SERIAL NONPARTICIPATION IN REPEATED DISCRETE CHOICE MODELS

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We consider alternative econometric strategies for addressing serial nonparticipation, that is, repeated choice of the same alternative or same type of alternative across a series of choice occasions, in data typically analyzed within the repeated discrete choice framework. Single and double hurdle variants of the repeated discrete choice model are developed and applied to choice experiment and multisite seasonal recreation demand data. Our results suggest that hurdle models can generate significant improvements in statistical fit and qualitatively different policy implications, particularly in choice experiment applications where the proper treatment of serial nonparticipation is relatively more ambiguous.

Key words: choice experiments, discrete choice models, hurdle models, recreation demand, serial nonparticipation.

Serial nonparticipation, or repeated choice of the same alternative or same type of alternative across a series of choice occasions, is a common phenomenon in stated and revealed preference data that are typically analyzed within the repeated discrete choice framework. With stated preference choice experiment data, for example, one form of serial nonparticipation arises when the individual always chooses the status quo option, and another arises when the individual always chooses the alternative with the highest (or lowest) level of a particular attribute. With revealed preference seasonal recreation demand data, serial nonparticipation arises when the individual chooses the "no-trip" alternative on every choice occasion.[1] All of these types of serial nonparticipation can arise from the same behavioral process that gives rise to participation. In fact, probabilistic repeated discrete choice models predict some degree of serial nonparticipation. However, the prevalence of serial nonparticipation in many data sets suggests that a fundamentally different behavioral process may explain such behavior.

In choice experiment contexts, individuals who always choose the status quo option or the alternative with the highest level of a particular attribute may be engaging in a form of protest against the notion that they must trade-off various attributes. Alternatively, these individuals may have lexicographical preferences or be employing simplifying heuristics to make complex choices less difficult (Dhar 1997a, 1997b). In the context of seasonal recreation demand, serial nonparticipation may arise when a segment of the population has preferences or faces constraints such that they would never recreate at any site under any circumstance. All of these types of responses suggest that serial nonparticipants behave fundamentally differently than participants. Stated succinctly, serial nonparticipants may not be "playing the game" that participants play.

In this article, we develop repeated discrete choice econometric models that, in contrast to existing approaches for addressing serial nonparticipation, explicitly allow for the behavioral phenomena to arise from a fundamentally different process than participation. Single and double hurdle random coefficient and repeated discrete choice models are applied to data from a stated preference survey focused

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[1] Note that we are making a distinction between serial nonparticipation and choice occasion nonparticipation. The former refers to situations where the individual chooses the status quo or "no-trip" alternative on all choice occasions whereas the latter refers to situations where the individual chooses such alternatives on a single choice occasion.

on woodland caribou enhancement programs and a recreation survey of Mid-Atlantic seasonal ocean beach use. Both data sources have a significant proportion of serial nonparticipants and thus are well suited to illustrate the proposed models. In addition, our use of both data sets allows us to investigate how the welfare implications of the serial nonparticipation hurdles differ across choice experiment and recreation demand contexts.

Our estimation results suggest that substantial improvements in statistical fit can result when a different behavioral process is introduced to explain serial nonparticipation, although the gains in fit are less pronounced with the introduction of random coefficients that are equal across choice occasions for an individual. Based on alternative information criteria and nested and nonnested hypothesis tests, we also find that statistical fits with the single and double hurdle models are similar in both data sets. The choice experiment results consistently suggest that younger and more educated individuals are less likely to be serial nonparticipants while the recreation demand results suggest that younger individuals, vacation property owners, and in some cases parents of young children are less likely to be serial nonparticipants. Results from choice experiment and recreation demand data sets suggest that significant preferences for the status quo and the "no-trip" alternatives, respectively, remain in the hurdle models after accounting for serial nonparticipation.

We also explore the implications of our single and double hurdle models for welfare measurement in both applications. We argue that the inclusion of serial nonparticipation hurdles gives the analyst additional discretion when constructing welfare measures. How this discretion should be used in the choice experiment context is, however, far from certain due to competing hypotheses about why individuals always choose the status quo. Consequently, we assess the sensitivity of welfare measures to alternative arbitrary but plausible strategies for treating serial nonparticipation hurdles in the choice experiment context. Our assessment also considers alternative treatments of status quo preference among participants, an unresolved issue in the choice experiment context. Our results suggest that alternative judgments in these regards can generate qualitatively different policy implications. For example, we find that although sample median welfare measures from traditional repeated discrete choice models can be positive or negative depending on the treatment of participant preferences for the status quo, sample median welfare measures from the hurdle models are consistently positive across alternative treatments of status quo preference and serial nonparticipant hurdles. By contrast, in the seasonal recreation demand context, we argue that the behavioral interpretation of serial nonparticipation hurdles is clear—assuming weak complementarity (Mäler) holds, the hurdles account for individuals who would not benefit from site-quality improvements under any circumstance. As a result, welfare measurement with serial nonparticipation hurdles is conceptually straightforward in the recreation demand context. In our application, we find that differences in welfare estimates across traditional, single hurdle, and double hurdle repeated discrete choice models are small for our quasi-nested logit specifications but larger in our panel random coefficient specifications.

The remainder of the paper is structured as follows. The next section develops the generic single and double hurdle repeated discrete choice structures and highlights their statistical and behavioral properties. We then discuss the data sets, parameter estimates, information criteria, and hypothesis test results from our choice experiment and seasonal recreation demand applications. The issues arising with welfare measurement as well as a menu of welfare estimates for each application are also presented. We conclude with a discussion of the advantages from using repeated discrete choice models that explicitly account for individuals who do not "play the game" as well as issues for further research.

Econometric Model

In both the choice experiment and seasonal recreation demand contexts, the repeated discrete choice-modeling framework is widely used. Given that individuals are confronted with a series of hypothetical choices consisting of attribute-varying choice alternatives as well as a status quo alternative, the repeated discrete choice framework is the natural modeling structure for choice experiment data. In seasonal recreation demand applications where an individual's total trip counts to a potentially large number of heterogeneous sites is observed, the framework is often used because of the difficulties in estimating flexible demand systems models (von Haefen and Phaneuf).

In both cases, however, the generic setup is similar. Preferences on each choice occasion (i.e., a hypothetical choice in the choice experiment context, a week or day in the seasonal recreation demand context) are separable from those on other choice occasions. Each choice occasion involves the individual making a discrete choice from a finite set of alternatives (hypothetical bundles of attributes and a status quo alternative in choice experiments, quality differentiated sites and a "no-trip" option in seasonal recreation demand). This choice is generated from a random utility maximizing (RUM) behavioral process (McFadden) that assumes that both observable and unobservable factors (from the analyst's perspective) enter consumer preferences and determine choice. The unobserved factors are known by the individual but treated as random draws from some probability distribution by the analyst. In combination with the RUM behavioral structure that governs choice, these probability distributions imply likelihoods of observing various choice combinations conditional on a set of underlying model parameters. Observable choices and these conditional probabilities can be used to recover estimates of the underlying parameters within the maximum likelihood framework.

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

$$V_j(y_t - p_{jt}, q_{jt}, \beta) + \varepsilon_{jt}$$

where y_t is normalized income, p_{jt} and q_{jt} are the observable choice occasion specific normalized price and attributes of the jth alternative,[2] β are estimable parameters, and the additive 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, that is:

$$\text{Alternative } i \text{ chosen if}$$
$$\max_j \{V_j(y_t - p_{jt}, q_{jt}, \beta) + \varepsilon_{jt}, \forall j \in J_t\}$$
$$= V_i(y_i - p_{it}, q_{it}, \beta) + \varepsilon_{it}.$$

If the analyst assumes that each ε_{jt} can be treated as an independent and identically distributed draw from the normalized type I extreme value distribution,[3] the likelihood of observing the individual choosing the ith alternative on choice occasion t, L_{it}, takes the standard multinomial logit form:

$$L_{it} = \frac{e^{V_i(y_t - p_{it}, q_{it}, \beta)}}{\sum_j^{J_t} e^{V_j(y_t - p_{jt}, q_{jt}, \beta)}}.$$

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

$$L^{\mathrm{RDC}} = \prod_t^T \prod_j^{J_t} (L_{jt})^{1_{jt}}$$

where 1_{jt} is an indicator function equal to one if the jth alternative is chosen on the tth choice occasion and zero otherwise.[4]

The traditional repeated discrete choice model places a strictly positive probability mass on every series of choices. Consequently, the model predicts that repeated choice of the same alternative or same type of alternative, that is, serial nonparticipation, will arise over a sufficiently large sample. For example, if alternative 1 is the status quo or "no-trip" alternative and serial nonparticipation is defined as repeated choice of this alternative, the probability mass associated with serial nonparticipation is $\prod_t^T (L_{1t})$. Where the traditional model fails in many applied situations, however, is in predicting the frequency of these outcomes. Analysts have addressed this limitation in one of three ways. One involves simply purging from the estimation sample all serial nonparticipants. In the choice experiment context, this frequently involves dropping all individuals who repeatedly choose the status quo or "choose neither" alternative or the alternative with the highest level of a particular attribute (e.g., Adamowicz et al.). In the recreation context, all nonrecreators are sometimes purged from the estimation sample (von Haefen 2003; Moeltner and

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[2] In seasonal recreation demand applications, data limitations often require that the analyst assumes each site's price and quality attributes are treated as time invariant. Moreover, these same limitations also require that the elements of each individual's choice set are treated as invariant across choice occasions.

[3] Extensions to the generalized extreme value variant of the type I extreme value distribution (Morey) are possible but do not substantively change the discussion below.

[4] See Morey for an alternative derivation of L^{RDC} that exploits the multinomial distribution and can be used when the individual's choice set, prices, and quality attributes are invariant across choice occasions.

Englin), but many researchers employ on-site or targeted sampling procedures that remove a priori serial nonparticipants from the sampling frame. Although sometimes convenient, dropping or ignoring serial nonparticipants prevents the analyst from drawing any inference about the factors that give rise to this form of behavior. Moreover, it introduces a truncation problem that can lead to inconsistent parameter and welfare estimates if not properly addressed. Another common strategy for addressing serial nonparticipation is to add an alternative specific constant (i.e., a status quo constant term in the choice experiment context and a "no-trip" constant term in the recreation context) for the alternative that is repeatedly chosen across choice occasions. This approach has the potential of increasing the probability mass associated with serial nonparticipation, but it restrictively assumes that serial nonparticipants' marginal rates of substitution are the same as participants'.[5]

A third approach for addressing serial nonparticipation introduces correlations across choice occasions through random coefficients. These "panel" random coefficient models (Train 1998) assume a subset of the parameters entering the utility function (β) vary randomly across individuals but are fixed across choice occasions for a given individual. As such, they have the potential to introduce correlations in the unobserved determinants of choice across choice occasions and thus increase the probability mass associated with serial nonparticipation. In the process, they also allow for a more substantial degree of preference heterogeneity relative to fixed coefficient specifications. As McFadden and Train have argued, any structure of substitution underlying an observed set of choices can be approximated by appropriate choice of the random coefficients' mixing distribution. Although attractive in many ways, random parameter approaches do not explicitly differentiate preference heterogeneity from serial nonparticipation, and as such prevent the analyst from treating serial nonparticipants differently from participants in welfare analysis.

In this paper, we consider "hurdle" approaches to addressing serial nonparticipation. Although widely used in microeconometric demand models to account for the so-called "excess zero" problem (e.g., Haab and McConnell; von Haefen and Phaneuf; von Haefen), these mixture models have not been considered in the repeated discrete choice context to our knowledge (see Swait and Ben-Akiva for an application in transportation). Since hurdle models introduce a separate data generating process to explain serial nonparticipation, they differ from previous approaches that deal with the issue more indirectly.

As discussed in detail by Shonkwiler and Shaw, hurdle models can be grouped into two broad categories. Both introduce a separate probability model or hurdle, π, to explain serial nonparticipation. In general, π is bounded between zero and one may depend on exogenous demographic, socioeconomic, cognitive, or health status variables that are likely correlated with serial nonparticipation. In the single hurdle framework, π *replaces* the probability of serial nonparticipation implied by the traditional repeated discrete choice framework (i.e., $\prod_t^T(L_{1t})$). Thus for a given individual, the probability of serial nonparticipation equals π. By contrast, the double hurdle framework assumes that the separate probability model π *augments* the probability of serial nonparticipation implied by the traditional repeated discrete choice model. For a given individual, the likelihood of serial nonparticipation is $\pi + \prod_t^T(L_{1t})$, and thus one of two hurdles, π or $\prod_t^T(L_{1t})$ may explain serial nonparticipation. In essence, what differentiates the frameworks is that π is assumed to explain all serial nonparticipation in the single hurdle framework but only a fraction of serial nonparticipation in the double hurdle framework. Relative to traditional repeated discrete choice models, both single and double hurdle models assume that a different data generating process (i.e., the π hurdle) explains serial nonparticipation at least in part. The full structures of their fixed coefficient likelihoods, L^{SH} and L^{DH}, respectively, relative to the traditional repeated discrete choice likelihood L^{RDC}, take the general form:

$$L^{\mathrm{SH}} = \pi^{\tilde{1}}(1-\pi)^{1-\tilde{1}} \times \left(L^{\mathrm{RDC}}\left(1-\prod_t^T L_{1t}\right)^{-1}\right)^{1-\tilde{1}}$$

[5] In the recreation demand context, it is common to combine a no-trip alternative dummy variable with a nested logit choice structure that places the no-trip alternative in a separate nest from all sites (e.g., Parsons; Morey, Rowe, and Watson). Although nested logit models introduce correlations in the unobserved determinants of choice on a given choice occasion, they do not introduce correlations in the unobserved determinants of choice across choice occasions or substantially add probability mass to the no-trip alternative. As a result, introducing a nested logit structure into a repeated discrete choice framework represents at best a relatively blunt instrument for addressing serial nonparticipation. For an example of treatment of a similar phenomenon in the transportation literature, see Swait and Ben-Akiva.

$$L^{\mathrm{DH}} = \pi^{\tilde{1}} + (1-\pi)L^{\mathrm{RDC}}$$

where the indicator function $\tilde{1}$ equals one when the individual is a serial nonparticipant (i.e., she always chooses the first alternative) and zero otherwise.

It is worth emphasizing that the structure of L^{SH} suggests that the maximum likelihood estimates of β from the single hurdle model have a close relationship to those derived from repeated discrete choice models applied to just the subsample of participants. Note that L^{SH} can be decomposed into multiplicatively separable components that depend on just π (i.e., $\pi^{\tilde{1}}(1-\pi)^{1-\tilde{1}}$) or $\beta((L^{\mathrm{RDC}}(1-\prod_t^T L_{1t})^{-1})^{1-\tilde{1}})$. This decomposition suggests that if the analyst were to recover maximum likelihood estimates of β from a repeated discrete choice model that is applied to just the subsample of participants and consistently account for the induced truncation (i.e., the impossibility of serial nonparticipation), she would generate the same estimates for β as she would from maximizing $\ln(L^{\mathrm{SH}})$. The main difference between the two strategies is that the single hurdle model employs a separate probability model to explain the behavior of serial nonparticipants while the repeated discrete choice model applied to just participants does not. In this way, the single hurdle model can be thought of as a generalized version of the common empirical strategy of estimating a repeated discrete choice model on just the subsample of participants while consistently accounting for the induced truncation.

The above discussion raises a point we feel is worth emphasizing—the single and double hurdle frameworks should not necessarily be thought of as substitute strategies for addressing serial nonparticipation relative to those that past researchers have exploited. In principle, single and double hurdle models can be used in conjunction with alternative specific constants for the status quo or "no-trip" alternatives to better address serial nonparticipation. Moreover, random coefficient variants of the single and double hurdle models can be estimated that may generate additional improvements in statistical fit relative to fixed parameter variants. In our view, the single and double hurdle frameworks should be thought of as additional instruments the analyst can use to address serial nonparticipation in a given application. Whether the frameworks generate significant improvements in statistical fit and qualitatively different policy implications is an empirical question. In the next sections, we address this question in the context of choice experiment and seasonal recreation demand applications.

Data

Choice Experiment Application

Our choice experiment data come from a 1995 forestry management mail survey described in Adamowicz et al. The choice experiment repeatedly asks each respondent to choose from three alternatives: two hypothetical "futures" and the status quo. Each choice alternative is described in terms of five attributes: (*a*) woodland caribou populations; (*b*) wilderness area size; (*c*) restrictions on recreation activities; (*d*) the number of jobs in the forestry industry; and (*e*) the change in income tax paid by the respondents. Each attribute has four levels with one level corresponding to the status quo. For each hypothetical future, the five attributes were chosen using a main effects, fractional factorial design.[6]

A total of 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 eight choice tasks. Our empirical analysis focuses on the choices made by these 429 individuals. Included in this sample are 88 individuals (roughly 20% of our sample) who always chose the status quo alternative. We define this group as the serial nonparticipants in our study. For the remaining 341 individuals, a significant preference for the status quo alternative remained. On roughly 49% 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 simply a strong preference for the status quo—but we cannot identify which of these factors is relevant for participants in our sample without additional data.

Recreation Application

Our recreation data come from a 1997 Mid-Atlantic beach recreation mail survey. The

[6] The design selected the minimum number of combinations of attributes required to identify main effects of the attributes and generated choice set with uncorrelated attributes. See Louviere, Hensher, and Swait for a discussion of experimental design in choice experiments.

survey collected information on the visitation patterns of Delaware residents to 62 Mid-Atlantic ocean beaches. These beaches run along the coast from the northernmost beach in New Jersey, Sandy Hook, to the southernmost beach on the Delmarva Peninsula, Assateague Island. Respondents were asked how many day, short overnight, and long overnight trips they took to each ocean beach in the region during 1997. Of the 1086 surveys that were mailed and delivered to a stratified random sample of Delaware residents, 565 were completed and returned. Massey and Parsons and Massey contain detailed discussions of the survey instrument, data collection efforts, and data cleaning procedures.

Our analysis focuses on the day trip choices of 540 respondents.[7] These individuals took an average of 9.8 day trips to the ocean beaches in the region. Because the most day trips taken by any respondent was seventy-three, we choose to set the number of choice occasions in our repeated discrete choice model to seventy-five.[8] In total, the respondents collectively took 5,279 trips out of 40,500 potential recreation opportunities, implying that on average they took day trips on roughly 13% of their assumed choice occasions. A total of 165 of the 540 respondents, or roughly 31% of the sample, did not visit a single beach over the course of the year. We define this group as serial nonparticipants.

Results

Choice Experiment Parameter Estimates

We estimated numerous variations of the traditional, single hurdle, and double hurdle repeated discrete choice models with the choice experiment data and report a representative set of our findings in table 1. All estimated models assume each choice alternative's conditional indirect utility function has a simple linear-in-parameters form. Included in the conditional indirect utility functions are the hypothetical choice experiment attributes and a status quo dummy variable interacted with individual specific characteristics (i.e., the respondent's age, sex, a high school diploma indicator, and a four-year college degree dummy variable). To allow for nonlinear income effects, the difference between the individual's income and marginal tax burden (i.e., her after-tax consumption of the Hicksian composite good) is specified in quadratic form. Finally, for the hurdle models, π was specified in logit form and assumed to be a linear function of the same demographic variables interacted with the status quo constant.[9]

We consider fixed and random coefficient variants of the traditional, single hurdle, and double hurdle models. For the random coefficient models, we assumed a selected set of parameters varied randomly across individuals in the target population. Specifically, these panel random coefficient models assume that a subset of parameters entering each individual's conditional indirect utility functions can be treated as independent and identically distributed draws from the multivariate normal distribution, $N(\mu, \Sigma)$ where we restrict the off-diagonal elements of Σ to equal zero. For computational tractability and economic coherence, we restrict the parameters entering the quadratic specification for the Hicksian composite good to be equal across individuals. Although we experimented with allowing the parameters in π to vary randomly across individuals, we found no improvement in fit arising from this additional heterogeneity, and therefore assumed these parameters were fixed across individuals. Estimation of the random coefficient model exploited maximum simulated likelihood techniques (Train 2003) and analytical gradient-based search routines.[10]

The fixed and random coefficient estimates reported in table 1 show that the parameter estimates are generally statistically significant, plausibly signed, and stable across all six models. On average individuals value increases in caribou population and wilderness area, and generally favor less recreation restrictions to

[7] Following von Haefen, Phaneuf, and Parsons, 25 of 565 completed surveys were excluded from the analysis because the respondents in our judgment reported taking implausibly large numbers of day trips.

[8] We investigated the sensitivity of welfare estimates to alternative choice occasion specifications in the context of fixed parameter models. Our results suggested that welfare estimates were quite robust across specifications with 75, 100, 150, and 200 choice occasions. The only systematic pattern we found as we varied the number of choice occasions was a very slight upward drift in the absolute value of welfare estimates, but this drift was quite similar across traditional, single hurdle, and double hurdle models. We conclude from this investigation that the qualitative results we report in this article are not substantively affected by our arbitrary choice of 75 choice occasions.

[9] To evaluate the sensitivity of our results to our use of logit hurdles, we also estimated probit hurdle models for all specifications reported in this article. In all cases we found relatively small differences in log-likelihood values between the logit and probit hurdle models, and virtually no differences at all in most cases.

[10] The GAUSS 5.0 estimation code for all specifications and welfare estimates reported in this article are available from the authors upon request.

Table 1. Choice Experiment Coefficient Estimates

	Repeated Discrete Choice Model								
	Traditional			Single Hurdle			Double Hurdle		
	Fixed Coefficient	Random Coefficient		Fixed Coefficient	Random Coefficient		Fixed Coefficient	Random Coefficient	
Log-likelihood	−2,948.2	−2,620.0		−2,742.7	−2,604.9		−2,742.6	−2,604.5	
Repeated discrete choice parameters		Mean	SD		Mean	SD		Mean	SD
Caribou/1,000	5.37 (14.1)	7.06 (13.4)	1.08 (6.38)	5.61 (13.9)	6.93 (13.5)	1.03 (5.13)	5.62 (13.9)	6.96 (13.5)	1.06 (5.22)
$(\text{Caribou}/1{,}000)^2$	−2.66 (13.8)	−3.60 (13.1)	0.33 (2.50)	−2.79 (13.6)	−3.51 (13.2)	0.37 (3.15)	−2.79 (13.6)	−3.54 (13.1)	0.35 (2.82)
Wilderness area acreage/100,000	0.34 (8.36)	0.48 (8.93)	0.18 (1.01)	0.37 (8.64)	0.47 (8.53)	0.11 (0.34)	0.37 (8.64)	0.47 (8.64)	0.11 (0.33)
Recreation level 1[a]	0.60 (5.93)	0.65 (4.78)	0.71 (3.78)	0.60 (5.59)	0.65 (4.86)	0.52 (2.13)	0.60 (5.59)	0.66 (4.82)	0.55 (2.20)
Recreation level 2[a]	0.52 (5.39)	0.70 (5.93)	0.50 (3.08)	0.53 (5.14)	0.68 (5.71)	0.50 (3.13)	0.53 (5.14)	0.70 (5.84)	0.51 (2.90)
Recreation level 3[a]	0.20 (2.29)	0.24 (2.25)	0.53 (2.29)	0.21 (2.38)	0.23 (2.06)	0.59 (1.98)	0.21 (2.38)	0.23 (2.07)	0.56 (1.83)
Forestry jobs/1,000	−0.15 (1.63)	−0.21 (1.64)	0.82 (2.76)	−0.13 (1.30)	−0.19 (1.48)	1.08 (3.79)	−0.13 (1.31)	−0.17 (1.38)	1.04 (3.62)
(Income-tax)/100	0.58 (5.01)	0.70 (5.13)	–	0.57 (4.71)	0.69 (5.01)	–	0.57 (4.67)	0.70 (5.03)	–
$((\text{Income-tax})/10{,}000)^2$	−2.55 (2.39)	−2.71 (2.18)	–	−2.39 (2.17)	−2.72 (2.18)	–	−2.36 (2.14)	−2.72 (2.18)	–
Status quo constant (SQ)	0.19 (0.65)	0.04 (0.09)	1.72 (15.6)	−0.15 (0.57)	−0.42 (1.18)	1.11 (10.6)	−0.15 (0.54)	−0.44 (1.08)	1.21 (9.08)
SQ × age/100	2.02 (4.14)	3.34 (4.48)	–	0.82 (1.81)	1.20 (1.92)	–	0.80 (1.77)	1.33 (1.86)	–
SQ × high school diploma	0.04 (0.17)	0.03 (0.07)	–	0.38 (1.88)	0.61 (2.21)	–	0.38 (1.87)	0.70 (2.15)	–
SQ × four-year college degree	−0.40 (2.79)	−0.72 (3.23)	–	−0.21 (1.54)	−0.37 (1.93)	–	−0.21 (1.52)	−0.42 (1.93)	–
SQ × male	0.06 (0.49)	0.07 (0.36)	–	0.11 (0.89)	0.11 (0.66)	–	0.11 (0.90)	0.17 (0.87)	–
Hurdle parameters									
Constant	–	–	–	−2.14 (4.15)	−2.14 (4.15)	–	−2.16 (4.13)	−2.45 (3.50)	–
Age/100	–	–	–	3.39 (3.83)	3.39 (3.82)	–	3.40 (3.78)	3.98 (3.17)	–
High school diploma	–	–	–	−0.53 (1.57)	−0.52 (1.56)	–	−0.52 (1.54)	−0.88 (1.99)	–
Four-year college degree	–	–	–	−0.72 (2.25)	−0.72 (2.25)	–	−0.72 (2.21)	−0.88 (1.49)	–
Male	–	–	–	−0.02 (0.07)	−0.02 (0.09)	–	−0.03 (0.10)	−0.22 (0.54)	–

Note: Random coefficient estimates generated with 500 Halton draws. Absolute value of asymptotic *t*-statistics based on robust standard errors in parentheses.

[a]Four recreation levels were considered in the survey. Level 1 (i.e., the least stringent) permits off-road vehicles, horses, helicopters, and overnight camping in general as well as hunting and fishing in designated areas. Level 2 permits off-road vehicles, horses, helicopters, overnight camping, hunting, and fishing in designated areas only. Level 3 does not permit hunting, fishing, off-road vehicles, or helicopters, but allows for horses and overnight camping in designated areas. Level 4 (the most stringent) involves reduced speeds on highways in the area and does not permit hunting, fishing, off-road vehicles, horses, or helicopters. Level 4 does allow for hiking on designated trails and limited access to overnight camping. The reported parameter estimates should be interpreted as the marginal value of the recreation level with respect to the excluded level 4.

more. The jobs coefficients suggest that individuals are not significantly affected by the loss of forestry jobs, and the quadratic specification for the Hicksian composite good has the proper increasing and concave shape over the relevant range. The status quo constant—demographic interaction terms generally suggest that preferences for the status quo are independent of sex, but significantly negative for younger and more educated individuals. Turning to the hurdle parameters, we also find that younger, more educated individuals are less likely to be serial nonparticipants. Across the four hurdle specifications, we found that the hurdles, or the probabilities of not playing the game, had sample mean values ranging between 0.146 and 0.205.

To compare the relative statistical fits of the six alternative specifications, we use their log-likelihoods (LL) and two information criteria—the Bayesian information criteria (BIC) as well as the consistent Akaike information criteria (CAIC):

$$\mathrm{BIC} = -2\mathrm{LL} + \ln(N)P$$

$$\mathrm{CAIC} = -2\mathrm{LL} + (1 + \ln(N))P$$

where 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 likelihood ratio and Vuong nonnested hypothesis tests (Vuong). These results are summarized in table 2. They suggest that for the fixed coefficient specifications, 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 ambiguous—in general the BIC, CAIC, and the Vuong tests suggest that the models are indistinguishable. This finding is similar to Greene and Haab and McConnell's 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 serial nonparticipation. Finally, comparing the fixed coefficient and panel random coefficient models, we find that panel random coefficient models fit the data significantly better.

Choice Experiment Welfare Estimates

In addition to comparing statistical performance, we also examine welfare measures derived from the traditional and hurdle models associated with a hypothetical change in quality attributes. The scenario examined is the same one explored by Adamowicz et al. and involves a change in caribou population from 400 to 600, wilderness area from 150,000 to 300,000 hectares, and recreation restrictions from level 2 (hunting, fishing, off-road vehicles, helicopters, horses, and overnight camping in designated areas) to level 3 (no hunting, fishing, off-road vehicles, or helicopters allowed; horses and overnight camping in designated areas).

Following Hanemann, choice experiment researchers frequently employ the following implicit definition of the Hicksian consumer surplus, CS^{H}, associated with a quality change from q^0 to q^1 as:

$$V(y, q^0, \beta, \varepsilon^0) = V(y - \mathrm{CS}^{\mathrm{H}}, q^1, \beta, \varepsilon^1)$$

where $V(\cdot)$ has the same structure as the conditional indirect utility functions specified in the choice experiment model. Because our empirical specification employs a quadratic specification in the Hicksian composite good, no closed form solution for CS^{H} exist, and thus iterative techniques must be used to numerically solve for CS^{H} conditional on $(\beta, \varepsilon^0, \varepsilon^1)$.[11] Moreover, because $(\beta, \varepsilon^0, \varepsilon^1)$ are random variables from the analyst's perspective, simulation techniques are necessary to estimate the expected Hicksian consumer surplus, $\mathrm{E}(\mathrm{CS}^{\mathrm{H}})$.

Two additional issues arise with the calculation of $\mathrm{E}(\mathrm{CS}^{\mathrm{H}})$ in our application—the treatment of serial nonparticipation and status quo preference by participants. With the hurdle models, the analyst must decide how to treat individuals who do not play the game. In our view, the appropriate treatment will depend on each individual's reason for not participating. If, for example, an individual's serial nonparticipation arises from cognitive difficulties associated with comprehending the survey instrument, the most defensible treatment might be to simply ignore the hurdle altogether.

[11] Note that we are assuming that the change in quality introduces a new state with a new random error ε^1 attached to it, but the same random coefficients.

Table 2. Statistical Comparisons of Alternative Choice Experiment Models

	Fixed Coefficient Traditional	Fixed Coefficient Single Hurdle	Fixed Coefficient Double Hurdle	Panel Random Coefficient Traditional	Panel Random Coefficient Single Hurdle	Panel Random Coefficient Double Hurdle
Fixed coefficient traditional	LL (−2,948.2) BIC (6,010.3) CAIC (6,024.3)					
Fixed coefficient single hurdle	V1 (D,0.0031) V2 (←,0.0000)	LL (−2,742.7) BIC (5,640.0) CAIC (5,659.0)				
Fixed coefficient double hurdle	V1 (D,0.0000) V2 (←,0.0000)	V1 (ND,0.9999)	LL (−2,742.6) BIC (5,639.8) CAIC (5,658.8)			
Panel random coefficient traditional	LR (←,0.0000)	V1 (D,0.0304) V2 (←,0.0000)	V1 (D,0.0000) V2 (←,0.0000)	LL (−2,620.0) BIC (5,419.0) CAIC (5,411.0)		
Panel random coefficient single hurdle	V1 (D,0.0000) V2 (←,0.0000)	LR (←,0.0000)	V1 (D,0.0000) V2 (←,0.0000)	V1 (D,0.0011) V2 (←,0.0048)	LL (−2,604.9) BIC (5,429.6) CAIC (5,456.6)	
Panel random coefficient double hurdle	V1 (D,0.0000) V2 (←,0.0000)	V1 (D,0.0432) V2 (←,0.0000)	LR (←,0.0000)	V1 (D,0.0411) V2 (←,0.0036)	V1 (ND,0.9371)	LL (−2,604.5) BIC (5,428.9) CAIC (5,455.9)

Note: All likelihood ratio tests employed the standard critical values from the chi-squared distribution with the appropriate degrees of freedom. Chen and Cosslett have shown that these critical values are too large and thus lead on average to infrequent reject of the null hypothesis. Although the null hypotheses are consistently and strongly rejected in the above table, our *p*-values are likely overstated.

V1(·,·) = Not statistically distinguishable (ND) or statistically distinguishable (D) in first stage of Vuong nonnested hypothesis test ($\alpha = 0.1$). *p*-Value also reported.

V2(·,·) = If distinguishable in first stage, second stage Vuong test results reported with arrow pointing to statistically preferred model ($\alpha = 0.1$). *p*-Value also reported.

LL(·), CAIC(·), and BIC(·) = Log-likelihood, consistent Akaike information criteria, and Bayesian information criteria, respectively.

LR(·,·) = Likelihood ratio test with arrow pointing to restricted model if it could not be rejected, unrestricted model otherwise ($\alpha = 0.1$). *p*-Value also reported.

Table 3. Choice Experiment Sample Median Welfare Estimates (1995 Canadian Dollars)

Repeated Discrete Choice Model	Including Status Quo Constant (SQ)	Ignoring Status Quo Constant (SQ)
Traditional		
Fixed coefficient	−\$32.60 (13.61)	\$104.99 (24.56)
Random coefficient	−\$28.88 (16.79)	\$105.15 (22.02)

	Including SQ and Ignoring Hurdle	Including SQ and Hurdle	Ignoring SQ and Hurdle	Ignoring SQ and Including Hurdle
Single hurdle				
Fixed coefficient	\$43.37 (16.00)	\$33.24 (12.14)	\$115.73 (28.02)	\$88.81 (21.56)
Random coefficient	\$45.11 (16.25)	\$34.76 (12.24)	\$106.33 (27.21)	\$81.86 (20.71)
Double hurdle				
Fixed coefficient	\$43.40 (15.99)	\$33.43 (12.18)	\$115.92 (28.05)	\$89.38 (21.69)
Random coefficient	\$30.05 (15.03)	\$24.71 (11.87)	\$104.29 (26.80)	\$86.13 (21.93)

Note: Two-thousand simulations used to construct all point estimates. Parametric bootstrap standard errors based on 200 replications in parentheses. When including the status quo constant, we set the status quo constant equal to one for the baseline state but equal to zero for the proposed policy state. Alternatively, when excluding the status quo constant, we set the status quo constant equal to zero for the baseline and proposed policy states. Similarly when including the hurdle, we scale the welfare measure implied by the application of the Hanemann formula by the probability of participation, $1 - \pi$. Conversely when ignoring the hurdle, we do not scale the welfare measure implied by the application of the Hanemann formula by $1 - \pi$.

Alternatively, if the individual's serial nonparticipation reflects opposition to any form of government intervention, then imputing a zero (or possibly negative) welfare measure may be appropriate. Since we cannot empirically differentiate between these alternative hypotheses for serial nonparticipation, we present two sets of welfare estimates—those that ignore the hurdle (and thus serial nonparticipation) entirely and those that scale the Hicksian consumer surplus estimate by the probability of participation (i.e., $1 - \pi$). These latter estimates implicitly assume that nonparticipants' value for the policy change is zero.

The second issue arises in both the traditional and hurdle repeated discrete choice models where strong status quo preferences among participants were found. In general, including status quo preference in welfare calculations will produce lower estimates than those that exclude it. Moreover, it is possible that including the status quo constant will imply negative sample welfare estimates from policy changes that improve environmental quality.[12] Again, our sense is that the appropriate treatment will depend on the reasons for individuals exhibiting this preference. Because our data set does not contain information that would allow us to empirically test these competing hypotheses, we have chosen to calculate welfare measures with and without the status quo constants for all models. Since for each of the hurdle models we also present estimates that ignore or incorporate the hurdle, we present a total of four sets of estimates for the hurdle models, but only two for the traditional models.[13]

Table 3 presents the sample welfare estimates for the fixed and random coefficient models. Following standard practice in the stated preference literature, we report sample medians for each model and welfare estimation approach as well as their standard errors. The estimates suggest that the largest differences in welfare measures arise from the treatment of the status quo preference, although the differences arising within the hurdle models are smaller than those associated with the traditional repeated discrete choice models. As expected, including the status quo preference significantly reduces the magnitude of the welfare measures. Moreover, the traditional repeated discrete choice model estimates that incorporate the status quo preferences are consistently negative, while the hurdle models are consistently positive. These empirical findings reflect the fact that the hurdle is in some sense disentangling status quo preference found in the traditional models into components associated with those who are and are not playing

[12] We recognize that with a heterogeneous population, it is entirely possible that some individuals will experience a decrease in utility from policies that improve environmental quality. Our point here is that including the status quo constant can imply average welfare effects that are negative, even though individuals in the population, on average, benefit from marginal changes in each of the changing attributes.

[13] By presenting a range of estimates based on alternative plausible yet arbitrary assumptions, our approach is conceptually similar to Beenstock, Goldin, and Haitovsky and Hartman, Doane, and Woo.

the game. By distinguishing these groups of individuals, the analyst can make separate judgments as to how to treat their welfare measures. In our view, the fact that the hurdle models give the analyst this additional flexibility represents a significant advantage over traditional repeated discrete choice models and may result in more credible welfare measures.

A few additional insights emerge from the welfare results. Comparing welfare estimates across the traditional and hurdle models, we find that the estimates are quite similar if the analyst ignores the status quo preference and hurdles. Within the hurdle models, we also find that scaling the welfare estimates by the probability of participation generally reduces their absolute value by roughly 20% (i.e., the approximate sample mean values of the hurdles). A comparison of welfare estimates across fixed and panel random coefficient models suggests that there is no systematic difference, except that estimates ignoring the status quo tend to be lower in the random parameter case.

Recreation Parameter Estimates

In our seasonal recreation demand application, we assume the choice occasion conditional indirect utility functions are linear and additive in price (i.e., a constant marginal utility of income) and beach attributes (beach length, boardwalks, facilities, parking, etc.). A no-trip dummy variable interacted with individual specific characteristics (age, presence of children under ten and between ten and sixteen in the household, ownership of a Delaware vacation property, and retired and student dummies) is also included, and the hurdle parameter π is assumed to take the logit form[14] and be a function of a linear index of the same individual specific characteristics. Quasi-nested (Herriges and Phaneuf) and panel random coefficient parameter estimates are reported in table 4, respectively.[15] For the quasi-nested logit estimates, the coefficients on the no-trip dummy variable, the New Jersey beach dummy variable, and the Delmarva dummy variable (equal to one for all beaches outside New Jersey, or conversely, all beaches along the Delaware, Maryland, and Virginia Peninsula, zero otherwise) were treated as normally distributed random variables with zero covariance that varied across individuals and choice occasions. For identification, we restricted the mean of the Delmarva dummy variable coefficient to zero. As Herriges and Phaneuf have argued, this structure mimics the structure of a three-level nested logit model where the no-trip alternative and the 62 sites enter separate top-level nests, and within the 62-site nest, New Jersey and Delmarva beaches are separated into distinct bottom-level nests. Because the only difference between this specification and the standard nested logit model is the distribution of the unobserved heterogeneity that introduces correlations within nests, we refer to it here as the quasi-nested logit specification.[16] For the panel random coefficient models, experimentation led us to treat only a subset of parameters entering the conditional indirect utility functions as random (i.e., independent and identically distributed draws from the multivariate normal distribution, $N(\mu, \Sigma)$ with all off-diagonal elements of Σ restricted to zero). For both the quasi-nested logit and panel random coefficient specifications, analytical gradient-based search routines were used to recover maximum simulated likelihood estimates.

Across the six specifications, the coefficient estimates were found to be plausibly signed, statistically significant, and generally quite robust. The results suggest that Delaware residents prefer to visit beaches that have access to amusement parks and convenient parking as well as those that are located at least partially within a park and have long beachfronts. *Ceteris paribus*, these individuals also prefer beaches that involve lower travel costs to visit, have beach widths that are not too narrow or wide, and are located along the Delmarva Peninsula. For the hurdle models, the hurdle parameter π was found to range in value between 0.158 and 0.306, and to be consistently positively correlated with age and negatively correlated with the presence of young children and the ownership of a Delaware vacation property.

Similar to table 2 above, table 5 contains the LL, BIC, and CAIC results as well as Vuong test statistics that shed some light on the relative statistical fits of the alternative models. For the quasi-nested logit models, the hurdle

[14] Similar to the choice experiment application, probit hurdle models produce virtually identical parameter estimates to the logit hurdle estimates reported here.

[15] Fixed parameter traditional, single hurdle, and double hurdle estimates are available from the authors upon request.

[16] Although quasi-nested logit models require simulation in estimation, a significant advantage they have over-nested logit models is that the coherency difficulties arising when the nested logit's inclusive value parameters fall outside the theoretically acceptable range (Herriges and Kling) are avoided.

Table 4. Seasonal Recreation Demand Coefficient Estimates

	Repeated Discrete Choice Model								
	Traditional			Single Hurdle			Double Hurdle		
	Quasi-Nested	Random Coefficient		Quasi-Nested	Random Coefficient		Quasi-Nested	Random Coefficient	
Log-likelihood	−27,642	−22,717		−26,348	−22,699		−26,346	−22,684	
Repeated discrete choice parameters		Mean	SD		Mean	SD		Mean	SD
Marginal utility of income (MUI)	6.96 (10.9)	−6.10 (19.8)	–	6.88 (11.0)	−5.59 (18.7)	–	6.87 (11.0)	−5.47 (11.2)	–
Log beach length	0.16 (1.91)	0.20 (2.47)	–	0.16 (1.94)	0.16 (2.11)	–	0.16 (1.91)	0.16 (1.61)	–
Boardwalk	0.50 (1.98)	0.14 (0.54)	1.26 (7.66)	0.50 (2.22)	0.21 (0.77)	1.18 (12.1)	0.46 (2.08)	0.21 (0.76)	1.02 (9.04)
Amusement park nearby	1.02 (4.88)	1.08 (5.72)	–	1.02 (4.96)	1.10 (5.67)	–	1.02 (4.97)	1.12 (5.38)	–
Private/limited access	−0.85 (4.50)	−1.49 (6.96)	1.77 (5.11)	−0.85 (4.51)	−1.96 (8.51)	1.62 (13.8)	−0.85 (4.48)	−2.41 (5.44)	1.93 (6.20)
Federal/state park	0.20 (0.83)	−0.48 (1.81)	1.59 (16.5)	0.25 (1.03)	0.02 (0.06)	1.72 (14.7)	0.22 (0.90)	−0.47 (1.68)	1.54 (16.2)
Beach width > 200 feet	−0.69 (5.11)	−1.07 (6.90)	1.29 (10.6)	−0.69 (5.15)	−1.11 (6.35)	1.37 (12.7)	−0.69 (5.13)	−0.91 (5.28)	1.34 (7.89)
Beach width < 75 feet	−0.61 (1.58)	−2.08 (5.00)	1.73 (7.35)	−0.61 (1.59)	−1.81 (6.24)	1.75 (13.3)	−0.60 (1.58)	−1.72 (5.44)	1.79 (5.63)
Atlantic City	1.36 (5.03)	1.36 (4.98)	1.00 (4.33)	1.34 (4.98)	1.21 (4.03)	1.16 (4.55)	1.34 (4.97)	1.50 (5.61)	0.93 (3.16)
Good surfing	0.67 (4.58)	0.69 (5.14)	–	0.67 (4.66)	0.69 (5.13)	–	0.67 (4.67)	0.71 (4.91)	–
Highly developed	−0.20 (1.32)	−0.12 (0.83)	–	−0.21 (1.41)	−0.21 (1.40)	–	−0.21 (1.41)	−0.24 (1.54)	–
Partially inside park[a]	1.22 (5.75)	1.12 (5.14)	–	1.22 (5.78)	1.19 (5.19)	–	1.22 (5.75)	1.23 (4.20)	–
Bathrooms available	−0.23 (1.55)	−0.16 (1.04)	–	−0.22 (1.46)	−0.19 (1.27)	–	−0.23 (1.53)	−0.19 (−1.13)	–
Public parking	0.66 (2.58)	0.78 (2.88)	–	0.59 (2.36)	0.76 (2.98)	–	0.64 (2.55)	0.81 (2.65)	–
New Jersey	−10.5 (2.70)	−1.40 (5.46)	2.96 (18.9)	−6.71 (2.58)	−1.87 (5.49)	3.28 (16.8)	−6.71 (2.61)	−1.88 (2.27)	3.15 (7.26)
No-trip dummy (NT)	−1.77 (0.54)	2.82 (3.31)	2.29 (22.1)	1.05 (0.30)	4.65 (6.54)	1.99 (20.5)	1.06 (0.30)	4.70 (4.88)	2.19 (13.6)
NT × log age	2.07 (2.28)	0.13 (0.54)	–	1.18 (1.23)	−0.53 (2.58)	–	1.17 (1.23)	−0.49 (2.07)	–
NT × kids under ten years[b]	0.55 (1.23)	0.15 (0.81)	–	0.83 (1.71)	0.18 (2.00)	–	0.84 (1.72)	1.20 (5.15)	–
NT × kids ten to sixteen years[b]	−0.86 (1.87)	−0.99 (6.19)	–	−0.67 (1.34)	0.56 (4.15)	–	−0.66 (1.32)	0.38 (1.91)	–
NT × DE vacation property[c]	−4.85 (5.08)	−3.46 (16.8)	–	−4.14 (4.33)	−1.63 (7.86)	–	−4.13 (4.34)	−1.55 (5.65)	–
NT × retired	0.46 (0.73)	2.14 (12.6)	–	0.14 (0.20)	1.63 (9.06)	–	0.14 (0.20)	1.27 (4.04)	–
NT × student	−0.86 (0.91)	−0.41 (1.29)	–	−1.21 (1.21)	−0.52 (3.00)	–	−1.23 (1.24)	−0.69 (2.43)	–
NT quasi-nested SD	4.63 (6.94)	–	–	5.17 (6.80)	–	–	5.14 (6.82)	–	–
Delmarva beach quasi-nested SD[c]	0.20 (0.78)	–	–	0.45 (1.28)	–	–	0.39 (1.14)	–	–
New Jersey beach quasi-nested SD	7.60 (4.06)	–	–	5.86 (4.06)	–	–	5.85 (4.11)	–	–
Hurdle parameters									
Constant	–	–	–	−7.07 (3.87)	−7.07 (3.87)	–	−6.96 (3.76)	−7.69 (1.98)	–
Log age	–	–	–	1.65 (3.49)	1.65 (3.49)	–	1.61 (3.37)	1.63 (1.62)	–
Kids under ten years[b]	–	–	–	−0.04 (0.16)	−0.05 (0.17)	–	−0.13 (0.46)	−2.13 (2.39)	–
Kids ten to sixteen years[b]	–	–	–	−0.20 (0.77)	−0.20 (0.74)	–	−0.16 (0.59)	−0.85 (0.98)	–
DE vacation property[c]	–	–	–	−1.54 (2.01)	−1.54 (2.01)	–	−1.53 (1.97)	−2.25 (2.58)	–
Retired	–	–	–	−0.07 (0.24)	−0.07 (0.24)	–	−0.04 (0.13)	0.15 (0.31)	–
Student	–	–	–	0.17 (0.30)	0.17 (0.31)	–	0.19 (0.34)	0.41 (0.32)	–

Note: Parameter estimates generated with 500 Halton draws. Absolute value of asymptotic t-statistics based on robust standard errors in parentheses.

[a]Beach is partially located in a public park.

[b]Respondent has at least one child less than ten or between ten and sixteen years old.

[c]Respondent owns vacation property in Delaware.

Table 5. Statistical Comparisons of Alternative Seasonal Recreation Models

	Quasi-Nested Traditional	Quasi-Nested Single Hurdle	Quasi-Nested Double Hurdle	Panel Random Coefficient Traditional	Panel Random Coefficient Single Hurdle	Panel Random Coefficient Double Hurdle
Quasi-nested traditional	LL (−27,642) BIC (55,473) CAIC (55,498)					
Quasi-nested single hurdle	V1(D,0.0777) V2 (←,0.0000)	LL (−26,348) BIC (52,938) CAIC (52,970)				
Quasi-nested double hurdle	V1 (D,0.0817) V2(←,0.0000)	V1 (ND,0.9999)	LL (−26,346) BIC(52,942) CAIC(52,974)			
Panel random coefficient traditional	V1 (D,0.0000) V2 (←,0.0000)	V1 (D,0.0000) V2 (←,0.0000)	V1 (D,0.0000) V2 (←,0.0000)	LL (−22,717) BIC (45,662) CAIC (45,692)		
Panel random coefficient single hurdle	V1 (D,0.0000) V2 (←,0.0000)	V1 (D,0.0000) V2 (←,0.0000)	V1 (D,0.0000) V2 (←,0.0000)	V1 (ND,0.5083)	LL (−22,699) BIC (45,678) CAIC (45,715)	
Panel random coefficient double hurdle	V1 (D,0.0000) V2 (←,0.0000)	V1 (D,0.0000) V2 (←,0.0000)	V1 (D,0.0000) V2 (←,0.0000)	V1 (ND,0.4570)	V1 (ND,0.8744)	LL (−22,684) BIC (45,649) CAIC (45,686)

V1(·,·) = Not statistically distinguishable (ND) or statistically distinguishable (D) in first stage of Vuong nonnested hypothesis test ($\alpha = 0.1$). p-Value also reported.
V2(·,·) = If distinguishable in first stage, second stage Vuong test results reported with arrow pointing to statistically preferred model ($\alpha = 0.1$). p-Value also reported.
CAIC(·), and BIC(·) = consistent Akaike information criteria and Bayesian information criteria, respectively.

Table 6. Sample Mean Recreation Welfare Estimates (1997 U.S. Dollars)

	Traditional Repeated Discrete Choice Model	Single Hurdle Repeated Discrete Choice Model	Double Hurdle Repeated Discrete Choice Model
Closing of northern Delaware beaches			
Quasi-nested logit	−\$79.07 (8.97)	−\$86.69 (8.86)	−\$80.53 (8.46)
Random coefficient[a]	−\$112.78 (9.46)	−\$131.57 (10.17)	−\$107.35 (16.79)
Lost beach width at all Delmarva beaches			
Quasi-nested logit	−\$24.47 (14.12)	−\$26.03 (13.60)	−\$24.13 (12.77)
Random coefficient[a]	−\$55.76 (12.61)	−\$40.02 (7.89)	−\$35.79 (13.19)

Note: Parametric bootstrap standard errors based on 200 replications in parentheses. All estimates employ the sampling weights implied by the county-stratified sampling design.

[a]For the quasi-nested and random coefficient point estimates, a total of 11,000 simulations were generated. The first 1,000 simulations were discarded as burn-in and every tenth simulation thereafter was used to construct the estimates.

models dominate the traditional models, but the single hurdle and double hurdle models are not distinguishable. For the panel random coefficient models, table 5 also suggests that the addition of hurdles to the panel random coefficient repeated discrete choice model generates relatively modest improvements in fit, with the gains more pronounced with the double hurdle specification. Finally, the panel models consistently dominate the fixed coefficient models as expected.

Recreation Welfare Estimates

We consider two policy scenarios in our beach recreation application: (*a*) the closure of all northern Delaware beaches (seven in total) and (*b*) the loss of beach width to less than 75 feet at all Delmarva beaches. These scenarios are generically representative of the kinds of scenarios recreation demand modelers often consider, and the interested reader can consult Massey and von Haefen, Phaneuf, and Parsons for a detailed discussion of their policy relevance.

For the traditional repeated discrete choice models, we follow Hanemann and Train (1998) and use the well-known "log-sum" formula to simulate the expected Hicksian consumer surplus, $E(CS^H)$, associated with the two scenarios above. For the double hurdle models, we also use the log-sum formula, but need to adjust for welfare implications of the hurdle. In our view, serial nonparticipation in the recreation context has a relatively unambiguous interpretation compared to the choice experiment context. Serial nonparticipants are individuals who would not recreate under any circumstance, and assuming weak complementarity holds (Mäler), these individuals experience no welfare loss or gain from changes in site access or quality. Therefore, serial nonparticipants should be given a zero Hicksian consumer surplus for both scenarios. When constructing welfare measures for the double hurdle model, the estimates implied by the product of the log-sum formula and the number of choice occasions should be rescaled by $(1 - \pi)$. For the single hurdle framework, an additional complexity arises relative to the double hurdle framework because the structure of the model implies that all participants take at least one trip. Thus the analyst must develop seasonal welfare measures that incorporate this restriction. To do this, we develop a Markov Chain Monte Carlo algorithm that, similar to von Haefen (2003), employs an adaptive Metropolis–Hastings subroutine. The details of the algorithm are in an appendix available from the authors upon request.

Point and standard error estimates for the two policy scenarios are presented in table 6. The results suggest that the quasi-nested logit welfare estimates are only marginally affected by the addition of hurdles, but the panel random coefficient estimates, particularly for the loss of beach width scenario, suggest that qualitatively different policy inference can arise between the traditional, and single and double hurdle models. This latter conclusion should be interpreted cautiously, however, because of the relatively large standard errors associated with the point estimates. We also find larger absolute welfare effects in the panel random coefficient models relative to the quasi-nested logit models. Since the panel random coefficient models fit the recreation data better than the quasi-nested logit models, we believe the larger (in absolute terms) estimates are more defensible for policy purposes in this application.

Conclusions

This study has investigated alternative strategies for accounting for serial nonparticipation, or repeated choice of the same alternative or same type of alternative across a series of choice occasions. We introduce single and double hurdle repeated discrete choice models that, in contrast to past approaches to addressing serial nonparticipation, allow for a fundamentally different process to generate this common empirical phenomena. We apply these models to choice experiment and seasonal recreation demand data, where a significant proportion of the sample always chooses the status quo or no-trip alternative. Our estimation 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 are equal across an individual's choice occasions. We also find evidence that policy inference can be affected by the introduction of hurdles to account for serial nonparticipation, particularly in the context of choice experiment data, where the proper treatment of serial nonparticipants is less clear. In sum, we believe the single and double hurdle models that we develop in this paper significantly expand the menu of approaches that analysts can use to address serial nonparticipation, and in the process, improve the quality of policy inference drawn from data analyzed within the repeated discrete choice framework.

Several extensions to the research presented in this paper are possible, and we discuss what we feel are the most promising in closing. In our choice experiment application, we did not have access to any information that would help us to identify why individuals do not play the game or strongly prefer the status quo alternative, and therefore presented a range of welfare estimates that were generated under different plausible yet arbitrary assumptions. In future work, it would be instructive to explore the specific nature of these determinants in an applied setting. In particular, ascertaining whether serial nonparticipation and status quo preference arise as responses to choice complexity and processing limitations (Dhar 1997a, 1997b; Swait and Adamowicz), protests against any form of government action, genuine satisfaction with the status quo, or other factors will help researchers formulate more precise and defensible welfare estimates. Moreover, this information could help researchers design future choice experiment instruments in ways that mitigate these effects if they are determined to be undesirable. Our sense is that carefully crafted exit questions, follow-up questionnaires, and verbal protocols might be fruitful approaches for acquiring this information.

Similarly, it would be instructive to learn about the factors that explain serial nonparticipation in the seasonal recreation demand context. Data limitations with our beach study forced us to model serial nonparticipation as a function of individual demographics, but our sense is that unobserved features of individual preferences and constraints better explain why some individuals do not recreate. Also, our hurdle models restrictively assumed that individuals who do not play the game will continue to not play the game under any circumstance, but introspection suggests that this restriction may be too strong. In our view, it may be more plausible in some cases to recognize that serial nonparticipation has a behavioral dimension that is influenced by preferences and constraints, and as preferences and constraints evolve over time, serial nonrecreators might become recreators. For example, if individuals seek variety in their recreational experience, accumulation of nonparticipation "capital" over time will generate an increased probability of future participation (e.g., Adamowicz). Incorporating this dimension to human behavior within the hurdle framework represents an important and challenging area for future research.

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