, in a fashion similar to Eq. (1a).

above assumes independence of the errors over time. This implies that the lagged "representative" utilities (the observed components of utilities) in our model are exogenous and thus we can include them in the model. The initial utilities are also parameters estimated in the model and are essentially averages over the sample of the expected initial utility.[2]

The probability expressions (4) are relatively straightforward, with a *meta-utility* $\tilde{V}_{it}$ that is a function of utilities in current and previous periods, initial utilities, as well as past-dependence parameters. Note that these probability expressions and utilities can be estimated using traditional discrete choice approaches.

The model illustrated by expression (3) relates current utility to historical observed attribute levels in a fashion that is consistent with learning about attributes or updating. Attribute levels in previous periods are combined with current attribute levels to form a "weighted average" perception of attribute levels. Alternately, this formulation can be thought of as one in which current utility is influenced by historical utilities (the deterministic components of utility). If temporal dependence is detected in the model it implies that utility in a period is affected by utility from previous periods as a form of "memory". Depending on the estimated decay parameters this type of utility structure may result in a form of "smoothing" in which, for example, single period inferior attribute levels at a site are compensated for by historically superior levels. Conversely, a history of inferior attribute levels or utility will not be easily overcome by a single superior period, as would necessarily happen in a cross-sectional model. One could consider this a form of updating of perceptions based on observations and experience, or equivalently, a form of temporal averaging of utility levels. The model can also include historical choices to capture state dependence.

Depending on the choice of the functional form for the meta-utility, a number of special cases arise.[3] In the empirical analysis presented later we employ a simple geometric decay formulation[4] of the model, as follows: let $\alpha_{js} = \rho_j^s,\ 0 \leqslant \rho_j \leqslant 1,\ j = 1, \ldots, J,\ s = 0, \ldots, t,$ then meta-utility

[2] Many treatments of the initial conditions problem employ information on the sample of individuals to address the fact that unobserved heterogeneity essentially "causes" the bias arising from the unknown initial utilities. In our approach we estimate sample average initial utilities; however, these could easily be augmented to depend on characteristics of the sample or could be estimated as random parameters and thus would include heterogeneity considerations in the determination of initial utilities.

[3] As pointed out by an anonymous reviewer the form of the meta utility function we employ is not unique. For example, an additive specification of utility over time could be used in place of our multiplicative (or additive in logarithms) form. However, an additive form could not be estimated using standard discrete choice software and the utilities from previous periods could have negative impacts (or impacts with changing signs) on current utility. In addition, there will likely be difficulties in identifying the parameters in the additive form because of the multiplicative interaction between utility parameters, temporal discount factors and error term scales.

[4] There are many specifications of decay that can be employed. The geometric decay employed here is a special case of the Schmidt Decay Model. Let $\alpha_{js} = \rho_j^s (s+1)^{\delta_j/(1-\delta_j)}$, $0 \leqslant \rho_j \leqslant 1$, $0 \leqslant \delta_j < 1$, $j = 1, \ldots, J$, $s = 0, \ldots, t$. Utilities (3b) become

$$\tilde{V}_{it} = \sum_{s=0}^{t} \left(V_{it-s} + s \ln \rho_i + \frac{\delta_i}{1-\delta_i} \ln(s+1) \right), \quad i = 1, \ldots, J, \quad t = 1, \ldots, T,$$

and choice probabilities are given by (3a) using the utility function above. This model has as a special case the geometric decay model, when $\delta_j \equiv 0, \forall j$. In the Schmidt decay model, past utilities can have a greater impact than current utilities, so it can be useful to capture inertia in behavior, habit, etc.

function (1a) becomes simply

$$\tilde{V}_{it} = \sum_{s=0}^{t} (V_{it-s} + s \ln \rho_i), \quad i = 1, \ldots, J, \quad t = 1, \ldots, T, \tag{5}$$

and choice probabilities are given by (4) using utilities (5). Note that the decay parameters estimated provide information on the degree to which previous observed utilities affect current choices, with large values of ρ corresponding to long "memories" or high degrees of temporal dependence. These decay factors are alternative-specific, allowing for differing degrees of decay across alternatives; however, note that only the ratios, $\rho_j/\rho_J, j = 1, \ldots, J$, are actually identifiable, so one of the decay factors must be set arbitrarily. Thus, one will be able to identify whether an alternative has a decay factor smaller or larger than the base decay factor.

The meta-utility in (5) can also include other factors that influence choice. For example, a dummy variable indicating whether this alternative was chosen in the previous period is included in our empirical model. This captures state dependence effects. Also, since our model explains participation and site choice we include a variable that indicates how many time periods have elapsed since the person chose to participate in the activity. This attempts to capture a kind of habit formation or variety seeking associated with the activity that is not specific to any particular alternative.

2.2. Applying meta-utilities to other model forms

The MNL panel data model presented above does not result from the form of the meta-utility (1), but arises due to the error distribution assumption. This implies that meta-utility functions can be used in choice models with more general error structure representations (e.g. more complex GEV—generalized extreme value—models, or probit models).

The meta-utility model defined by (3) is a generalization of the random utility model from cross-sectional to conditional time-series models that permit modeling:

1. Initial conditions (y_{i0}).
2. Temporal dependence on past attribute level via past utilities (α_{js}).
3. State dependence (via inclusion of past choices in the information set I_t).

   These components arise from the multiplicative specification (expression (1)) that we use as a maintained hypothesis about the temporal nature of utility. Other specifications of history would generate different meta-utilities and probability expressions. Nevertheless, we feel our specification is quite general. This model can be estimated using standard discrete choice software with appropriate specification of the utility function.

   Specification of appropriate error structures added to meta-utility (3) can lead to choice models that have

4. Time-varying scales and covariance structures.
5. Time-varying tastes (identification restrictions apply, however).

With respect to point (4), note that the meta-utilities can be used in *any* generalized extreme value (GEV) model [11]: MNL, nested MNL, tree extreme value are only some examples. (For that matter, the same concept can be generalized to other discrete model types, such as multinomial

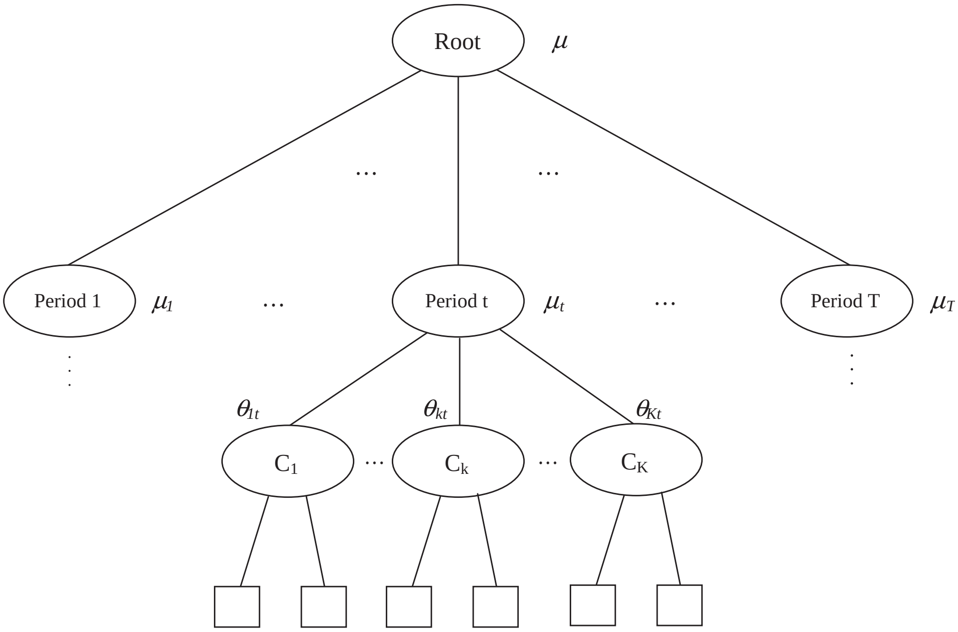

Fig. 1. Dynamic nest structure of a 2-level TVS model with time-varying covariance matrix.

probit models.) In our empirical example we include time-varying scales (TVS).[5] Note that in a 2-level TEV model with a constant tree structure, the node parameters θ_k do not change over time, implying that the covariance matrix is fixed over time, whereas in a 2-level TVS with time-varying structure the covariance matrix can change over time, thus exemplifying point (4) above. Fig. 1 outlines the general structure for such 2-level TVS models, with an overall "root" node, followed by nodes for time periods, which are themselves followed by the usual tree structure represented by clustering or nesting of elemental alternatives (C_ks); the tree structure is repeated under each time period node. For such a model to be consistent with stochastic utility maximization the scale terms in the tree structure proper must be greater than the time scale terms μ_t for all time periods, and the time period scales must be greater than the overall scale μ. Basically, lower level scale terms must be greater than scale terms higher up the tree.

Estimation requires decomposition of the observation's likelihood into a product of conditional probabilities. Assuming individual parameters stacked in ψ_n, the likelihood of a choice sequence for individual n over T time periods is simply

$$\begin{aligned} P_n(\delta_{nt}, \delta_{nt-1}, \ldots, \delta_{n1} \mid \psi_n) &= \int_\psi (P_n(\delta_{nt} \mid \delta_{nt-1}, \ldots, \delta_{n1}, \psi_n) P_n(\delta_{nt-1}, \ldots, \delta_{n1}, \psi_n)) f_t(\psi)\, d\psi \\ &= \int_\psi \left(\prod_{t=1}^{T} P_n(\delta_{nt} \mid I_{nt}, \psi) f_t(\psi) \right) d\psi, \qquad (6) \end{aligned}$$

[5] In other literature these are referred to as tree extreme value models (TEV). Nested MNL models are simply TEV models in which construct node scales are constrained to be equal at the same level of the tree.

where δ_{nt} is a vector of indicator variables for the chosen alternative in period $t = 1,\ldots,T$, person n, I_{nt} is the information set at period t, and $f_t(\psi)$ is the time-varying distribution describing the occurrence of parameters in the population. For a sufficiently large random sample of N decision makers, maximization of the log likelihood

$$L(\psi_n) = \sum_{n=1}^{N} \ln\left(\int_{\psi}\left(\prod_{t=1}^{T} P_n(\delta_{nt} \mid I_{nt}, \psi) f_t(\psi)\right) d\psi\right) \tag{7}$$

will yield consistent and unbiased estimates of the taste vector and temporal process parameters included in ψ. If parameters are assumed the same over people and time periods, $f_t(\psi)$ becomes a degenerate distribution with all mass concentrated at a single point, and the likelihood function reduces to

$$L(\psi_n) = \sum_{n=1}^{N} \ln\left(\prod_{t=1}^{T} P_n(\delta_{nt} \mid I_{nt}, \psi)\right). \tag{8}$$

The substitution of a specific choice model P_n with utility functions given by (3) (and restrictions to it) will complete the detailing of the likelihood function.[6]

Consistency with stochastic utility maximization also allows the computation of welfare measures based on the theory of welfare in GEV models. Choi and Moon [5] provide an overview of nested logit or GEV models and their corresponding welfare measures. In our case this allows for the computation of welfare measures that contain temporal dependence. Many policy-relevant applied analyses have been conducted without consideration of dynamic elements because of the difficulties in developing tractable models of choice and welfare in a dynamic context. Several authors (see the review in [16]) have discussed the importance of this omission. Thus, development of models that permit welfare analysis in a temporal context will represent a significant contribution to the literature and to policy analysis.

We now turn to an application of this model to a case of recreational fishing in Western Australia.

3. Description of data

Data for the application were collected by issuing a log book to 68 beach anglers who reside in the metropolitan area of Perth, capital city of Western Australia. Survey participants were asked to record details of their day fishing trips taken within a defined study area over a period of 20 weeks, the last 19 of which are used in our analysis. The study area consists of approximately 60 miles of coastline, along which there are many popular fishing options. Focus group discussions with anglers revealed that 18 options are recognized as being the main access points for beach fishing. Survey participants were asked to record information about their trips to these options. Details included trip destination, trip duration (hours), trip costs, catch expectations prior to going fishing (by three target fish types) and actual, ex post catches.

[6] The data and further description of the estimation procedure and likelihood function are available from the authors upon request. In our empirical work we employed a likelihood function that contains the product of T nested logit transition probabilities, as illustrated by the tree in Fig. 2.

For the purposes of modeling site choice behavior, individual fishing options were aggregated into three different sites or locations. Thus, the choice set comprises three fishing sites, with Sites 1, 2, and 3 containing six, four, and eight individual fishing options, respectively, within each site. Aggregation was necessary because insufficient catch rate information from the sample of anglers was available to establish a reliable weekly indicator of fish stocks at each of the 18 options. Whilst aggregation bias is a possibility, it is not expected to be a major issue because focus group discussions identified that the options or "sub-sites" within each of the sites are relatively homogenous with respect to fishing quality, travel distance, and other attributes. Thus the bulk of attribute variation occurs between sites rather than between options within a particular site.[7]

In addition to collecting specific trip information, survey participants were asked to rank each of the sites in terms of their reliability at "delivering" good-sized fish and a diversity of fish types over the course of an average season. Separate indicators were specified for fish size and species diversity. Catch expectations were collected for every trip but this information was limited to the respondent's intended destination. While it would have been ideal to elicit angler catch expectations for every site in the choice set each time a trip was made, this was not practical owing to the excessive burden it would have placed on respondents. Instead, expectations data were used to estimate an "expectations function" which was used to generate weekly catch rate expectations for each target fish type and each site in the choice set. For details see [17].

Complete records for 671 trips were obtained from the returned logbooks. Site 1 attracted the majority of trips (55%), whilst fewer trips were taken to Sites 2 and 3 (35% and 10%, respectively) owing to their greater distance from the Perth residential area. Recorded actual catch rates and catch expectations were highly variable over the survey period, reflecting the migratory and feeding behavior of the fish types involved. The abundance of Fish Type 1 tended to increase towards the end of the season at most fishing locations, while catches of Fish Type 2 declined. This variability strengthens the case for specifying a choice model that allows catch expectations at each site to change over time.

Fishing utility was assumed to be a function of a number of site attributes. The model specification includes: length of the coastline comprising the site, fuel cost of a return trip to the site, respondent perceptions of the reliability of the site in producing "good-sized" fish (a rating scale), and expected catch rates for three target fish groups. The participation decision was assumed to be influenced by angler characteristics ("Fishing Club Member" and "Retiree"), which were included as interaction terms with an alternative-specific constant (ASC) for staying at home. The number of weeks without fishing (linear and quadratic terms) was also included as an interaction term with the ASC. Finally, the last site fished at was included as a previous choice variable.

3.2. *Estimation results*

Four models are estimated on the panel data described above and presented in Tables 1 and 2 (the former contains utility function parameters, and the latter scale, or covariance matrix, parameters). The estimation method was maximum likelihood, based on expression (14) above. All models but the simple static model are TVS variants, with the tree/covariance structure

[7] In this paper we focus on temporal disaggregation rather than spatial disaggregation. Of course both issues are immense importance in choice modeling. We simplify the latter to focus on the former.

Table 1
Panel tree extreme value model estimation results: utility function

Variables	(1) Cross-sectional TEV	(2) (1) + Time-varying tree and period scales	(3) (2) + Dynamics	(4) Final model: (3) w/ restrictions
Utility function				
Length of coast @ location	0.049 (3.56)	0.002 (2.46)	0.004 (0.81)	0.004 (1.01)
Fuel cost to access location	−0.202 (−4.80)	−0.006 (−2.41)	−0.018 (−2.41)	−0.018 (−2.57)
Size reliability @ location	0.124 (5.09)	0.004 (2.85)	0.012 (3.32)	0.011 (3.89)
Expected catch rate type 1	0.020 (0.74)	0.007 (1.28)	−0.012 (−0.69)	−0.012 (−0.75)
Expected catch rate type 2	−0.140 (−2.01)	−0.011 (−1.69)	0.002 (0.15)	0.002 (0.13)
Expected catch rate type 3	−0.026 (−0.55)	−0.002 (−0.27)	0.026 (1.29)	0.027 (1.44)
Last region fished?	0.235 (4.38)	0.054 (3.30)	0.111 (4.46)	0.109 (5.91)
Retiree (Base = stay home)	0.654 (4.47)	0.028 (3.33)	0.034 (3.56)	0.035 (3.96)
Fishing club member (base = stay home)	−0.828 (−4.85)	−0.024 (−2.79)	−0.027 (−2.69)	−0.030 (−3.04)
Weeks w/o fishing (stay home)	0.428 (7.79)	0.025 (2.63)	−0.004 (−0.27)	0.001 (0.08)
(weeks w/o fishing)^2 (stay home)	−0.021 (−3.96)	−0.002 (−2.02)	0.0002 (0.11)	−0.0003 (−0.25)
Initial utilities[b]				
Location 1	0 (—)	0 (—)	−0.123 (−3.37)	−0.118 (−4.13)
Location 2	0 (—)	0 (—)	−0.117 (−3.30)	−0.114 (−3.98)
Location 3	0 (—)	0 (—)	−0.121 (−3.01)	−0.117 (−3.50)
Stay home	0 (—)	0 (—)	0 (—)	0 (—)
Decay factors[a,c]				
Location 1	$-\infty$	$-\infty$	0.663 (72.45)	0.664 (107.05)
Location 2	$-\infty$	$-\infty$	0.666 (72.01)	0.667 (96.21)
Location 3	$-\infty$	$-\infty$	0.673 (65.21)	0.673 (77.21)
Stay home	$-\infty$	$-\infty$	0.704 (—)	0.704 (—)
Compatible with utility maximization?	✓	✓	×	✓
Goodness-of-Fit				
Number of parameters	12	46	52	46
Log likelihood @ convergence (LL(0) = −2084.43)	−1182.38	−1072.29	−1037.62	−1039.20
$\bar{\rho}^2$	0.427	0.464	0.477	0.479

t-Statistics are in parentheses.

[a] Decay factors defined as $\rho = [1 + \exp(-\gamma)]^{-1}$, where γ is value shown.

[b] An identification restriction requires that at least one of the initial utilities be zero.

[c] Decay factor for stay at home is held constant due to lack of identification: only $(J-1)$ decay factors can be identified, so one must be fixed to a convenient value. In this model, the stay at home factor was set to the value shown (selected by the optimization routine), then the models were brought to full convergence to obtain standard errors of remaining parameters.

Table 2
Panel tree extreme value model estimation results: scale parameters

Variables	(1) Cross-sectional TEV	(2) (1) + Time-varying tree and period scales	(3) (2) + Dynamics	(4) Final model: (3) w/ restrictions
Tree root scale $\ln(\mu)$				
	0 (—)	0 (—)	0 (—)	0 (—)
Time period scales				
$\ln(\mu_1)$	$\equiv \ln(\mu)$	3.769 (7.26)	3.250 (6.04)	3.310 (6.83)
$\ln(\mu_2)$	$\equiv \ln(\mu)$	2.291 (6.08)	2.255 (7.13)	2.218 (7.70)
$\ln(\mu_3)$	$\equiv \ln(\mu)$	2.289 (6.71)	2.040 (6.44)	2.018 (7.11)
$\ln(\mu_4)$	$\equiv \ln(\mu)$	1.182 (2.79)	0.819 (1.80)	0.800 (1.86)
$\ln(\mu_5)$	$\equiv \ln(\mu)$	0.828 (1.73)	0.909 (2.42)	0.877 (2.49)
$\ln(\mu_6)$	$\equiv \ln(\mu)$	1.027 (2.80)	0.878 (2.59)	0.851 (2.73)
$\ln(\mu_7)$	$\equiv \ln(\mu)$	1.285 (3.95)	1.288 (4.51)	1.255 (4.93)
$\ln(\mu_8)$	$\equiv \ln(\mu)$	1.351 (4.41)	1.149 (4.09)	1.119 (4.51)
$\ln(\mu_9)$	$\equiv \ln(\mu)$	0.212 (0.47)	0.223 (0.60)	$\equiv \ln(\mu)$
$\ln(\mu_{10})$	$\equiv \ln(\mu)$	0.917 (2.84)	0.763 (2.55)	0.728 (2.68)
$\ln(\mu_{11})$	$\equiv \ln(\mu)$	1.021 (3.33)	0.895 (3.25)	0.860 (3.52)
$\ln(\mu_{12})$	$\equiv \ln(\mu)$	0.535 (1.62)	0.231 (0.74)	$\equiv \ln(\mu)$
$\ln(\mu_{13})$	$\equiv \ln(\mu)$	1.248 (4.16)	1.118 (3.98)	1.005 (5.68)
$\ln(\mu_{14})$	$\equiv \ln(\mu)$	1.018 (3.33)	0.744 (2.57)	0.723 (2.86)
$\ln(\mu_{15})$	$\equiv \ln(\mu)$	0.622 (1.98)	0.190 (0.64)	$\equiv \ln(\mu)$
$\ln(\mu_{16})$	$\equiv \ln(\mu)$	0.269 (0.79)	−0.132 (−0.41)	$\equiv \ln(\mu)$
$\ln(\mu_{17})$	$\equiv \ln(\mu)$	0.390 (1.23)	−0.257 (−0.80)	$\equiv \ln(\mu)$
$\ln(\mu_{18})$	$\equiv \ln(\mu)$	$\equiv \ln(\mu)$	$\equiv \ln(\mu)$	$\equiv \ln(\mu)$
$\ln(\mu_{19})$	$\equiv \ln(\mu)$	$\equiv \ln(\mu)$	$\equiv \ln(\mu)$	$\equiv \ln(\mu)$
Tree scales[a]				
$\ln(\theta_{1,1})$	1.929 (9.36)	6.343 (13.59)	5.115 (10.16)	5.157 (10.83)
$\ln(\theta_{1,2})$	1.929 (—)	5.864 (6.93)	4.480 (6.87)	4.539 (7.22)
$\ln(\theta_{1,3})$	1.929 (—)	2.884 (7.30)	2.341 (8.49)	2.354 (9.95)
$\ln(\theta_{1,4})$	1.929 (—)	3.695 (7.88)	2.770 (6.41)	2.810 (7.00)
$\ln(\theta_{1,5})$	1.929 (—)	2.564 (6.72)	1.793 (5.68)	1.820 (6.52)
$\ln(\theta_{1,6})$	1.929 (—)	3.003 (7.76)	2.262 (6.72)	2.288 (7.56)
$\ln(\theta_{1,7})$	1.929 (—)	2.781 (6.92)	2.017 (5.78)	2.046 (6.54)
$\ln(\theta_{1,8})$	1.929 (—)	2.343 (6.30)	1.686 (5.62)	1.710 (6.51)
$\ln(\theta_{1,9})$	1.929 (—)	2.642 (6.66)	1.919 (5.45)	1.952 (6.18)
$\ln(\theta_{1,10})$	1.929 (—)	2.334 (5.92)	1.617 (4.78)	1.644 (5.42)
$\ln(\theta_{1,11})$	1.929 (—)	2.384 (5.66)	1.657 (4.38)	1.692 (4.88)
$\ln(\theta_{1,12})$	1.929 (—)	3.348 (5.75)	2.701 (4.87)	2.740 (5.17)
$\ln(\theta_{1,13})$	1.929 (—)	1.748 (4.75)	0.874 (2.70)	$\equiv \ln(\mu)$
$\ln(\theta_{1,14})$	1.929 (—)	1.760 (4.61)	0.834 (2.26)	0.886 (2.75)
$\ln(\theta_{1,15})$	1.929 (—)	2.214 (5.17)	1.288 (3.03)	1.389 (3.76)
$\ln(\theta_{1,16})$	1.929 (—)	2.099 (4.91)	1.296 (3.21)	1.291 (3.40)
$\ln(\theta_{1,17})$	1.929 (—)	2.575 (5.20)	1.757 (3.71)	1.717 (3.55)
$\ln(\theta_{1,18})$	1.929 (—)	2.436 (4.76)	1.539 (2.82)	1.571 (3.17)
$\ln(\theta_{1,19}) \equiv \ln(\theta_{1,18})$	1.929 (—)	2.436 (—)	1.539 (—)	1.571 (—)

t-Statistics are in parentheses.
[a] All models constrain $\theta_{2,t}$, $t=1,\ldots,19$, to be equal to the period scale μ_t, $t=1,\ldots,19$, for identification purposes.

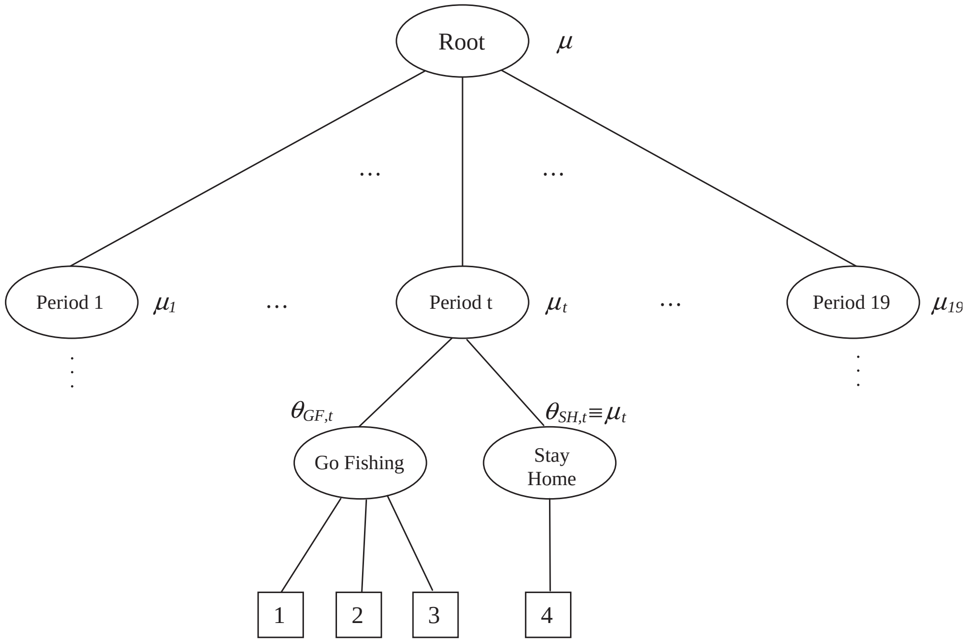

Fig. 2. Dynamic nest structure for recreational fishing application.

reflecting a separate "Go Fishing" versus "Stay Home" partition, with the fishing sites (1, 2 and 3) being the elemental alternatives under the "Go Fishing" branch; the elemental "Stay Home" alternative is indexed "4" in Fig. 2, which presents the entire model structure graphically. The fully specified model allows for time-varying scales as well as time-varying "inclusive value parameters" on the Go Fishing branch.

The first model is a simple cross-sectional model that includes no temporal dependence in the sense that the meta-utilities are restricted to be equal to current utilities: there are no previous utilities considered, and the time-varying scale parameters are restricted to unity, though the model does include state dependence through the "Last Site Fished?" dummy.[8] The second model includes time-varying scales and inclusive value parameters for the "Go Fishing" nest, which makes it equivalent to a series of TVS models that differ through period-specific covariance matrices (thus, both variances and covariances change in this model). We refer to this model as time-varying covariance or TVC. The third model adds "history" (initial conditions, past utilities, etc., as per meta-utility function (5)) to the second. The fourth and final model applies certain restrictions to the third model (subsequently explained). Note that all models except the first assume that the identifiable tree scale factors ($\theta_{GF,t}$ in Fig. 2) are time-varying. These four models are referred to as

1. cross-sectional,
2. TVS + TVC,

[8] Note that all scale factors reported in Table 2 are actually the logarithm of the scale factors. This transform was employed to guarantee non-negativity of scale estimates.

3. TVS + TVC + history,
4. TVS + TVC + history (restricted).

3.2.1. Model 1: cross-sectional

The results for the basic static model show that angler site choice is affected by the length of coast at that site, costs of access, angler perceptions of fish size, and if the site was visited on the previous trip (i.e. first-order state dependence). Note that expected catch rates appear to not strongly influence site choice, as measured through the significance of the respective parameters. The tree scale parameter for "Go Fishing" versus staying at home is highly significant and approximately equal to $\hat{\theta}_{GF} \approx \exp(1.9285) \approx 6.88$ (all scale parameters estimated must actually be exponentiated to yield the estimate of scale; see details of Table 2). Note that this scale parameter and the commonly estimated inclusive value parameter are simply inverses one of another. Hence, the usual stochastic utility consistency tests which require that inclusive value parameters be between zero and one, and more generally, that they decrease as one goes deeper into the tree, are simply inverted to require that scale factors increase monotonically down the tree. (See [2,8] for further details on testing stochastic utility maximization consistency.) For Model 1, as we stated above, the tree scale is approximately 6.88, so the inclusive value coefficient is about 0.145; since the root scale and inclusive value are unity, we can consider Model 1 to be consistent with utility maximizing behavior.

Continuing our examination of Model 1, note that the number of weeks that the angler does not go fishing has a quadratic relationship with probability of site choice. Initially, the longer an angler stays at home, the less likely he/she is to go fishing the next week. However, after some time staying home (estimated to be about 10 weeks in this data) the probability of continuing to stay home decreases, implying an increase in the likelihood of going fishing. This effect of weeks without fishing is strongly significant in the static model, but as we shall see, it becomes less relevant in the time-series versions of the model. Note that state dependence (introduced via the dummy variable "Last Region Fished?") is significant and distinguishable, in the "Stay Home" alternative, from the effect of weeks without fishing.

The Retiree and Fishing Club Member dummies indicate that being in these categories influences the probability of choosing any fishing site (versus choosing to not go fishing). Retirees are more likely to go fishing while Fishing Club Members, somewhat surprisingly, are not as likely to go fishing. A possible explanation for this result is that club members were found to have higher income and, correspondingly, a higher opportunity cost of time. This could have been responsible for the negative correlation observed between income and fishing activity participation.

3.2.2. Model 2: TVS+TVC

Model 2 enhances the prior model by permitting the covariance matrix (i.e. both heteroscedasticity and inter-alternative substitutability) to vary over time. Thus, scale factors for each time period are estimated, as are "Go Fishing" node scale factors within each period. (The corresponding "Stay Home" scale factors are not identified, of course, since only one alternative is present in that nest. Accordingly, in Model 2, as well as subsequent models, those scale factors are set equal to the scale of their parent node in the tree as a normalizing condition—

see Fig. 2.) This model, when compared to Model 1, generates a chi-squared statistic of 220.2 with 34 degrees of freedom, which is statistically significant at the 95% confidence level.[9] Much of the improvement seems to be due to the highly significant variation in time period and ''Go Fishing'' scale factors, since there is very little change in the parameters of the utility function (except for linear scaling effects due to time-varying scales). Looking ahead, it should be noted that the introduction of the time-varying covariance matrix is the single most important improvement in the goodness-of-fit of the models tested in this exercise. Finally, observe that Model 2 is consistent with stochastic utility maximization, as evidenced through a period-by-period comparison of the tree node and time period scale factors.

3.2.3. Model 3: TVS+TVC+history

Model 3 generalizes Model 2 through the inclusion of history, in the form of (1) memory decay, or habit persistence, effects and (2) initial utilities. This addition is highly significant: the chi-squared statistic is 69.3 with 6 degrees of freedom. In Model 3 the weeks without fishing parameters are no longer significant, as they were in the first two models, neither of which included true temporal effects. This indicates that when temporal dependence is explicitly included in the model through the history terms and initial utilities, ad hoc ''dynamicizing'' measures are likely to become less significant. Despite the estimation of initial utilities in this model, note that the last-region-fished variable is still significant, indicating a degree of state dependence. The parameters on the initial utilities are significant and indicate that the ''Stay Home'' alternative has the highest overall sample average initial utility, while the fishing sites have very similar, but lower, initial utilities. In general, the significance of the initial utility estimates is likely to be a function of the length of the observation window: the longer the window, the less significant these parameters should be. Finally, this model is *not* consistent with stochastic utility-maximizing behavior since the tree scale in period 13 ($\exp(0.8739) \approx 2.40$) is smaller than the corresponding period scale ($\exp(1.1177) \approx 3.06$). In addition, the scale factors for periods 16 and 17 are both smaller than the unit-valued root scale factor.

The decay factor parameters estimated in Model 3 are all highly significant. (Due to identification restrictions, the factor for one alternative must be held constant. In this model, the decay factor of ''Stay Home'' was established by the optimization process, then held constant to permit identification of remaining parameters.) The parameters in Table 1 imply decay factors of about 0.66 for all four alternatives (see Note 2 of Table 1), which means that after about 8 periods the impact of a period's utility is only about 4% of its original value. This is a relatively strong persistence effect, particularly given the short duration of the fishing season in this data.

3.2.4. Model 4: TVS+TVC+history (restricted)

Model 4 is a restriction of Model 3 that imposes constraints on several time period scale factors and period 13 ''Go Fishing'' tree node scale factor (see Tables 1 and 2 for implementation details). Using a likelihood ratio test, the hypothesis for the restrictions cannot be rejected based on the

[9] In this and subsequent models we add parameters to the basic cross sectional model. While these additional parameters improve the statistical performance of the models they may not lead to improved behavioral predictions. Tests of such performance are items for future research.

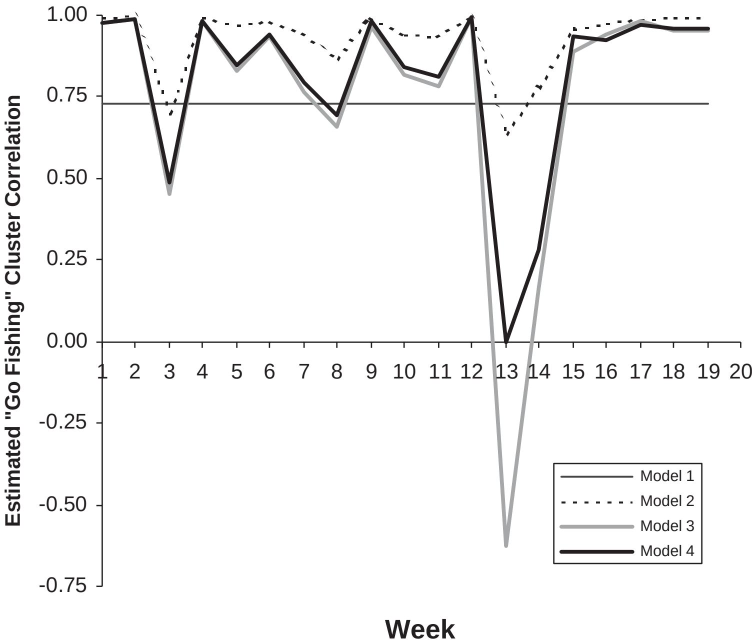

Fig. 3. "Go Fishing" cluster (Sites 1, 2 and 3) correlations (covariance matrix estimates).

calculated chi-squared value of 3.2, with 6 degrees of freedom. Under this somewhat simplified model, behavior is found to be consistent with utility maximization.

To contrast these four models, we present in Fig. 3 a comparison of the predicted correlation between alternatives in the "Go Fishing" cluster over time. Models 2–4, all of which permit the covariance matrix to vary over time, generally predict correlations that are higher than Model 1, which we consider a default, or base, specification. The only significant exception to this is in period 13, where Model 3 predicts a *negative* correlation within the cluster. This, of course, is a direct result of violating the conditions for utility maximizing behavior (conditions for inclusive values in nested logit models). Thus, in the final specification (Model 4), the net effect of the restrictions on the scale factors is to produce a correlation of 0 in period 13, which is to say, the observed behavior is consistent with Independence of Irrelevant Alternatives in that period. Examination of the raw data and other sources has not helped to elucidate this peculiar feature of the data, particularly noticeable since periods 14–19 seem in line with those preceding 13.

Fig. 4 displays simulations of the predicted probabilities for each week within the sample for two of the four models (base Model 1 and Model 4), plus the observed shares for the "Stay Home" alternative and Site 1. Note how the model with temporal dependence appears to fit the sample well in the early periods (due to initial utility estimates) and in the later periods (as the approach of the end of the season begin to affect behavior). The static model seems to reflect a "smoothing" of the variability in week-to-week site choice variation by anglers, rather than capturing the variation. Overall, Model 4 appears to track the observed data quite well, especially at the endpoints of the series.

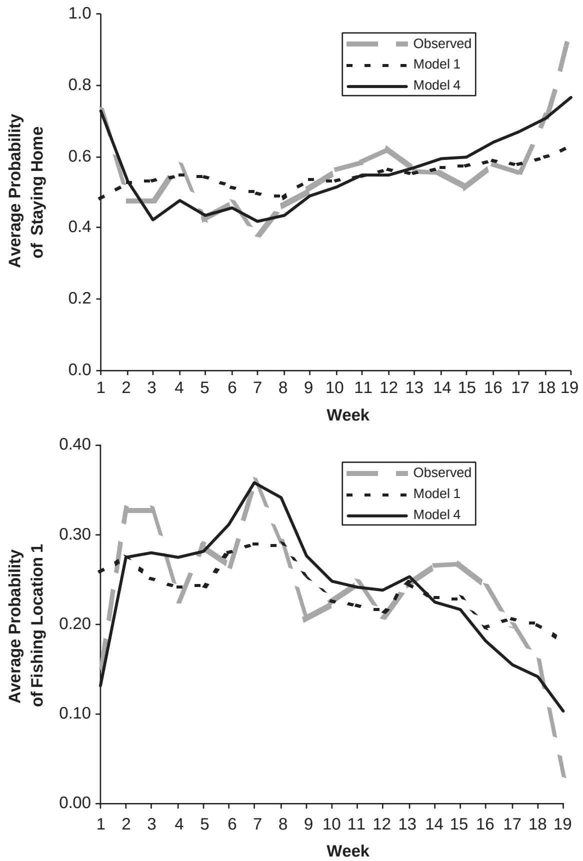

Fig. 4. Base simulations of probabilities of "Stay Home" and choosing Site 1.

3.3. Welfare and policy analysis

As described above, one of the most important uses of choice models of this type is the assessment of environmental impacts or policy changes in terms of welfare and/or changes in behavior (demand). The theory of welfare measurement for cross-sectional nested logit/generalized extreme value models has been well documented by Choi and Moon [5]. In this case we assume that there are no income effects, and apply the standard analytical form for the expected value of compensating variation. We assume that the meta-utility function represents the angler preferences and that they essentially use a weighted average of current and previous attributes levels when making decisions. These "perceived" attribute levels are assumed to drive the welfare measurement. The individuals are not assumed to make mistakes by choosing based on incorrect attribute levels; rather, we simply assume that the angler's utility function is more complex as it depends on previous period's utilities. The utilities include current and past attribute levels, therefore utility from fishing days later in the season will depend on the historical pattern of attribute levels and choices. If the temporal dependence parameters are not significant then the model reduces to a static random utility model in which only current attribute levels affect utility and welfare measurement proceed as in the static case; otherwise, the sequence of attribute levels establishes current utility. We shall employ two models in our comparisons: Model 1 (base cross-sectional model) and Model 4 (TVS + TVC + history with restrictions).

We examine next simulations of impacts of four different scenarios or policies, to wit:

Policy 1: An increase in the price (access cost) of 100% for all angling alternatives starting in week 4 and proceeding throughout the observation period.

Policy 2: The closure of Site 2, beginning in week 4 and continuing until week 7 (a total of 1 month).

Policy 3: Deterioration of fishing quality (movement to the lowest level of the scale) at Site 1, again for weeks 4 to 7.

Policy 4: Deterioration of fishing quality at Site 1 for weeks 13–19, which is simply Policy 3 delayed for 9 more weeks into the season.

In the evaluation of these scenarios, we have chosen to define state dependence in a policy-dependent fashion. When models include state dependence and history, changes in attributes arising from a policy change could affect the pattern of choices and thus could affect utility through the state dependence term. For example, if fishing quality declines at a site and anglers choose to fish elsewhere, the fact that they fish elsewhere must be captured in the representation of state dependence in future utility functions. One cannot employ actual choices as state dependence "data" since the quality changes may have generated new choices. Specifically, we have redefined the dummy for "last region fished" on the basis of predicted probabilities for the prior week. Hence, as choice probabilities are affected by policy impacts, state dependence also becomes policy sensitive. This is found to have a major impact on our results.

3.3.1. Policy 1: price increase

Policy 1 results in welfare losses for all weeks starting with week 4, with the time-series model producing much larger per trip and cumulative welfare losses (these cumulative losses are shown in Fig. 5). In fact, by the end of the season, Model 4's predicted welfare impacts are almost an order of magnitude larger than those of Model 1. The negative impacts of the price increase are compounded in the temporal model since previous utilities affect current utilities (via both past attribute levels as well as state dependence), making the utility of staying home much more attractive than would otherwise have been the case. These results are not unexpected since the angler's habits associated with fishing have been negatively affected by the price increase. Note how Model 1, omitting temporal dependence, predicts that the impact of the policy is uniform throughout the final 16 weeks of the observation period (i.e. the slope of its cumulative welfare loss graph is constant); in contrast, Model 4 predicts a steeper pattern of welfare losses throughout the entire period.

3.3.2. Policy 2: site closure for 4 weeks

Policy 2 provides much more interesting dynamics, and also presents interesting conceptual problems to be simulated. Beach closures or fishing area closures due to chemical spills or other similar incidents are often the focus of natural resource damage assessment (NRDA) cases. In this simulation, Site 2 is closed for 4 weeks, that is, it is made unavailable to anglers for this period. To simulate this closure effect, two approaches were taken: (a) fuel costs for Site 2 were made extremely large during the affected period, effectively creating large disutilities for the location,

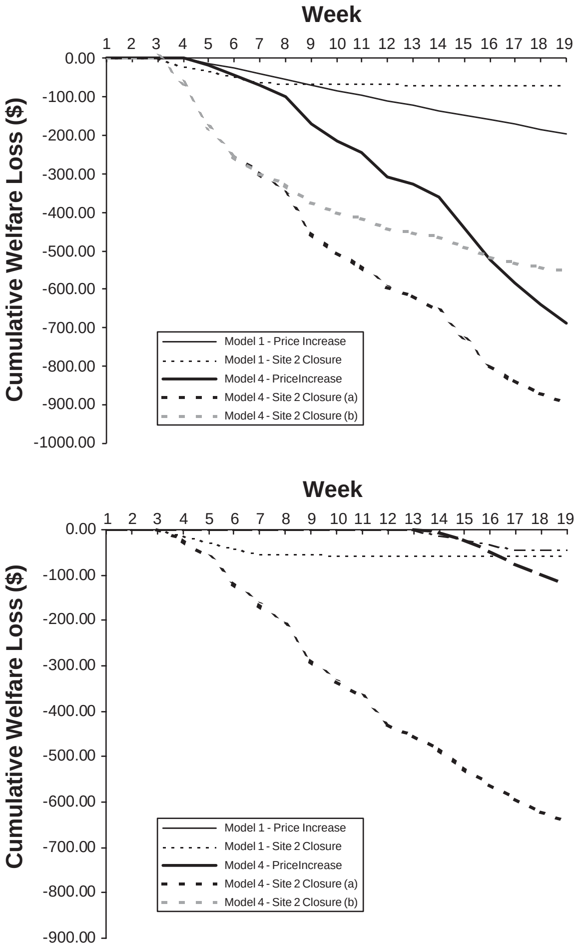

Fig. 5. Welfare measures for 4 simulated policy changes.

which then were used in subsequent periods as part of determining current preferences; (b) Site 2 was removed from the choice set during the affected weeks, but the utility of the site during those weeks was impacted by increasing fuel costs significantly (though not nearly as much as in method (a)). The fuel cost increase in method (b) is intended to associate some disutility with the closure itself, which one would reasonably expect to occur. What should the magnitude of this disutility be? Clearly, the optimal solution would have been to observe closures in the data itself, and estimate (for example) dummies reflecting the disutility. In the absence of such information, this impact must become a parameter of the simulation process that the analyst must establish through other means than the model.

Fig. 6 shows how the two methods compare in terms of their predicted share of trips to Site 2, over time. Model 1 predicts that the impact of closure is felt only during the weeks in question; the predictions of Model 4 are a function of the method of implementing the closure. Specifically, under method (a) the share of visits to Site 2 remains zero from week 4 onwards, due to the heavy penalty imposed on the utility of that site during the affected period and the memory process

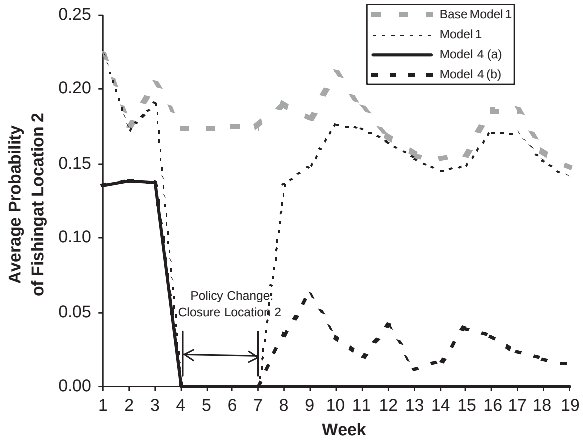

Fig. 6. Simulations of probabilities of choosing Site 2 under policy 2—Site 2 closure, weeks 4–7.

captured by the dynamics of Model 4. Under method (b) the disutility associated with the closure was assumed to be equivalent to a 400% increase in fuel price for trips to Site 2; this more reasonable disutility creates the depicted pattern of recuperation of trips to the site following re-opening, which is between that of Model 1 and the likely over-pessimistic predictions of Model 4 with method (a). The greater the penalty factor used in method (b), the more nearly like method (a) will be the ensuing trip pattern after week 7. Thus, the impacts predicted under method (b) are bounded by those of Model 1 and of Model 4, method (a).

Returning to Fig. 5, the graphs therein illustrate that Model 4 predicts a much larger and longer lasting welfare impact than the static model. Note that the rate of cumulative welfare increases arising from the time-series model (method a) do eventually become somewhat smaller (i.e. the slope tends to flatten out), but at the end of the season the impact of the closure is still strong. In the static model the impact of closure is felt only for the 4 weeks that the site is unavailable, and then there are no further negative impacts of the closure (i.e. after week seven the slope of the line is zero). Again, the time-series components in Model 4 imply that anglers retain the negative effect of the closure in future periods. Note again that the parametrization of the fuel penalty in simulating Policy 2 by methods (a) and (b) imply that an envelope enclosing the welfare impacts can be derived, as was suggested in Fig. 6.

A key issue in the simulation of site closure is the fact that the observation of site closure is seldom present in revealed preference data, and certainly is not present in our data. Thus, the issue of most common concern in natural resource damage assessment is difficult to assess using the time-series model because the determination of the impact of closure on “memory” is not well defined without observations of closures. Static models do not reflect this difficulty since no “memory” is required for these models—the consumer simply returns to the original preference structure after the damage has been removed.

3.3.3. Policy 3: deterioration of fishing quality (early in season)

Policy 3 causes Site 1 to suffer a fishing quality deterioration to the lowest level for a 4 week period, beginning the 4th week of the season. Fig. 5 provides details on the welfare loss dynamics

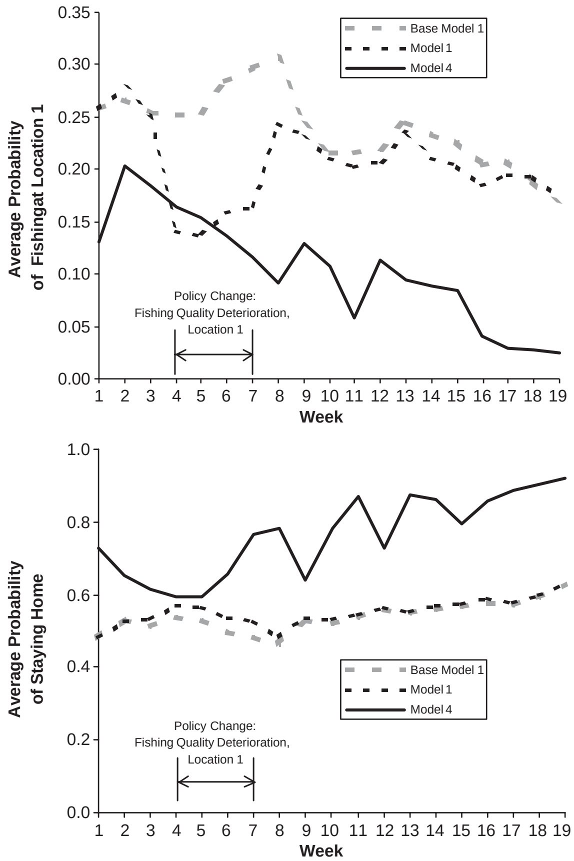

Fig. 7. Simulations of probabilities of choosing Site 1 and "Not-Going" under policy 3—fishing quality deterioration, Site 1, weeks 4–7.

of this case, while Fig. 7 shows simulated choice probabilities for Site 1 and staying home under this policy. The probability of choosing Site 1 shows that the static model responds more significantly to the change in quality, reducing choice of Site 1 to a lower level at the beginning of the 4 week period of the quality deterioration. The time-series model shows inertia or habit persistence because choice of Site 1 initially declines less, and then the experience of the decline in fishing quality persists on in the temporal model, as the probability of choosing Site 1 remains below that estimated by the static model for the rest of the season. This illustrates that the time-series model tends to dampen the initial effect of a reduction in quality, but carries the effect on for a longer period. The overall welfare impact is, consequently, significantly larger in the time-series model (Fig. 5, lower panel). The graph of the probability of not going fishing under this policy (see Fig. 7) shows that the temporal model predicts a persistence of the quality impact that increases the probability of anglers staying home, relative to the static model.

3.3.4. *Policy 4: deterioration of fishing quality (late in season)*

Policy 4 causes the same impact (fishing quality deterioration) as Policy 3, but it is assumed to occur later in the season (beginning in week 14). A similar pattern to Policy 3 arises (Fig. 5), but the welfare impacts are smaller than Policy 3 since the impact occurs later in the season and the temporal elements are shifting more probability to staying home, rather than choosing other angling sites. This suggests that not only are the time elements important in identifying welfare impacts, but specifying the seasonal nature of the activity and the time within that season that the impact occurs is important in the determination of "damages."

These simulations emphasize the very real and high value of representing the time dimension of choice by capturing habit persistence and state dependence, initial utilities and so forth. Extending choice models to straightforwardly incorporate these features should help improve the diffusion of the improvements made possible by this research into practical policy cases (including natural resource damage assessment) since the theory for welfare impact assessment has already been extended to this family of models.

4. Conclusions and future research

As expected we have found that choice probabilities and welfare measures differ when one specifies a time-series model instead of a static model. The actual form of these differences is also not surprising. The static model results in anglers returning to sites immediately after a change, "forgetting" about any impact at that site and being unaffected by the change in quality or their own change in participation and site choice. The models with temporal dependence, on the other hand, illustrate habit/inertia effects and the persistence of impacts of changes in quality. The magnitudes of some of these impacts are surprising. The static model welfare measures for policy 2 (site closure), for example, are one-tenth the time-series model measures. Similarly, the temporal model measures for policy 3 (quality change) are 6 times larger than those of the static model. In the case of the quality change we see that the value of environmental impacts depends on the point in the season at which they occur. Impacts late in the season have a smaller effect in the case examined here since the angler has likely consumed a significant "stock" of trips and is less likely to choose angling (relative to staying home). Therefore, the response to a late season shock is smaller. While all of these results are case-specific, they do point out the importance, in empirical terms, of incorporating history and expectations into behavior and welfare analysis.

The use of the time-series model for simulation and welfare measurement has raised several issues that are not apparent when using static models. Some of these issues include the specification and interpretation of time-varying covariance structures, and the interpretation of hierarchies of scale (inclusive value) parameters. However, the most challenging issue arising from this study is the specification and interpretation of the welfare measures in the case of temporal demand. Policy changes or environmental changes will have temporal impacts. Thus, certain changes (e.g. a loss in environmental quality) will remain in the memory of the consumer for several periods and will affect choice and welfare for several periods, even after the effect has been eliminated. This is particularly challenging for the case of site closures due to environmental damage. Unless there have been observations of closure, and the impact of closures modeled explicitly, it is difficult to specify exactly what the dynamic impact will be. A static model treats this issue simplistically—individuals return to their original utility levels after the site has been re-opened. However, temporal models require that the "memory" of the disutility associated with the closure be reflected in previous period utility weights when specifying the utility in the current period. This issue opens a wide variety of research questions, including the assessment of closures of different types (environmental damage, administrative closures, etc.) and the appropriate modeling of each when they are observed. Certainly it would seem recommendable that the decay, or memory, factors proposed in the models here become a function of the nature of the closure.

A more subtle consequence of the model form proposed here results from the structure of the meta-utility function. As made clear in expression (3), current utility is a function of both present and past attributes, to the extent dictated by the associated memory structure. Equivalently, the meta-utility can be viewed as being influenced by current attributes and past utilities. Current utility being dependent on previous utility/attribute levels is a form of reference dependence. It may seem that for this model structure to hold that we assume that decision makers must have infinite memory resources. However, two factors might mitigate this: decision makers need remember only the weighted past utility of each option, and this utility need involve only a limited number of periods (as indicated by the size of the decay parameters). This interpretation is appealing because it does not seem so cognitively burdensome from the decision maker's perspective. On the other hand, although this intertemporal utility structure does not change the basic approach to welfare analysis, if utility in a period does depend on historical utilities/attributes then welfare calculations necessarily become more complex and temporally intertwined.

The temporal model we employ is an extension of a traditional random utility maximization model. These extensions are achieved through appropriate definition and parametrization of the utility function. Because of this, it is possible to apply the same concepts to other discrete choice models, e.g. the Multinomial Probit model. Because of their computational advantages, we have chosen to emphasize application of the extensions to the generalized extreme value family. Depending upon the member of the GEV family that is employed, it is possible to straightforwardly allow for time-varying covariance matrices, thus capturing both heteroscedasticity and inter-temporal differences in cross-substitutions among alternatives. For example, if the MNL model is used with our approach, the resulting model can be temporally heteroscedastic, though all alternatives will have identical error variances at a given time period and all covariances will be zero; if a TVS or NMNL model is specified, however, the covariances identified through the tree structure will be estimable (either constant or varying across time, as we have done in our empirical application).

In practice, GEV models, particularly the more standard members (MNL, NMNL), are relatively easy to estimate via standard methods. We particularly see the TVS and NMNL extensions as being useful tools to support welfare assessment efforts in practice. These methods are still "reduced forms" in comparison to the structural approaches employed in dynamic programming discrete choice models, but they provide insights into dynamic behavior and capture some of the essential components of dynamic discrete choice.

This paper presents a tractable time-series discrete choice model, but the empirical work presented does suffer from several shortcomings. We have not included taste heterogeneity in our empirical work, but it is straightforward to do so in these extensions of the GEV family, as shown in the log likelihood expression (6), particularly using simulated maximum likelihood methods (e.g. [3,12]). This topic also brings up another shortcoming of our current work, which is the omission of serial correlation from the temporal dependence. This omission can be partially accounted for through the inclusion of parameter heterogeneity in models, but future research should extend the suggested approach to include serial correlation.

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