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Abstract

Identification and estimation of multinomial probit models are examined for recreation demand with a large number of choices. Two logit and three probit models are estimated and IIA restrictions, site substitution patterns, trip prediction, and welfare estimation are investigated using a range of policy scenarios. Assumptions about the error distribution of a model are shown to be important.

Key words: recreational fishing, recursive smooth simulator, multinomial probit, nested logit, IIA, repeated random utility model, welfare estimation.

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An Empirical Assessment of Multinomial Probit and Logit Models for Recreation Demand

1 Introduction

The random utility model is widely used in contemporary travel cost studies of recreation demand. Almost all random utility models in the recreation literature are specified as multinomial logit or as nested logit. One reason for this is the ability of these models to incorporate a large number of substitutes without sacrificing ease of estimation. Another strength of these models is that measuring the welfare effects of changes in site characteristics is straightforward (Bishop and Heberlein 1979, Small and Rosen 1981, Hanemann 1982, among others).

The independence of irrelevant alternatives (IIA) property of multinomial logit is a well known and often cited drawback of the multinomial logit formulation of random utility models (see for example Chapter 4 by Morey). With nested logit models, IIA is partially relaxed.¹ In many empirical studies, the generalization embodied in the nested logit has been shown to be important (Morey, Rowe, and Watson 1993; Kling and Herriges 1995; Hausman, Leonard, and McFadden 1995). As an alternative to the logit model, the multinomial probit model can be used to provide a general correlation pattern across choices without exhibiting the IIA property. This model has seen little application in recreation demand because the probit model with more than four choices was difficult to estimate prior to recent advances in econometric theory and computing power.

This chapter empirically investigates the implications of error distributions which relax IIA. The application is to Great Lake fishing site choices made by Michigan trout

¹Specifications such as the random parameter logit or random parameter probit can also relax IIA, see Chapter 5 by Train or Chen and Cosslett (1996).

and salmon anglers. The underlying theoretical framework is the repeated random utility model. The following repeated random utility models were estimated: (i) a simple multinomial logit, (ii) a nested logit, (iii) a simple multinomial probit with independent errors, and (iv) two multinomial probits with correlated errors. The probit models were estimated using simulated maximum likelihood methods. The results demonstrate the feasibility of estimating multinomial probits for the large choice sets encountered in recreation demand analysis.

In the remaining sections of this chapter, the logit and probit models are specified and the estimation and identification of multinomial probit are also reviewed for recreation demand. Next, by using a recreation fishing demand data set, the parameter estimates are presented for each of the models. Predictions of fishing trips under baseline site quality characteristics and under a range of changes in site quality characteristics are compared across the models. Examining a range of changes in site quality allows the changes in trip demand to be compared across model specifications at site level. Trip predictions are also calculated for sites where quality was not changed so that the implications of IIA can be illustrated. In addition, welfare measures for the various changes in site quality characteristics are calculated for each of the estimated models.

2 Multinomial Logit and Probit Models

Let the random utility of choosing alternative j be written as $U_j = x_j\beta + u_j$, where x_j are the explanatory variables for the utilities of alternatives $j = 1, \dots, J$. u_j is the random taste term, unobservable to the researcher. By the hypothesis of random utility maximization, if j is chosen, it implies $U_j \geq U_l$ for $l = 1, \dots, J$. These inequalities are used to specify the probability that each of the alternatives is chosen. The model for the choice probabilities will follow from the distribution of the error terms u .

2.1 Multinomial Logit Models

If the u_j are assumed to be i.i.d. with a type I extreme value (EV) distribution, then the joint distribution of the errors is

$$F(u) = \exp \left(- \sum_{j=1}^J \exp(-u_j) \right),$$

and the choice probabilities are given by

$$(1) \quad \Pr(j) = \frac{\exp(x_j \beta)}{\sum_j \exp(x_j \beta)}.$$

From (1), it is clear that the probability ratio between choices j and k is independent of the utility functions other than that of alternatives j and k

$$\frac{\Pr(j)}{\Pr(k)} = \frac{\exp(x_j \beta)}{\exp(x_k \beta)}.$$

This is often referred to as the IIA property of the multinomial logit model (1).

To partially relax IIA by deriving a two-level nested logit, we can partition the set of alternatives into G groups as $\{J_g\}$ where J_g is the number of choices in group g for $g = 1, \dots, G$. Assume that the vector of errors u is i.i.d. and has the following form of generalized EV distribution function,

$$F(u) = \exp \left\{ - \sum_{g=1}^G \left(\sum_{j \in B_g} \exp(-u_{j_g}/\lambda_g) \right)^{\lambda_g} \right\}.$$

It can be shown that the corresponding choice probabilities are

$$(2) \quad \begin{aligned} \Pr(j) &= \Pr(j|B_g) \times \Pr(g) \\ &= \frac{\exp(x_j \beta / \lambda_g)}{\sum_{j \in B_g} \exp(x_j \beta / \lambda_g)} \times \frac{\exp(\lambda_g IV_g)}{\sum_{g=1}^G \exp(\lambda_g IV_g)} \\ &= \frac{\exp(x_j \beta / \lambda_g)}{\exp((1 - \lambda_g) IV_g)} \times \frac{1}{\sum_{g=1}^G \exp(\lambda_g IV_g)}, \end{aligned}$$

where $IV_g = \ln(\sum_{j \in B_g} \exp(x_j \beta / \lambda_g))$. Similar to the multinomial logit model, it is easy to see that the probability ratio of any two alternatives that are within the same group

g is still independent of the utility functions of the other alternatives (IIA holds within groups). What is different now is that the probability ratio between alternatives j and k that are not within the same group, say group g and group s , depends not only on the utility functions of alternatives j and k , but also on the group inclusive values IV_g and IV_s . That is,

$$\frac{Pr(j)}{Pr(k)} = \frac{\exp(x_j\beta)}{\exp(x_k\beta)} \times \frac{\exp((1 - \lambda_s)IV_s)}{\exp((1 - \lambda_g)IV_g)}.$$

The probability ratio remains independent of all alternatives in groups other than g and s . Thus, the nested logit exhibits a property similar to IIA, which we will call independence of irrelevant groups (IIG).

2.2 Multinomial Probit Models

One way to avoid the restricted substitution patterns embodied in models with IIA and IIG is to employ the normal distribution for the random terms, i.e., assume $u \sim N(0, \Sigma_u)$ with the density function

$$f(u) = \frac{1}{\sqrt{2\pi|\Sigma_u|}} \exp\left(-\frac{1}{2}u'\Sigma_u^{-1}u\right)$$

where Σ_u is the covariance matrix. The resulting choice probability $Pr(j)$ is

$$(3) \quad \begin{aligned} Pr(j) &= \int_{-\infty}^{\infty} du_j \int_{-\infty}^{(x_j - x_1)\beta + u_j} du_1 \cdots \int_{-\infty}^{(x_j - x_J)\beta + u_j} du_J \cdot f(u_1, \dots, u_J | \Sigma_u) \\ &= \int_{-\infty}^{\infty} F_j((x_j - x_l)\beta + u_j, \forall l \neq j) du_j \end{aligned}$$

Unlike the logit models, the probability ratio between any two alternatives $Pr(j)/Pr(k)$ depends on utility functions of all alternatives regardless of the covariance structure in Σ_u . Thus, the IIA assumption is not maintained for the multinomial probit model. This generalization comes at the cost of having to evaluate the high dimension integrals in (3).

Several simulators have been introduced recently to approximate multinomial probit choice probabilities through Monte Carlo simulations. We demonstrate the feasibility of multinomial probit estimation using the smooth recursive simulator, often called the GHK simulator, independently introduced by Geweke (1991), Hajivassiliou and McFadden (1990), and Keane (1990). We use the GHK simulator because it is continuous in the parameter space $\beta \otimes \Sigma_u$. Based on the rooted mean squared error criterion, Hajivassiliou, McFadden, and Ruud (1992) show that the GHK simulator is unambiguously the most reliable method for simulating normal probabilities, compared to the twelve other simulators they considered.

To estimate the probit models using simulated maximum likelihood estimation, the choice probabilities in the likelihood function are replaced by the simulated probabilities from (3). The resulting likelihood function is then maximized so that estimation can be achieved by using conventional optimization packages. As the sample size and the number of replications in the simulation of the choice probabilities increase, maximization of the simulated likelihood function yields parameter estimates that possess the asymptotic properties of conventional maximum likelihood estimates (Gourieroux and Monfort, 1993). Consequently, statistical inference based on these asymptotic properties can be implemented with simulated maximum likelihood estimates.

2.3 The Empirical Comparisons and The Probit Model Identification

In this chapter, we take an empirical approach to compare the probit and logit models. The estimated models are assessed in terms of welfare measurement and trip predictions, which can highlight the role of IIA. The empirical comparison is motivated in part by the difficulty of directly comparing the error distributions between the two models. For example, consider a logit model with $J=3$. We can nest the first two alternatives into

one group and the third alternative into another group. A generalized extreme value distribution with this nesting structure is

$$F(u) = \exp \left\{ -(\exp(-u_1/\lambda) + \exp(-u_2/\lambda))^{\lambda} - \exp(-u_3) \right\}$$

provided $0 < \lambda \leq 1$. It is not clear which normal distribution matches this generalized extreme value distribution.

Furthermore, in specifying the covariance matrix for the probit model, the normalization reduces the covariance matrix dimension by one (Dansie 1985 or Bunch 1991). There could exist multiple covariance matrices that correspond to the same underlying preference. To see this point, let the covariance matrix of the three alternative probit model be

$$\Sigma_u = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \sigma_2^2 & \sigma_{23} & \sigma_3^2 \end{pmatrix}.$$

The normalization of the utility function $U_j = x_j\beta + u_j$ based on, say, choice 3 yields $U_j^* = x_j^*\beta + u_j^*$ with $x_j^* = x_j - x_3$ and $u_j^* = u_j - u_3$ for $j = 1$ and 2. The covariance matrix for u^* is

$$\Sigma_{u^*} = \begin{pmatrix} \sigma_1^{*2} & \sigma_{12}^* \\ \sigma_2^{*2} & \end{pmatrix}$$

with $\sigma_1^{*2} = \sigma_1^2 + \sigma_3^2 - 2\sigma_{13}$, $\sigma_2^{*2} = \sigma_2^2 + \sigma_3^2 - 2\sigma_{23}$, and $\sigma_{12}^* = \sigma_1^2 - \sigma_{13} - \sigma_{23} + \sigma_{12}$. The probit model can only be identified if either one of the β 's or one of the σ^* 's is preset to a constant. If we fix σ_{12}^* , there are only two identifiable parameters out of the six in Σ_u with

$$(4) \quad \Sigma_u = \begin{pmatrix} \sigma_1^2 & \bar{\sigma}_{12} & \bar{\sigma}_{13} \\ \sigma_2^2 & \bar{\sigma}_{23} & \bar{\sigma}_{33} \end{pmatrix}$$

where σ_1^2 and σ_2^2 are to be estimated, $\bar{\sigma}_{12}$, $\bar{\sigma}_{13}$, $\bar{\sigma}_{23}$, and $\bar{\sigma}_{33}^2$ are some fixed constants required by the identification conditions. Thus, $\bar{\sigma}_{ij}$'s and σ_{ij} 's, are inter-dependent, and the estimates of β 's also depend on $\bar{\sigma}_{ij}$'s. In the empirical examples that follow, we will

also illustrate how different $\bar{\sigma}_{ij}$'s will lead to different parameter estimates by estimating correlated probit models using distinct rescaling assumptions.

3 The Models, Data, and Estimation Results

We model the fishing choices of Michigan anglers for trips targeting Great Lakes trout and salmon. The fishing sites are defined by the stretch of Great Lakes shoreline within each of Michigan's coastal counties. In all, there are 41 counties that support salmon and trout fishing on the Great Lakes. When the stay-home alternative is included, the choice set can be as large as 42 alternatives per choice occasion. Before we discuss the data set and the model estimation results, we will first specify the covariance matrices of the probit models for recreation fishing demand in Michigan.

3.1 Covariance Matrices of The Probit Model for Recreation Demand

While the dimension of the covariance matrix for our empirical examples can be as large as 42 ($J+1$), computational and data limitations mean that we can not recover every element in the matrix even after imposing the normalization and rescaling conditions. One approach is to impose restrictions on the covariance matrix based on researchers' judgments about the relative similarity and difference between alternatives. For example, in a repeated random utility model of recreation demand, one might believe that the variance of the random term for the stay-home alternative is different from the variance of the random terms for the fishing sites. In this case, one can adopt the following block structure for the covariance matrix

$$\Sigma_u = \begin{pmatrix} \sigma_d^2 & \sigma_o & \cdots & \sigma_o & \sigma_{dh} \\ \sigma_d^2 & \cdots & \sigma_o & \sigma_{dh} \\ \ddots & \vdots & \vdots & & \\ \sigma_d^2 & \sigma_{dh} & & & \\ & \sigma_h^2 & & & \end{pmatrix}.$$

There are only four different parameters σ_d^2 , σ_h^2 , σ_o , and σ_{dh} in this matrix. If we normalize against the stay-home choice h , the resulting J -dimensional matrix for $u^* = u - u_h$ is

$$\Sigma_{u^*} = \begin{pmatrix} \sigma_d^{*2} & \sigma_o^{*2} & \cdots & \sigma_o^{*2} \\ & \sigma_d^{*2} & \cdots & \sigma_o^{*2} \\ & & \ddots & \vdots \\ & & & \sigma_d^{*2} \end{pmatrix}.$$

If we pre-fix σ_o^* in Σ_{u^*} to a constant due to the rescaling condition, there is only one parameter to be estimated in Σ_u . One of $\{\sigma_d^2, \sigma_h^2, \sigma_o, \sigma_{dh}\}$ can be estimated by pre-fixing the rest. For example, we can elect to estimate σ_d^2 by pre-fixing $\sigma_h^2 = c_{hh}$, $\sigma_o = c_o$, and $\sigma_{dh} = c_{dh}$

$$(5) \quad \Sigma_u = \begin{pmatrix} \sigma_d^2 & c_o & \cdots & c_o & c_{dh} \\ \sigma_d^2 & \cdots & c_o & c_{dh} & \\ \ddots & \vdots & \vdots & & \\ & \sigma_d^2 & c_{dh} & & \\ & & c_{hh} & & \end{pmatrix}.$$

Alternatively, we can elect to estimate σ_h^2 by pre-fixing $\sigma_d^2 = c_d$, $\sigma_o = c_o$, and $\sigma_{dh} = c_{dh}$

$$(6) \quad \Sigma_u = \begin{pmatrix} c_d & c_o & \cdots & c_o & c_{dh} \\ c_d & \cdots & c_o & c_{dh} & \\ \ddots & \vdots & \vdots & & \\ & c_d & c_{dh} & & \\ & & & \sigma_h^2 & \end{pmatrix}.$$

In the empirical application, we will estimate two correlated probit models using (5) and (6), and consider different constants for c_d , c_o , c_{dh} , and c_{hh} to illustrate how the parameter estimates change with the covariance matrix specification.

3.2 Data Sets

The behavioral data comes from a 1994 survey of recreational fishing in Michigan that was conducted at Michigan State University. See the report by Hoehn, Tomasi, Lupi, and Chen (1996) for details. From the Michigan data, we selected individuals with at least one single-day trip targeting Great Lakes trout and salmon during the 1994 open

cations. The log likelihood value for the I-Probit is -1504.54. The independent probit model fits the data better than the independent logit model.

C-Probit(5) is specified by using (5), and σ_d^2 is identified by fixing $c_o = 0.1$, $c_{dh} = 0$, and $c_{hh} = 1$. Alternatively, estimation of C-Probit(6) is based on (6), and σ_h^2 is identified by fixing $c_{dd} = 3$, $c_o = 2$, and $c_{dh} = 0$. As expected, the log likelihood values for the both correlated probit models are the same, -1443.95, and provide significantly better fits than the I-Probit model.

The coefficient estimates of the two probit models are different due to the arbitrary selection of the values for the constants for the identification conditions. However, if the coefficients are divided by the trip cost coefficient, they are virtually the same. For each of the models, Table 2 presents the standardized coefficients of site quality, the site quality coefficient divided by the negative of the trip cost coefficient. The sum in the final column is the sum of the standardized site quality coefficients for each model.

Table 2: Catch Rate Coefficients / Trip Cost Coefficient

Models	Chinook salmon	Coho salmon	Lake trout	Rainbow trout	Sum
C-Probit(5)	6.769	2.533	0.831	16.132	26.265
C-Probit(6)	6.769	2.533	0.831	16.132	26.265
I-Probit	3.809	3.151	1.389	10.126	18.475
N-Logit	6.434	2.903	0.098	14.600	24.035
I-Logit	1.976	2.963	0.965	8.463	14.365

From the last column of the table, we see that the two correlated probit models are identical to each other. The nested logit model is also similar to the correlated models. The independent models appear to be different. However, one should keep it in mind that the welfare measurements are function of both the error structure (the probabilities) and the standardized coefficients (Small and Rosen 1981). In the next section, we will empirically assess the welfare measurements for these models using some policies.

4 The Model Assessment Using Policies

This section addresses the empirical importance of the distributional assumptions on each model's trip predictions and benefit estimations. In order to illustrate the performance of each model, we examine policy scenarios ranging from site closure to drastic improvements in site quality. Specifically, we change site quality at Muskegon county (site i) by multiplying the catch rates at the site by $\{0.5, 1, 1.5, 2, 2.5, 3\}$. Muskegon county is centrally located on Lake Michigan. In addition, we close site i . We examine the IIA/IIG properties by estimating the choice probabilities to Oceana county (site j) and Ottawa county (site k), the two counties that are adjacent to site i . The predicted trips to each of these sites and the total trip participation will be compared. Welfare measurements are also compared across the models for both the site quality change policy and the site closure policy.

To examine the IIA/IIG restriction, the probability ratios of site j and site k are calculated. We only calculated these ratios for individuals with all three sites (i , j , and k) in their feasible choice set, about one third ($n^*=33$) of the individuals. This was done since IIA for these sites is only relevant if all three sites are in the choice set. In Table 3, the ratios are presented for each of the models and for each of the policies. For the independent logit model, the ratio remains constant for each individual with a mean of 10.96 for all policies due to the IIA assumption. For the nested logit model, the mean ratio is 30.52 since IIA is maintained within the group of fishing sites. The site closure policy and the site quality change policy yield the identical ratios for the logit models. On the other hand, the probit models don't exhibit the algebraic property of IIA/IIG. For the probit models, we do not have closed form solutions for the choice probabilities so the ratios are simulated using 1,000 replications.

Table 3: Mean Probability Ratios $\frac{1}{n^*} \sum_{t=1}^{n^*} (Pr_j^t / Pr_k^t)$

Models	close i	$0.5q_i$	q_i	$1.5q_i$	$2q_i$	$2.5q_i$	$3q_i$
C-Probit(5)	1184.47	1214.42	1262.38	1501.90	2251.86	4204.71	9272.98
C-Probit(6)	1184.87	1214.83	1262.81	1502.41	2252.67	4206.34	9276.94
I-Probit	53.24	56.31	56.55	57.14	48.36	60.60	64.27
N-Logit	30.52	30.52	30.52	30.52	30.52	30.52	30.52
I-Logit	10.96	10.96	10.96	10.96	10.96	10.96	10.96

As expected, the ratios of the probit models change as the quality at site i changes from the modest to the drastic, including the site closure. This is especially clear for the two correlated probit models, which are substantially larger than the independent probit or logit models. The large ratios for the correlated probit are due to the substantial variations in the predicted probabilities to sites j and k across individuals, as compared to the other models. As an example, suppose that the predicted probability to site j, k is 0.0001, 0.1 for individual A, and 0.1, 0.0001 for individual B, respectively. For each individual, the sum of the predicted probabilities to both sites are the same 0.1001. However, the mean ratio is $(0.0001/0.1 + 0.1/0.0001)/2 = 500.0005$. As the quality at site i increases, the trips to both site j and site k decrease disproportionately. The independent probit model does not show the same level of change as the correlated probit models. Although algebraically the ratios across the policy spectrum don't have to remain constant for the independent probit either.

The predicted trips to all sites, as well as a subset of the sites, are presented in Table 4. At the participation level, the baseline predicted total trips per individual are basically the same for the five models (the first five rows of column q_i in Table 4). At the site level, the correlated probit models and the nested logit model are similar to each other, though different from the independent probit and logit models (the q_i column and the remaining rows). When the policy change moves away from the baseline, the differences between models become more pronounced. As the quality at site i increases, the independent probit model predicts the largest total trip increase, which is due to 1)

the large increase of trips to site i and 2) the sluggish decrease of trips to other sites, such as sites j and k . The pattern of sluggish decreases is even more evidenced in the independent logit model in that it has both the least amount of trip increase to site i and the least amount of trip decrease to sites j and k . Thus, from the site substitution perspective, the independent logit model is least flexible due to IIA.

Table 4: The Estimated Trips Per Individual

	Models	close q_i	$0.5q_i$	q_i	$1.5q_i$	$2q_i$	$2.5q_i$	$3q_i$
Total trips	C-Probit(5)	3.57	3.58	3.60	3.66	3.80	4.03	4.34
	C-Probit(6)	3.57	3.58	3.60	3.66	3.80	4.03	4.34
	I-Probit	3.45	3.52	3.61	3.79	4.11	4.62	5.40
	N-Logit	3.60	3.60	3.61	3.64	3.69	3.78	3.89
	I-Logit	3.43	3.54	3.61	3.74	3.94	4.26	4.73
Trips to site i	C-Probit(5)	0	0.06	0.21	0.55	1.08	1.71	2.30
	C-Probit(6)	0	0.06	0.21	0.55	1.08	1.70	2.29
	I-Probit	0	0.11	0.23	0.46	0.86	1.51	2.41
	N-Logit	0	0.05	0.20	0.50	0.95	1.44	1.84
	I-Logit	0	0.11	0.20	0.34	0.56	0.91	1.43
Trips to site j	C-Probit(5)	0.14	0.13	0.10	0.05	0.02	0	0
	C-Probit(6)	0.14	0.13	0.10	0.05	0.02	0	0
	I-Probit	0.17	0.16	0.15	0.14	0.13	0.11	0.08
	N-Logit	0.14	0.12	0.09	0.04	0.01	0	0
	I-Logit	0.15	0.15	0.15	0.14	0.14	0.13	0.12
Trips to site k	C-Probit(5)	0.12	0.11	0.09	0.07	0.04	0.01	0
	C-Probit(6)	0.12	0.11	0.09	0.07	0.04	0.01	0
	I-Probit	0.16	0.16	0.15	0.15	0.14	0.12	0.10
	N-Logit	0.10	0.09	0.07	0.05	0.03	0.01	0
	I-Logit	0.16	0.16	0.15	0.15	0.15	0.14	0.14

Furthermore, the nested logit model has the smallest increase in the total trips, in part because the estimated inclusive value coefficient is very small ($\lambda = 0.04$). If we look at the site level, it also becomes clear that as the quality at site i increases, both the correlated probit models and the nested logit model yield basically the same level of trip reduction to the substitute sites j and k . But the correlated probit models yield a much larger trip increase to site i than the nested logit model. (This pattern is similar to the

independent probit v.s. independent logit.) For example, for the $3q_i$ policy when the trips to sites j and k are about zero, the difference in total trips between the correlated probit and the nested logit (4.34-3.89) is almost entirely due to the trip difference at site i between the two models (2.30-1.84) or (2.29-1.84 due to the rounding). Thus, the correlated probit models are more sensitive to the policy change with a larger net trip increase than the nested logit model.

Table 5: The Welfare Measurements Per Individual ²

Models	close q_i	$0.5q_i$	q_i	$1.5q_i$	$2q_i$	$2.5q_i$	$3q_i$
C-Probit(5)	-1.65	-1.32	0	3.92	12.65	27.91	49.81
C-Probit(6)	-1.60	-1.29	0	3.96	12.71	27.89	49.67
I-Probit	-1.83	-1.06	0	2.23	6.51	14.31	27.46
N-Logit	-1.47	-1.16	0	3.37	10.59	22.69	39.37
I-Logit	-1.55	-0.66	0	1.13	3.04	6.19	11.22

There are also some interesting difference across the models in terms of welfare measurements. Although the correlated probit models are ranked third in total trip change, the welfare gains are the largest as the quality at site i increases, followed by the nested logit model, the independent probit model, and the independent logit model with roughly 82%, 54%, 25%, respectively, of the values of the correlated probit models. While the independent logit model yields the largest trip change, the welfare gain appears to be the smallest for the site quality improvement due to, again, the IIA restriction and the small standardized site quality coefficients for the I-Logit (Table 2).

For the policies involving changes in site quality, the differences in the welfare measures minor the differences in the estimated standardized site quality coefficients (c.f., the last column Table 2) with substantial variability across the models. However, of all the policies considered, the welfare measures for the site closure policy exhibit the least variability across models. This may be because the site closure policy can be

²The welfare measures for the probit models were simulated using 1000 replications and following the procedure described in Chen and Cosslett (1996).

viewed as raising the trip cost of site i to ∞ , which dominates the other terms associated with the site quality coefficients in the utility function. As a result, the welfare measures for the site closure policy depend more on the probabilities and less on the standardized site quality coefficients, as compared with the site quality policies.

5 Some Remarks

As illustrated in the preceding tables, the two correlated probit models with different covariance matrices yield different coefficient estimates for β 's and Σ . However, if the coefficient estimates of β are divided by the trip cost coefficient, they are virtually the same. Furthermore, the trip predictions, welfare measurements, and the log likelihood values are the same as well (with some minor variation due to the simulations). This illustrates that for any given covariance structure, how one chooses to parameterize the elements of the covariance matrix will affect the coefficient estimates, but it should not be important as the two correlated probit models identify the same underlying preference.

Interestingly, even though the nested logit suffers from IIA/IIG, the nested logit model fits the data set better than the other models considered in this chapter. Of course, both the nested logit and correlated probit fit the data significantly better than their counterparts with independent errors. This reinforces the importance of distinguishing between diverse alternatives (stay-home versus fishing sites) when selecting an error structure for a model. In terms of the IIA property, the results showed that the correlated probit exhibited site substitution patterns that were in some cases dramatically different than the patterns of the other models. As might be anticipated from the independence of the errors, the probability ratios for the I-Probit model didn't change as much as with the correlated probit models – despite the fact that the I-Probit does not algebraically exhibit the IIA property.

Of course, the results presented here are based on models with relatively simple

nesting and covariance structures. More complicated nesting structures could be compared to probits with more complicated covariance structures. With the nested logits one needs to be concerned about whether or not the estimated λ lies within the unit interval for the global consistency with the hypothesis of random utility maximization or close to it for local consistency (McFadden 1977, Kling and Herriges 1995). These concerns are only expected to be heightened as the nesting structure increases in complexity. On the other hand, with multinomial probits of comparable complexity, consistency with random utility maximization is maintained since the covariance matrix needs to be positive definite for the probit model to be estimated.

The baseline predictions of the total trips per individual are basically the same for the five models, regardless of whether one model fits the data set better than the others. The model differences are revealed as the policy scenarios move away from the baseline. At the site level, the independent probit model shows more interaction across sites than the independent logit model which is least flexible. The nested logit model shows a more rapid change in trips to sites i , j , and k than the independent logit model due to the two-level nest. The correlated probit models appear to be the most sensitive to the site quality improvement, showing a rapid trip increase at the policy site and a rapid trip decrease at the other sites. If we measure the model's flexibility of site substitution using two components 1) the trip increase at the policy-site and 2) the trip decrease at the other sites, the correlated probit models can be ranked as the most flexible, followed by the independent probit model or the nested logit model. The independent logit model is clearly the least.

The results have demonstrated the model's error distribution has significant impacts on the model's coefficient estimates and the policy analysis. For a given policy, the welfare measurement of one model could be 25% of the other, and the trip prediction of one model could be 72% of the other. Thus, the parametric distribution assumption

deserves further research.

Appendix

Independent Logit Model: I-Logit (LL = -1521.38)³

Parameters	Estimates	Est. / $-\beta_1$	t-Stat.
β_1 <i>cost/100</i>	-3.600	-1.000	-20.354
β_2 <i>chinook</i>	7.114	1.976	2.670
β_3 <i>coho</i>	10.667	2.963	2.772
β_4 <i>lake</i>	3.474	0.965	2.159
β_5 <i>rainbow</i>	30.468	8.463	4.089
β_6 <i>tpdy</i>	25.862	7.184	17.519
β_7 <i>region</i> ₁	0.284	0.079	0.715
β_8 <i>region</i> ₂	0.357	0.099	2.323
β_9 <i>ln(age)</i>	-2.920	-0.811	-14.117
β_{10} <i>ln(edu)</i>	-5.508	-1.530	-12.684
β_{11} <i>gender</i>	-1.904	-0.529	-8.642

Nested Logit Model: N-Logit (LL = -1420.97)

Parameters	Estimates	Est. / $-\beta_1$	t-Stat.
β_1 <i>cost/100</i>	-5.292	-1.000	-17.446
β_2 <i>chinook</i>	34.047	6.434	6.814
β_3 <i>coho</i>	15.362	2.903	2.255
β_4 <i>lake</i>	0.517	0.098	0.093
β_5 <i>rainbow</i>	77.253	14.600	6.520
β_6 <i>tpdy</i>	4.225	0.798	2.470
β_7 <i>region</i> ₁	1.306	0.248	3.437
β_8 <i>region</i> ₂	0.744	0.141	5.211
β_9 <i>ln(age)</i>	-0.002	-0.000	-0.009
β_{10} <i>ln(edu)</i>	-0.502	-0.112	-1.386
β_{11} <i>gender</i>	-0.812	-0.153	-3.684
λ	0.041	0.008	0.957

³*tpdy* is a dummy variable equaling 1 if a trip was taken during the choice occasion, 0 otherwise.

Independent Probit Model: I-Probit, $R=400$ (LL = -1504.54)

Parameters	Estimates	Est./ $-\beta_1$	t-Stat.
β_1 <i>cost/100</i>	-1.749	-1.000	-20.181
β_2 <i>chinook</i>	6.660	3.809	4.632
β_3 <i>coho</i>	5.510	3.151	4.632
β_4 <i>lake</i>	2.429	1.389	2.393
β_5 <i>rainbow</i>	17.708	10.126	4.427
β_6 <i>tpdy</i>	13.978	7.993	17.136
β_7 <i>region</i> ₁	0.172	0.098	0.819
β_8 <i>region</i> ₂	0.190	0.109	2.069
β_9 <i>ln(age)</i>	-1.522	-0.870	-12.717
β_{10} <i>ln(edu)</i>	-2.662	-1.522	-11.601
β_{11} <i>gender</i>	-1.006	-0.575	-7.863

Correlated Probit Model: C-Probit(5) with $R=400$,

$c_o = 0.1$, $c_{dh} = 0$, and $c_{hh} = 1$. (LL = -1443.95)

Parameters	Estimates	Est./ $-\beta_1$	t-Stat.
β_1 <i>cost/100</i>	-0.237	-1.000	-2.003
β_2 <i>chinook</i>	1.602	6.769	1.978
β_3 <i>coho</i>	0.600	2.533	1.378
β_4 <i>lake</i>	0.197	0.831	0.748
β_5 <i>rainbow</i>	3.819	16.132	2.037
β_6 <i>tpdy</i>	3.386	14.304	3.347
β_7 <i>region</i> ₁	0.628	2.655	3.740
β_8 <i>region</i> ₂	0.366	1.545	4.852
β_9 <i>ln(age)</i>	-0.148	-0.627	-1.129
β_{10} <i>ln(edu)</i>	-0.485	-2.048	-1.987
β_{11} <i>gender</i>	-0.485	-2.051	-4.098
σ_d	0.327	1.379	31.298

Correlated Probit Model: C-Probit(6) with $R = 400$,

$c_{dd} = 3$, $c_o = 2$, and $c_{dh} = 0$ (LL = -1443.95)

Parameters	Estimates	Est./ $-\beta_1$	t-Stat.
β_1 <i>cost/100</i>	-2.903	-1.000	-18.055
β_2 <i>chinook</i>	19.648	6.769	7.528
β_3 <i>coho</i>	7.352	2.533	1.861
β_4 <i>lake</i>	2.412	0.831	0.873
β_5 <i>rainbow</i>	46.829	16.132	6.622
β_6 <i>tpdy</i>	41.518	14.303	3.289
β_7 <i>region</i> ₁	7.705	2.654	1.584
β_8 <i>region</i> ₂	4.483	1.544	1.619
β_9 <i>ln(age)</i>	-1.820	-0.627	-1.723
β_{10} <i>ln(edu)</i>	-5.946	-2.048	-2.947
β_{11} <i>gender</i>	-5.952	-2.050	-2.317
σ_h	12.780	4.403	1.929

References

Bishop, Richard and T. Heberlein. "Measuring Values of Extra Market Goods: Are Indirect Measures Biased?." *American Journal of Agricultural Economics*, Vol. 61(5):926-30, 1979.

Bunch, David S. "Estimability in the Multinomial Probit Model." *Transportation Research - B*, Vol. 25B(1):1-12, 1991.

Chen, Heng Z. and Stephen R. Cosslett. "Environmental Quality Preference and Benefit Estimation in Multinomial Probit Models: A Simulation Approach." Draft manuscript, Department of Agricultural Economics, Michigan State University. 1996.

Dansie, B. R. "Parameter Estimability in the Multinomial Probit Model." *Transportation Research - B*, Vol. 19B(6):526-28, 1985.

Geweke, John F. "Efficient Simulation From the Multivariate Normal and Student-t Distributions Subject to Linear Constraints." *Computer Science and Statistics: Proceedings of the Twenty-Third Symposium on the Interface*. Alexandria, VA: American Statistical Association, 1991.

Gourieroux, Christian, and Alain Monfort. "Simulation-Based Inference, A Survey With Special Reference to Panel Data Models." *Journal of Econometrics*, Vol. 59, 1993.

Hajivassiliou, Vassilis, and Daniel McFadden. "The Method of Simulated Scores for the Estimation of LDV Models with an Application to External Debt Crises." Cowles Foundation Discussion Paper No. 967, 1990.

Hajivassiliou, Vassilis, Daniel McFadden, and Paul Ruud. "Simulation of Multivariate Normal Orthant Probabilities: Theoretical and Computational Results." Cowles Foundation Discussion Paper No.1021, 1992.

Hanemann, W. Michael. "Applied Welfare Analysis with Qualitative Response Models." Working Paper No. 241. California Agricultural Experimental Station, Giannini Foundation of Agricultural Economics, University of California, Berkeley, 1982.

Hausman, Jerry A., Gregory K. Leonard, and Daniel McFadden. "A Utility-Consistent, Combined Discrete Choice and Count Data Model: Assessing Recreational Use Losses Due to Natural Resource Damage." *Journal of Public Economics*, Vol. 56:1-30, 1995.

Hoehn, P. John, Theodore Tomasi, Frank Lupi, and Heng Z. Chen. "An Economic for Valuing Recreational Angling Resources in Michigan." Project report, Department of Agricultural Economics, Michigan State University. December, 1996.

Jones, Carol A. and Yusen D. Sung. "Valuation of Environmental Quality at Michigan Recreational Fishing Sites: Methodological Issues and Policy Applications." Project report, EPA Contract No. 816247-01-2, September, 1993.

Keane, Michael P. "Four Essays in Empirical Macro and Labor Economics." Ph.D. Dissertation. Brown University, 1990.

Kling, Cathy L. and Joseph A. Herriges "An Empirical Investigation of the Consistency of Nested Logit Models with Utility Maximization." *American Journal of Agricultural Economics*, Vol. 77(4):875-84, 1995.

McFadden, Daniel. "Modeling the Choice of Residential Location in Studies in Regional Science and Urban Economics", ed. by Ake Andersson and Walter Isard, 1977.

McFadden, Daniel. "Econometric Models of Probabilistic Choice, in Structural Analysis of Discrete Choice Data with Econometric Applications", ed. by Charles F. Manski and Daniel McFadden. MIT Press, 1981.

McFadden, Daniel. "A Method of Simulated Moments for Estimation of Discrete Response Models without Numerical Integration." *Econometrica*, Vol. 58(5):995-1026, 1989.

Morey, Edward R., Robert D. Rowe, and Michael Watson. "A Repeated Nested-Logit Model of Atlantic Salmon Fishing." *American Journal of Agricultural Economics*, Vol. 75(3):578-92. August, 1993.

Small, Kenneth A. and Harvey Rosen. "Applied Welfare Economics With Discrete Choice Models." *Econometrica*, Vol. 49(1):105-130, January, 1981.