Not Playing the Game: Modeling Non-Participation in Repeated Discrete Choice Models

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Abstract

This paper develops and empirically evaluates alternative econometric strategies for accounting for non-participation – repeated choice of the same alternative or same type of alternative – in data sets that are typically analyzed within the repeated discrete choice framework. Random coefficient single and double hurdle variants of the repeated discrete choice model are developed and applied to stated preference data. The empirical results suggest that significant statistical improvements in fit can arise with the single and double models relative to more traditional models. However, similar to Haab and McConnell's (1996) findings in the context of count data models, these gains are diminished when the analyst accounts for unobserved heterogeneity through random coefficients.

Introduction

Non-participation, or repeated choice of the same alternative or same type of alternative across a series of choice occasions, is a common phenomenon in data sets that are analyzed within the repeated discrete choice framework. In recreation data sets, for example, non-participation arises when the individual never chooses to recreate during the season. In stated preference data sets, one form of non-participation arises when the individual always chooses the status quo or "choose none" option, and another arises when the individual always chooses the alternative with the "best" level of a particular attribute[1]. All of these types of non-participation can arise from the same behavioral process that gives rise to participation, and traditional repeated discrete choice econometric structures traditionally employed in applied work in fact predict some degree of non-participation. However, the prevalence of non-participation in many data sets suggests that a fundamentally different behavioral process may partially explain such outcomes.

In the context of recreation demand, non-participation may arise because a segment of the population has preferences such that they would not choose to recreate at any site under any circumstance. In stated preference contexts, individuals who always choose the status quo, "choose none" option, or the alternative with the best level of an attribute may be engaging in a form of protest against the notion that they must tradeoff various attributes. Alternatively, these individuals might be employing a strategy that may reflect either lexicographical preferences or a simplifying heuristic that makes complex choices more manageable (Dhar, 1997a, 1997b). All of these types of responses suggest that non-participants are fundamentally different than participants. Stated succinctly, non-participants may not be "playing the game" that participants are playing.

Surprisingly, little formal modeling attention has been given to the issue of non-participation in repeated discrete choice models. In both recreation and stated preference applications, the most common strategy for addressing non-participation has been to purge from the sample all individuals who appear to be non-participants. von Haefen (2003), for example, drops all non-

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[1] We explore one type of non-participation as individuals who always choose the status quo alternative. This does not preclude the possibility of preference for the status quo, independent of the attributes of the situation. Such

recreators from the sample he uses in estimation, and Adamowicz et al. (1998) drop individuals who always choose the status quo. Although this strategy avoids difficult modeling issues arising when the behavioral process that gives rise to non-participation is fundamentally different than the process that generates participation, it can be criticized as ad hoc because it ignores potentially useful data and generates a truncation problem that biases parameter and welfare estimates if not properly addressed. Another approach for dealing with non-participation has been to include an alternative specific constant that is designed to capture the differences between participants and non-participants (e.g., Adamowicz et al. (2000)). Although this latter strategy can result in improved statistical fit, it restrictively assumes that non-participants have the same marginal rates of substitution for commodity attributes that participants do. Random parameter generalizations of the traditional repeated discrete choice model can relax some of these restrictive implications, but these models still assume that the same behavioral model explains the behavior of participants and non-participants alike.

To our knowledge, only recreation applications of the traditional demand system framework have developed more general strategies for modeling non-participation. Shonkwiler and Shaw (1996), Haab and McConnell (1996), von Haefen and Phaneuf (2003), and von Haefen (unpublished) develop econometric models that allow non-participation to arise from a behavioral process that is fundamentally different than the process that gives rise to participation. As Shonkwiler and Shaw emphasize, there are at least two conceptually distinct approaches for developing explicit models of non-participation. The "single hurdle" approach assumes that all non-participation can be explained by a single behavioral process that is fundamentally different from the process that generates the behavior of participants, while the "double hurdle" approach assumes that non-participation may arise from either the same behavioral process that gives rise to participation or a fundamentally different process.

In this paper we develop repeated discrete choice econometric models that explicitly allow for non-participation to arise from a fundamentally different behavioral process than participation. Single and double hurdle random coefficient, repeated discrete choice models are applied to data

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"status quo bias" has been observed in both stated and revealed preference examples (Samuelson and Zeckhauser, (1988), Beenstock et al. (1998) and Hartman et al. (1991)).

from a stated preference survey designed to elicit the benefits of alternative woodland caribou enhancement programs. As described in Adamowicz et al. (1998), a significant proportion of sample respondents always choose the status quo option in this choice experiment, and thus models that explicitly account for non-participation may be particularly well-suited for this application[2]. We explore the relationship between non-participation and observable demographic characteristics. We also compare our proposed models to several repeated discrete choice models to gauge the contribution of introducing a separate behavioral process to explain non-participation.

Our estimation results suggest that a substantial improvement in statistical fit can result when a different behavioral process is introduced to explain non-participation. Using a battery of non-nested hypothesis tests, we also find only small differences in statistical fit between the single and double hurdle repeated discrete choice models. The results consistently suggest that younger and more educated individuals are less likely to be non-participants. In general, our results suggest that so-called "panel" random coefficients models generate significantly improved statistical fits.

The remainder of the paper is structured as follows. The next section develops the single and double hurdle repeated discrete choice structures and highlights their statistical and behavioral properties. We then turn to discussions of the data set, parameter estimates, and our non-nested hypothesis test results from our empirical illustration. We conclude by suggesting the relevance of the methods developed in this paper for other applications of the repeated discrete choice framework.

Econometric Model

Traditionally when modeling a series of consumer choices within the repeated discrete choice framework, analysts have employed the following set of assumptions. Preferences on each choice occasion are separable from those on other choice occasions. Each choice occasion is

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[2] It is possible, of course, that individuals who always choose the status quo are "playing the game" in that they are responding in the same fashion as all other respondents only their optimal choice is always the status quo. Our econometric strategy will help examine whether in fact the process underlying these individuals' choices is the same as that underlying the particpants'.

assumed to involve the individual making a discrete choice from a finite set of choice alternatives. This choice is generated from a random utility maximizing behavioral process (McFadden (1974)) that assumes that both observable (form the analyst's perspective) and unobservable factors enter consumer preferences and determine an individual's choice. The unobserved factors are assumed to vary randomly across individuals and an individual's choice occasions and can be represented as random draws from a probability distribution. In combination with the utility maximizing behavior structure that governs choice, these probability distributions imply likelihoods of observing various choices conditional on a set of underlying model parameters. These probabilities and observed choices can be used to recover estimates of the underlying parameters within the maximum likelihood framework.

More concretely, consumer preferences for the *j*th alternative ($j \in J_t$) on choice occasion t $(t \in T)$ can be represented by the following conditional indirect utility function:

$$V_j(y_t - p_{jt}, \boldsymbol{q}_{jt}, \boldsymbol{\beta}, \varepsilon_{jt}),$$

where y_t is normalized income, p_{jt} and $\boldsymbol{q}_{jt}$ are the observable choice occasion specific normalized price and attributes of the *j*th alternative, $\boldsymbol{\beta}$ are estimable structural parameters, and ε_{jt} represents all other determinants of choice relevant to the choice alternative and occasion that are unobservable and random from the analyst's perspective. The rational individual is assumed to choose the alternative that generates the highest level of utility, i.e.:

$$\text{Alternative } i \text{ chosen if } \underset{j}{\text{Max}}\left\{V_j(y_t - p_{jt}, \boldsymbol{q}_{jt}, \boldsymbol{\beta}, \varepsilon_{jt}), \forall j \in J_t\right\} = V_i(y_i - p_{it}, \boldsymbol{q}_{it}, \boldsymbol{\beta}, \varepsilon_{it}).$$

To make this model useful for empirical work, the analyst must choose a parametric structure for the conditional indirect utility function. For convenience, a simple linear-in-parameters and additive structure is often employed, i.e.,

$$V_i(y_t - p_{it}, \boldsymbol{q}_{it}, \boldsymbol{\beta}, \varepsilon_{it}) = \lambda f(y_t - p_{it}) + \boldsymbol{q}_{it}^{\mathsf{T}}\boldsymbol{\beta} + \varepsilon_{it},$$

where λ is an additional estimable parameter and $f(\cdot)$ is a monotonically increasing, concave function. If the analyst assumes that each ε_{it} $(\forall j, t)$ can be treated as an independent and identically distributed draw from the type I extreme value distribution, the likelihood of observing the individual choosing the *i*th alternative on choice occasion t (l_{it}) takes the standard multinomial logit form:

$$l_{it} = \frac{e^{\lambda f(y_t - p_{it}) + \boldsymbol{q}_{it}^{\top}\boldsymbol{\beta} + \varepsilon_{it}}}{\sum_{j}^{J_t} e^{\lambda f(y_t - p_{jt}) + \boldsymbol{q}_{jt}^{\top}\boldsymbol{\beta} + \varepsilon_{jt}}}.$$

If one assumes that the same basic modeling structure underlies consumer choice on each choice occasion, the likelihood of observing a series of discrete choices, l^{RDC}, is simply the product of the relevant logit probabilities:

$$l^{RDC} = \prod_{t}^{T} \prod_{j}^{J_t} (l_{jt})^{1_{jt}}$$

where 1_{jt} is an indicator function equal to one if the *j*th alternative is chosen on the *t*th choice occasion and zero otherwise.

The traditional repeated discrete choice model places a strictly positive probability mass on every possible series of choices. Thus, the model predicts that over a sufficiently large sample, non-participation will arise - some individuals will be observed to choose the same alternative (or same type of alternative) on every choice occasion. Where the traditional model often fails, however, is in predicting the *frequency* of non-participation. One approach to account for this limitation is to introduce a more flexible error structure that better predicts these anomalous outcomes. As discussed in Train (2003), this can be accomplished by allowing the parameters of the utility function to vary randomly across individuals and (possibly) choice occasions. In particular, by assuming ($\lambda, \boldsymbol{\beta}$) vary randomly across the target population, one can develop probabilistic models of choice that place greater mass on non-participation. As McFadden and Train (2002) have argued, any structure of substitution that gives rise to an observed set of choice outcomes can be approximated by choosing the appropriate distribution for these random parameters.

Alternatively, another strategy the analyst could pursue to address this deficiency of traditional repeated discrete choice models is to introduce a separate statistical process that predicts non-participation. This approach is conceptually akin to statistical approaches used in the microeconometric demand models to account for the prevalence of nonconsumption (e.g., Haab and McConnell (1996), von Haefen and Phaneuf (2003), and von Haefen (unpublished)). As discussed in detail by Shonkwiler and Shaw (1996), these modeling approaches can be grouped into two broad categories. The first, commonly referred to as the single hurdle approach, replaces the probability of non-participation implied by the traditional repeated discrete choice framework with a separate probability model. Thus for a person to switch from being a non-participant to being a participant, she must exceed only the hurdle embedded in the separate non-participation model. The second approach, commonly referred to as the double hurdle approach, augments the probability of non-participation implied by the traditional repeated discrete choice model with a separate probability model. For an individual to be a participant, these models require that two hurdles be passed – the first one arising from the augmenting probability model and the second arising from the repeated discrete choice structure.

An examination of the likelihoods implied by these alternative structures may shed additional light on their structures and behavioral implications. For concreteness and with no loss in generality, assume that repeated choice of the first alternative (j = 1) corresponds to non-participation. Further assume that π is the probability of an individual being a non-participant, and the indicator function $\tilde{\mathbf{1}}$ equals one when non-participation arises ($\sum_t^T 1_{1t} = T$) and zero otherwise. Given these assumptions and notation, the single hurdle likelihood, l^{SH}, takes the form:

$$l^{SH} = \pi^{\tilde{\mathbf{1}}} \left((1-\pi) \frac{\prod_t^T \prod_j^{J_t} (l_{jt})^{1_{jt}}}{1 - \prod_t^T (l_{1t})} \right)^{1-\tilde{\mathbf{1}}}$$

Similarly, the structure of the double hurdle's likelihood, l^{DH}, is:

$$l^{DH} = \left(\pi + (1-\pi) \prod_t^T (l_{1t}) \right)^{\tilde{\mathbf{1}}} \left((1-\pi) \prod_t^T \prod_j^{J_t} (l_{jt})^{1_{jt}} \right)^{1-\tilde{\mathbf{1}}}$$

A comparison of these likelihoods suggests why they have been labeled the single and double hurdle models. l^{SH} implies that only a single model explains non-participation (i.e., π) while l^{DH} implies non-participation arises from two sources - π and the likelihood of non-participation arising from the traditional repeated discrete choice structure.

Although we have motivated our single and double hurdle repeated discrete choice models as alternatives to the random parameter repeated discrete choice model, they are not mutually exclusive. In principle one can estimate random parameter variants of l^{SH} and l^{DH} that may fit a given data set better than fixed parameter traditional, single hurdle, or double hurdle models. To evaluate the relative performance of these alternative specifications in an applied setting, we estimate fixed and random parameter variants of the models developed in this section with stated preference data described in the next section.

Data

The data are from the stated preference / choice experiment survey described in Adamowicz et al. (1998). The choice experiment component of their paper asks each respondent to choose from three forest management alternatives; the status quo and two alternative "futures". The non-status quo alternatives are designed using a main effects orthogonal fractional factorial design. The forest scenarios are described on the basis of 5 main attributes, Woodland Caribou populations, wilderness area size, the level of recreation restrictions, the number of jobs in forestry and the change in income tax paid by the respondents. Each attribute has 4 levels where one level is described as the status quo.

900 individuals were initially contacted about their willingness to participate in the survey. Of these 900, 519 returned surveys with at least one choice task completed, and 429 answered all 8 choice tasks. Our empirical analysis focuses on the choices made by these 429 individuals and Table 1 summarizes some of their demographic characteristics. Included in this sample are 88 individuals (roughly 20 percent of our sample) who always chose the status quo alternative. We define this group as the non-participants in our study. For the remaining 341 individuals, a significant preference for the status quo alternative remained. On roughly 49 percent of the subsample's 2,728 choice occasions, the status quo alternative was chosen. Several explanations for this lingering strong preference for the status quo can be advanced – cognitive difficulties associated with the choice task, rejection of the choice alternatives as implausible, or simple a strong preference for the status quo – and we plan to explore the implications of these alternative theories in future work.

Results

We estimated numerous variations of the traditional, single hurdle, and double hurdle repeated discrete choice models and report a selected set of our estimation results in Tables 2, 3, and 4. All of these results include in the conditional indirect utility function the following variables: 1) a status quo dummy variable interacted with individual specific demographic variables; 2) three dummy variables corresponding to the different levels of recreation restrictions with level 1 being the most restrictive; 3) caribou population specified in quadratic form; 4) wilderness area in hectares; 5) forest industry jobs in the region; and 6) the after-tax consumption level of the Hicksian composite good written in quadratic form. For the hurdle models, π was specified in a logit form and assumed to be a function of individual-specific demographics and a constant term.

The results presented in Tables 2, 3, and 4 differ in terms of the treatment of the coefficients entering the conditional indirect utility functions. In Table 2, these parameters are assumed fixed across all individuals and choice occasions in the sample. The results reported in Table 3 assume that these parameters vary randomly across individuals and choice occasions. Partially for econometric convenience, these random parameter models assume that the parameters entering each individual's conditional indirect utility functions on each choice occasion can be treated as independent and identically distributed draws from the multivariate normal distribution, $N(\mu,\Sigma)$ where the off-diagonal elements of Σ are restricted to equal zero. Table 4's results are also based on random coefficient specifications. Compared to the models in Table 3, however, these models assume that these coefficients only vary randomly across individuals but are constant across choice occasions. Train (2003) has called this specification a "panel" model because of conceptual similarity to random effects panel models, and we adopt his terminology. Hereafter we also refer to the models in Table 3 as "non-panel" models. For tractability and economic coherence, we also assume the parameters entering the quadratic specification for the Hicksian composite good in both the "panel" and "non-panel" models are also fixed across individuals and choice occasions.

Although the parameter estimates in Tables 2, 3, and 4 can be analyzed and compared along numerous dimensions, we focus on three important dimensions here. Across all nine sets of parameter results reported in these tables, the estimates are generally statistically significant, plausibly signed, and relatively stable. The only somewhat anomalous parameter estimates are found in Table 4 where the Recreation Level 2 location parameter is larger in magnitude than the Recreation Level 1 location parameter. This finding may be explained as reflecting a lingering preference for the status quo because current recreation conditions are consistent with Recreation Level 2. The status quo constant – demographic interaction terms generally suggest that preferences for the status quo are independent of sex but significantly negative for younger, college educated individuals. Interestingly, the results in columns 2 and 3 of Tables 3 and 4 consistently suggest that although college educated individuals are less likely to be non-participants or to choose the status quo if they are participants, high school educated individuals are less likely to be non-participants but more likely to choose the status quo if they are participants. Thus, high school graduates seem to have a higher propensity to "play the game" but nevertheless have a strong preference for the status quo.

To compare the relative statistical fits of these alternative specifications, we use the Bayesian Information Criteria (*BIC*) as well as the Consistent Akaike Information Criteria (*CAIC*):

$$BIC = -2LL + \ln(N)P,$$

$$CAIC = -2LL + (1 + \ln(N))P,$$

where LL is the model's log-likelihood, N is the number of observations used in estimation (429 in our study), and P is the number of estimated parameters. We also employ a series of Vuong non-nested hypothesis tests (Vuong (1989)). The results from these tests are summarized in Table 5. What they suggest is that for the fixed and non-panel random coefficient models, the single and double hurdle models consistently and significantly outperform the traditional repeated discrete choice models. Moreover, little difference in statistical fit is found between the single and double hurdle models. For the panel random coefficient models, the relative statistical performance of the traditional and hurdle models is somewhat uncertain – in general the *BIC*, *CAIC*, and the Vuong tests suggest that the models are indistinguishable. This finding is conceptually similar to Haab and McConnell's (1996) empirical findings in the context of count data models that the marginal gains in terms of improved statistical fit diminish substantially after the analyst has accounted for unobserved heterogeneity (in their context, moving from a Poisson to a negative binomial model). In our context, the result probably arises because the random coefficient on the status quo constant can predict a significant amount of non-participation. Finally, comparing the fixed, non-panel, and panel random coefficient models, we find that panel random coefficient models generally fit the data best of all.

Conclusions

This study has investigated alternative strategies for accounting for non-participation, or repeated choice of the same alternative or same type of alternative across a series of choice occasions. We develop single and double hurdle repeated discrete choice models that allow for a fundamentally different process to generate non-participation. Although the models developed in this paper are germane to recreation demand modeling and can be used to account for many important features of revealed preference data, we apply them to data from stated preference survey data where a significant proportion of the population always choose the status quo. Our empirical results suggest that in general substantial improvements in statistical fit can result from using our hurdle models compared to the traditional repeated discrete choice models, although these gains are somewhat diminished when we incorporate random coefficients that persist across an individual's choice occasions.

Several extensions to our work in this paper are possible, and we discuss two in closing. First, as Train (2003) discusses, one can develop error component random coefficient models that allow for persistence in the random coefficients across choice occasions as well as choice occasion specific random deviations. In some sense, this model would be a hybrid of the panel and non-panel models that we explored in this paper. Given our small sample size, such a model would be difficult to estimate in our application, but our belief is that a mixed model as Train proposes may result in a substantial improvement in fit and qualitatively different policy inference. An additional direction for future research would be to develop defensible approaches for welfare measurement when the estimation results suggest that individuals have a strong preference for the status quo. There is an emerging literature on this issue (Beenstock et al. (1998) and Hartman et al. (1991)) and transferring and augmenting insights from this line of research to the stated preference context would represent an important contribution.

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Table 1
Summary Statistics of Demographic Variables
(429 Respondents)

Age	39.76
	(14.17)
High School Diploma (%)	87.88
4-Year College Degree (%)	29.14
Male (%)	49.88
Household Income (1994 Dollars)	\$47,214
	(25,596)

Table 2
Parameter Estimates from Fixed Coefficient Models [a]

	Repeated Discrete Choice Model	*Single Hurdle Repeated Discrete Choice Model*	*Double Hurdle Repeated Discrete Choice Model*
Ln-Likelihood	-2,948.16	-2,742.68	-2,742.58
Repeated Discrete Choice Parameters			
Status Quo Constant (SQ)	0.1933 (0.654)	-0.1507 (-0.559)	-0.1492 (-0.553)
SQ × Age/100	2.0161 (4.141)	0.8153 (1.801)	0.8113 (1.790)
SQ × High School Diploma	0.0382 (0.174)	0.3802 (1.882)	0.3794 (1.871)
SQ × 4-Year College Degree	-0.4040 (-2.791)	-0.2143 (-1.544)	-0.2122 (-1.522)
SQ × Male	0.0637 (0.487)	0.1106 (0.893)	0.1121 (0.903)
Recreation Level 1	0.5962 (5.931)	0.6024 (5.590)	0.6029 (5.593)
Recreation Level 2	0.5146 (5.394)	0.5296 (5.135)	0.5298 (5.137)
Recreation Level 3	0.1953 (2.288)	0.2136 (2.381)	0.2138 (2.383)
Caribou/1,000	5.3686 (14.061)	5.6142 (13.882)	5.6156 (13.884)
$(\text{Caribou}/1{,}000)^2$	-2.6563 (-13.838)	-2.7861 (-13.580)	-2.7868 (-13.582)
Wilderness Area/100,000	0.3349 (8.359)	0.3727 (8.642)	0.3726 (8.641)
Jobs/1,000	-0.1539 (-1.626)	-0.1327 (-1.300)	-0.1331 (-1.305)
(Income-Tax)/100	0.5841 (5.005)	0.5719 (4.706)	0.5728 (4.707)
$((\text{Income-Tax})/10{,}000)^2$	-2.5476 (-2.389)	-2.3810 (-2.168)	-2.3875 (-2.171)
Hurdle Parameters			
Constant	-	-2.1344 (-4.142)	-2.1333 (-4.098)
Age/100	-	3.3796 (3.817)	3.3812 (3.763)
High School Diploma	-	-0.5247 (-1.561)	-0.5417 (-1.601)
4-Year College Degree	-	-0.7158 (-2.243)	-0.7178 (-2.205)
Male	-	-0.0221 (-0.088)	-0.0331 (-0.129)

[a] Asymptotic t-statistics based on robust standard errors in parentheses

Table 3
Parameter Estimates from Non-Panel Random Coefficient Models [a,b]

	Repeated Discrete Choice Model		***Single Hurdle Repeated Discrete Choice Model***		***Double Hurdle Repeated Discrete Choice Model***	
Ln-Likelihood	-2,932.58		-2,722.22		-2,722.71	
Repeated Discrete Choice Parameters						
	Location	Scale	Location	Scale	Location	Scale
Status Quo Constant (SQ)	-0.0299	0.5840	-0.5582	0.0044	-0.4623	0.1583
	(-0.079)	(2.825)	(-1.545)	(0.021)	(1.413)	(0.532)
SQ × Age/100	2.6969	-	1.1611	-	1.0772	-
	(4.280)		(1.974)		(1.974)	
SQ × High School Diploma	0.0927	-	0.6284	-	0.5467	-
	(0.319)		(2.247)		(2.166)	
SQ × 4-Year College Degree	-0.5706	-	-0.3221	-	-0.2813	-
	(-2.922)		(-1.765)		(-1.628)	
SQ × Male	0.0515	-	0.1217	-	0.1239	-
	(0.300)		(0.754)		(0.812)	
Recreation Level 1	0.7164	0.3613	0.7450	0.0809	0.6823	0.1211
	(5.304)	(1.503)	(4.906)	(0.457)	(4.870)	(0.558)
Recreation Level 2	0.7046	0.7824	0.7423	0.8746	0.6484	0.1745
	(5.483)	(3.423)	(4.995)	(2.789)	(4.986)	(0.539)
Recreation Level 3	-0.0351	1.2754	-0.1881	1.8294	-0.3914	2.0695
	(-0.192)	(3.965)	(-0.982)	(4.741)	(-1.411)	(4.285)
Caribou/1,000	6.9504	0.8338	7.6663	1.4103	7.0997	0.5451
	(11.452)	(1.410)	(10.862)	(3.209)	(11.700)	(0.667)
$(\text{Caribou}/1{,}000)^2$	-3.7438	0.9452	-4.1070	1.1299	-3.7918	1.1659
	(-9.832)	(4.959)	(-9.413)	(3.669)	(-10.194)	(4.628)
Wilderness Area/100,000	0.4243	0.0927	0.4745	0.0591	0.4569	0.0043
	(6.967)	(0.923)	(6.796)	(0.649)	(7.077)	(0.049)
Jobs/1,000	-0.0051	1.7411	-0.0368	1.8408	-0.0179	1.7275
	(-0.030)	(3.816)	(-0.214)	(3.311)	(-0.117)	(4.225)
(Income-Tax)/100	0.7306	-	0.7724	-	0.7681	-
	(4.761)		(4.507)		(4.636)	
$((\text{Income-Tax})/10{,}000)^2$	-3.4117	-	3.3751	-	-3.4926	-
	(-2.420)		(-2.186)		(-2.313)	
Hurdle Parameters						
Constant	-		-2.1343 (-4.142)		-2.1330 (-4.099)	
Age/100	-		3.3796 (3.817)		3.3795 (3.765)	
High School Diploma	-		-0.5247 (-1.561)		-0.5417 (-1.603)	
4-Year College Degree	-		-0.7158 (-2.243)		-0.7186 (-2.208)	
Male	-		-0.0221 (-0.088)		-0.0301 (-0.117)	

[a] Parameter estimates generated with 1000 random draws
[b] Asymptotic t-statistics based on robust standard errors in parentheses

Table 4
Parameter Estimates from Panel Random Coefficient Models [a,b]

	Repeated Discrete Choice Model		Single Hurdle Repeated Discrete Choice Model		Double Hurdle Repeated Discrete Choice Model	
Ln-Likelihood	-2,621.91		-2,606.75		-2,607.73	
Repeated Discrete Choice Parameters						
	Location	Scale	Location	Scale	Location	Scale
Status Quo Constant (SQ)	-0.0394	1.7208	-0.4446	1.1136	-0.4838	1.2093
	(-0.084)	(14.737)	(-1.211)	(10.219)	(-1.219)	(9.019)
SQ × Age/100	3.3292	-	1.1814	-	1.3434	-
	(4.188)		(1.838)		(1.886)	
SQ × High School Diploma	0.0981	-	0.6404	-	0.7296	-
	(0.283)		(2.273)		(2.223)	
SQ × 4-Year College Degree	-0.7321	-	-0.3482	-	-0.3858	-
	(-3.138)		(-1.801)		(-1.752)	
SQ × Male	0.0452	-	0.0990	-	0.1549	-
	(0.218)		(0.575)		(0.772)	
Recreation Level 1	0.6503	0.6573	0.6517	0.5672	0.6539	0.5902
	(4.775)	(3.269)	(4.877)	(2.479)	(4.852)	(2.827)
Recreation Level 2	0.7030	0.4642	0.6722	0.4775	0.6874	0.5403
	(5.900)	(2.259)	(5.632)	(3.209)	(5.772)	(3.326)
Recreation Level 3	0.2147	0.6254	0.2193	0.6193	0.2230	0.5591
	(1.991)	(3.037)	(2.013)	(2.313)	(2.013)	(1.833)
Caribou/1,000	7.1105	1.1960	6.9419	1.0784	6.9475	1.0970
	(13.352)	(7.003)	(13.607)	(3.618)	(13.137)	(3.581)
$(\text{Caribou}/1{,}000)^2$	-3.6190	0.1458	-3.5091	0.2945	-3.5333	0.3001
	(-13.057)	(0.771)	(-13.337)	(0.935)	(-12.972)	(1.038)
Wilderness Area/100,000	0.4783	0.1534	0.4705	0.0789	0.4722	0.1903
	(8.829)	(0.847)	(8.473)	(0.232)	(8.627)	(1.457)
Jobs/1,000	-0.1921	0.9226	-0.1772	1.0718	-0.1923	0.9418
	(-1.508)	(2.580)	(-1.394)	(3.680)	(-1.512)	(2.866)
(Income-Tax)/100	0.7064	-	0.6873	-	0.7062	-
	(5.129)		(4.967)		(5.087)	
$((\text{Income-Tax})/10{,}000)^2$	-2.6632	-	-2.6091	-	-2.7673	-
	(-2.153)		(-2.100)		(-2.202)	
Spike Parameters						
Constant	-		-2.1343 (-4.142)		-2.4684 (-3.561)	
Age/100	-		3.3796 (3.817)		3.9825 (3.201)	
High School Diploma	-		-0.5246 (-1.561)		-0.8455 (-1.950)	
4-Year College Degree	-		-0.7158 (-2.243)		-0.9254 (-1.516)	
Male	-		-0.0221 (-0.087)		-0.1913 (-0.472)	

[a] Parameter estimates generated with 1000 random draws
[b] Asymptotic t-statistics based on robust standard errors in parentheses

Table 5
Statistical Comparisons of Alternative Models

	Fixed RDC	*Fixed SH*	*Fixed DH*	*Non-Panel Random RDC*	*Non-Panel Random SH*	*Non-Panel Random DH*	*Panel Random RDC*	*Panel Random SH*	*Panel Random DH*
Fixed RDC	LL(-2,948.16) BIC(5981.17) CAIC(5995.17)								
Fixed SH	V1(D,0.0000) V2(←,0.0000)	LL(-2,742.68) BIC(5600.53) CAIC(5619.53)							
Fixed DH	V1(D,0.0000) V2(←,0.0000)	V1(ND,0.9999)	LL(-2,742.58) BIC(5600.33) CAIC(5619.33)						
Non-Panel Random RDC	V1(ND,0.6424)	V1(D,0.0000) V2(↑,0.0000)	V1(D,0.0000) V2(↑,0.0000)	LL(-2,932.58) BIC(5998.51) CAIC(6020.51)					
Non-Panel Random SH	V1(D,0.0000) V2(←,0.0000)	V1(ND,0.3714)	V1(ND,0.3064)	V1(D,0.0000) V2(←,0.0000)	LL(-2,722.22) BIC(5608.10) CAIC(5635.10)				
Non-Panel Random DH	V1(D,0.0000) V2(←,0.0000)	V1(ND,0.3080)	V1(ND,0.1973)	V1(D,0.0000) V2(←,0.0000)	V1(D,0.8648)	LL(-2,722.71) BIC(5609.07) CAIC(5636.07)			
Panel Random RDC	V1(D,0.0023) V2(←,0.0000)	V1(D,0.0043) V2(←,0.0000)	V1(D,0.0034) V2(←,0.0000)	V1(D,0.0004) V2(←,0.0000)	V1(D,0.0086) V2(←,0.0000)	V1(D,0.0027) V2(←,0.0000)	LL(-2,621.91) BIC(5377.17) CAIC(5399.17)		
Panel Random SH	V1(D,0.0000) V2(←,0.0000)	V1(D,0.0000) V2(←,0.0000)	V1(D,0.0000) V2(←,0.0000)	V1(D,0.0000) V2(←,0.0000)	V1(D,0.0008) V2(←,0.0000)	V1(D,0.0000) V2(←,0.0000)	V1(ND,0.7928)	LL(-2,606.75) BIC(5377.16) CAIC(5404.16)	
Panel Random DH	V1(D,0.0000) V2(←,0.0000)	V1(D,0.0000) V2(←,0.0000)	V1(D,0.0000) V2(←,0.0000)	V1(D,0.0000) V2(←,0.0000)	V1(D,0.0003) V2(←,0.0000)	V1(D,0.0000) V2(←,0.0000)	V1(ND,0.7525)	V1(ND,0.9639)	LL(-2,607.73) BIC(5379.12) CAIC(5406.12)

Key

V1(·,·) = Not statistically distinguishable (ND) or statistically distinguishable (D) in 1st stage of Vuong non-nested hypthesis test ($\alpha = .1$). P-value also reported.

V2(·,·) = If distinguishable in 1st stage, 2nd stage Vuong test results reported with arrow pointing to statistically prefered model ($\alpha = .1$). P-value also reported.

CAIC(·) & BIC(·) = Consistent Akaike Information Criteria & Bayesian Information Criteria, respectively.

LL(·) = Ln-Likelihood