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Valuing a Beach Day with a Repeated Nested Logit Model of Participation, Site Choice, and Stochastic Time Value

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Abstract *Beach recreation values are often needed by policy-makers and resource managers to efficiently manage coastal resources, especially in popular coastal areas like Southern California. This article presents welfare values derived from random utility maximization-based recreation demand models that explain an individual's decisions about whether or not to visit a beach and which beach to visit. The models utilize labor market decisions to reveal each individual's opportunity cost of recreation time. The value of having access to the beach in San Diego County is estimated to be between $21 and $23 per day.*

Key words Recreation demand, repeated nested logit, labor supply, opportunity cost of leisure, time, beach recreation.

JEL Classification Codes Q26, J22, Q51.

Introduction

What is a beach day worth? In coastal areas around the country, beach recreation is a popular activity among residents and visitors. In southern coastal areas, such as Southern California, it is also a major cultural and economic activity. Consequently, efficiently managing coastal resources necessarily involves accounting for the value of beach recreation. Along these lines, economic values of beach use are needed to evaluate coastal projects and policies that may restrict or enhance beach recreation, such as beach closures resulting from sewage overflows or sand replenishment projects to widen beaches. Beach day values are also important in natural resource damage assessment (NRDA) cases where environmental accidents temporarily restrict recreation opportunities along the coastline, since lost or impaired recreation opportunities are an important component of the overall economic damages.

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This article presents beach day[1] values for San Diego County in California, derived from random utility maximization-based recreation demand models that explain whether and where San Diego beach users choose to visit. Particular attention is given to the treatment of the time costs of recreation in these models. In contrast to the usually *ad hoc* ways of estimating the opportunity cost of time in recreation demand models, we estimate the shadow value of leisure time (SVLT) jointly with beach trip demand using information from beach users' labor market choices. Since the SVLT is a latent variable, it is treated as stochastic in the estimation. This is a natural way to generate correlated choices in a fixed parameter choice model; as a result, choice probabilities do not exhibit the well-known Independence of Irrelevant Alternatives (IIA) property symptomatic of standard multinomial logit models.

The beach demand model is a repeated nested logit model of beach recreation participation and site choice that explicitly accounts for unobserved opportunity costs of time using information from labor market choices. Using data collected from San Diego County residents, the model is used to estimate the economic value of a beach day. It presents both empirical and conceptual advances to the state of the art of estimating beach demand. Empirically, it provides new estimates of economic values for San Diego County beaches, which are among the most heavily used in the country. Conceptually, it advances the repeated nested logit recreation demand framework by rigorously incorporating time constraints to choice and jointly estimating a stochastic opportunity cost of time along with beach participation choices.

Economic Values of Beach Recreation

Since beach recreation is not traded in markets with explicit prices, its economic value is not easily observed. The primary methods used in the valuation of beach recreation are the travel cost model and contingent valuation method. Deacon and Kolstad (2004) review several studies that value saltwater beach recreation with values ranging from \$0.41 to \$13.00 per day (in 1990 dollars). Most past studies have focused on estimating recreational beach values for East Coast beaches (Bell and Leeworthy 1990; Binkley and Hanemann 1978; McConnell 1977, 1992; Silberman and Klock 1988; Parsons, Massey, and Tomasi 1999; Parsons and Massey 2003) or Great Lakes (Murray, Sohngen, and Pendleton 2001).

The current supply of California beach recreational value information useful for policy purposes is small. In the *American Trader* oil spill case, for instance, experts were unable to find suitable California beach values to assess beach recreation losses in Orange County in Southern California, instead using values for Florida beach recreation (Chapman and Hanemann 2001). Leeworthy and Wiley (1993) report several estimates of the value of beach recreation for three Southern California beach areas (Santa Monica, Leo Carillo, and Cabrillo-Long Beach) generated from recreation surveys conducted by the National Oceanic and Atmospheric Administration (NOAA).[2] Beach values ranged from \$8.16 to \$146.97 per person per day (in 1989 dollars), and varied significantly over sites and over assumptions about the opportunity cost of travel time. These estimates were generated from simple travel cost demand models that ignored substitute sites and income effects and consequently did not provide reliable beach value estimates.[3] More recently, studies by Hanemann

[1] In this article, a "beach day" is a beach trip taken by an individual for any amount of time up to a full day.
[2] In addition, Leeworthy, Schruefer, and Wiley (1991) use contingent valuation to estimate willingness-to-pay for access to five California beaches.
[3] The authors note that due to widespread item non-response, the demand specification excluded income.

et al. (2004) and by Lew and Larson (2005a,b) have provided utility-theoretic welfare estimates of Southern California beach recreation values based on random utility models that account for the full range of beach substitutes available to beachgoers.

Hanemann *et al*. (2004) provide estimates for beach closures and water quality changes at Los Angeles-area beaches. They estimate that the average value of a beach day, where one beach is closed but all others are open, is approximately $11 per person per day. They further analyze closures of a specific beach (Huntington State Beach) and find that a one-day closure of this beach, with all others remaining open, would cause a reduction in visits of approximately 1,200 and an aggregate welfare loss of about $100,000. Lew and Larson (2005b) provide estimates of the value of a beach trip from San Diego County using a model where trips are taken given a person decides to visit the beach, but this does not account for the decision of whether or not to visit a beach. That study also analyzed a single (most recent) trip for each respondent, which may lead to a site-selection bias to coefficients and welfare estimates because the most recently visited site is likely to be more frequently visited than the average beach. In this article, the use of the repeated nested logit model, which incorporates all of the sites the individual visits in their choice set, and including the opt-out alternative of staying home as part of the choice set, avoids these problems.

The Role of Time in Recreational and Labor Supply Choices: A Framework

This section explains the conceptual and empirical elements of the joint model used to estimate the value of a beach day. First, the labor supply model under both equilibrium and disequilibrium conditions is introduced, then it is integrated into a model of whether and where to go to the beach.

The opportunity cost of time spent traveling to and from the beach is a real cost that must be accounted for as part of the price of going to the beach.[4] This opportunity cost, or SVLT, is the value of time spent in the other activities forgone in lieu of going to the beach and as a rule is not directly observable.[5] Often, the wage rate is used as a proxy for the SVLT, although as discussed by Bockstael, Strand, and Hanemann (1987), this is problematic because it does not reflect the true opportunity cost of leisure time for workers facing fixed work schedules.

Economists have long recognized that individual's observed decisions in the labor market and elsewhere, which trade off time and money costs of activities, can be used to measure the SVLT more realistically than simply assuming that it is the hourly wage. Feather and Shaw (2000) and Lew and Larson (2005a,b) have modified the Heckman model of labor supply for use in better estimating the SVLT appropriate for recreation trips (Heckman 1974). This article also uses a labor supply model for that purpose. Because it follows Feather and Shaw (2000) and Lew and Larson (2005a) closely, the development of this model is brief, and interested readers can find the details in these sources.

Four categories describe people's involvement with the labor market: (*i*) workers with flexible work schedules, who can adjust the number or timing of hours worked; (*ii*) non-workers, who supply zero hours to the labor market (typically in-

[4] Cesario and Knetsch (1970) showed that failure to account for time costs in economic models of recreation behavior leads to biased economic values.
[5] The appropriate SVLT to use in recreation decision models is discussed in more detail in Shaw (1992) and Lew (2002).

cluding students, full-time homemakers, and other unemployed persons); and two types of workers with fixed work schedules: (*iii*) overemployed workers, who would work fewer hours if possible; and (*iv*) underemployed workers, who are working fewer hours than they prefer.[6] The importance of these distinctions is that they determine both the extent of the connection of the SVLT to the wage and, where they differ, the relationship between the magnitudes of the two. Category (*i*) describes the labor market in equilibrium, where the wage and SVLT are equal, while (*ii*), (*iii*), and (*iv*) are all cases of disequilibrium, where the wage and SVLT are different.

Under the standard assumption that work time does not yield utility, the SVLT for flexible schedule workers is their wage w, since they are able to adjust hours worked to balance the benefits of leisure with the benefit of another hour worked. The unemployed must have a SVLT that exceeds the wage they could earn (which is unobserved), for if this was not true, they would prefer to work. The SVLT of overemployed workers is greater than w; since they would prefer more leisure time, its value at the margin is higher. The opposite is true for underemployed workers: their SVLT is less than w at the current number of hours worked.

To summarize the labor market information available for use in estimating recreation trip choices, let the SVLT be $\rho(M, T, \boldsymbol{s}_1)$, a function of money income, M; time, T; and individual characteristics, $\boldsymbol{s}_1$. In turn, M is the sum of labor earnings $w \cdot h$ from working h hours and non-wage income A (*i.e.*, $M = w \cdot h + A$), while T is the discretionary time available after labor supply (*i.e.*, $T = T' - h$, where T' is the total time available). Letting the market wage function be $W(\boldsymbol{s}_2)$, where $\boldsymbol{s}_2$ is a vector of exogenous variables describing individual skills, Feather and Shaw (2000) show that the labor market relationships between the SVLT and the market wage are:

$$w = W(\boldsymbol{s}_2) = \rho(w \cdot h + A, T' - h, \boldsymbol{s}_1) \qquad \text{(flexible schedule workers)} \qquad (1)$$

$$W(\boldsymbol{s}_2) \leq \rho(A, T', \boldsymbol{s}_1) \qquad \text{(unemployed)} \qquad (2)$$

$$\rho(A, T', \boldsymbol{s}_1) < w = W(\boldsymbol{s}_2) < \rho[A + W(\boldsymbol{s}_2) \cdot h, T' - h, \boldsymbol{s}_1] \quad \text{(overemployed workers)} \quad (3)$$

$$\rho[A + W(\boldsymbol{s}_2) \cdot h, T' - h, \boldsymbol{s}_1] \leq w = W(\boldsymbol{s}_2) \quad \text{(underemployed workers).} \qquad (4)$$

To see how the SVLT also enters recreation decisions, begin first with the conditional indirect utility for the preferred beach, j, on a given choice occasion.[7] This conditional indirect utility function is the result of optimizing with respect to other activities, namely labor supply (h) and consumption of other goods $\boldsymbol{x} = [x_1, \ldots, x_m]$, as represented by the Lagrangian:[8]

$$L_j \equiv \max_{\alpha} \mathrm{U}_j(\boldsymbol{x}) + \lambda_j [A + w \cdot h - p_j - \boldsymbol{p} \cdot \boldsymbol{x}] + \mu_j [T' - h - t_j - \boldsymbol{t} \cdot \boldsymbol{x}], \qquad (5)$$

where beach alternative j has a money cost of p_j and a time price t_j, while other

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[6] Feather and Shaw (2000) showed how this additional piece of information about workers (whether they consider themselves overemployed or underemployed) can provide considerably more explanatory power in identifying the market wage function. It is straightforward to obtain and easily understood, because respondents are asked simply whether they are working more hours than they would like (given their current wage) or less hours.

[7] The relationship of this conditional indirect utility function (which describes choice on a single choice occasion) to the more familiar (unconditional) indirect utility function is described below when the repeated discrete choice model is developed.

[8] Similar money and time-constrained recreation demand models were explored by Bockstael, Strand, and Hanemann (1987); McConnell (1992); Larson (1993); and Larson and Shaikh (2001).

goods $\boldsymbol{x}$ have money costs $\boldsymbol{p} = [p_1,\ldots,p_m]$ and time costs $\boldsymbol{t} = [t_1,\ldots,t_m]$,[9] and the vector α represents the choice variables for the optimization problem. For flexible-schedule workers, $\alpha \equiv [\boldsymbol{x},h]$ since they choose the hours they work in the short run, while and $\alpha \equiv [\boldsymbol{x}]$ for all others. A key issue for specifying the beach choice model is whether the consumer is in equilibrium in the labor market, as this determines how the opportunity cost of time is handled.

Optimal Recreation Choices of Flexible-schedule Workers

When hours (h) are chosen freely, the first-order conditions can be solved for the optimized values of the choice variables, $\boldsymbol{x}_j(\boldsymbol{p}, \boldsymbol{t}, A, T')$ and the SVLT, $\rho_j(\boldsymbol{p}, \boldsymbol{t}, A, T') \equiv \mu_j/\lambda_j$ and $\rho_j(\boldsymbol{p}, \boldsymbol{t}, A, T') = w$, as in equation (1) above.[10] Optimal demands are of the form:

$$\boldsymbol{x}_j = \boldsymbol{x}_j(\boldsymbol{p} + w\cdot\boldsymbol{t}, A + w\cdot T'); \tag{6}$$

that is, they are functions of the full prices $\boldsymbol{p} + w\cdot\boldsymbol{t}$ and full income $A + w\cdot T'$, with the market wage, w, as the terms of trade between time and money (Bockstael, Strand, and Hanemann, 1987). Substituting the optimal demands (6) into the conditional utility function (5) yields the conditional indirect utility functions $V_j(\boldsymbol{p} + w\cdot\boldsymbol{t}, A + w\cdot T')$ that identify the maximum utility if beach j is chosen.

Optimal Recreation Choices of Non-workers and Fixed-schedule Workers

People who are not working or have fixed work schedules do not choose the number of hours they work per week. The key difference is that the SVLT is no longer equal to the discretionary wage rate, but the two have the relationships given in equations (2)-(4). Optimal demands for these cases are still functions of full prices and full income, though the terms of trade between time and money are the latent function $\rho_j(\boldsymbol{p}, \boldsymbol{t}, A, T')$ instead of w (Larson and Shaikh 2001); *i.e.*, other goods demands and conditional indirect utility are:

$$\boldsymbol{x}_j = \boldsymbol{x}_j(\boldsymbol{p} + \rho\cdot\boldsymbol{t}, M + \rho\cdot T)$$

and

$$V_j = V_j(\boldsymbol{p} + \rho\cdot\boldsymbol{t}, M + \rho\cdot T).$$

The labor supply model estimates both the market wage function $W(\boldsymbol{s}_2)$ and the SVLT $\rho(M, T, \boldsymbol{s}_1)$ for the four labor supply classes described in equations (1)-(4). The market wage equation for the ith individual is specified as:

$$W_i = \exp(\alpha'\boldsymbol{s}_{2i}) + e_i \quad \forall i = 1,\ldots,N,$$

where α is a vector of parameters and e_i is a normally distributed disturbance term. Empirical studies suggest that the market wage is positively influenced by labor market participants' education and experience (Mincer 1974). Additionally, Gunderson (1989), among numerous other studies, found that wages differ by gen-

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[9] It is assumed that the vector $\boldsymbol{x}$ includes both a time and money numeraire good to ensure that the budget constraints bind. The time numeraire good is time costly, but not money costly, while the converse is true of the money numeraire good.

[10] See Lew and Larson (2005a) for details about the first-order conditions.

der, with males typically earning higher wages than females, *ceteris paribus*. Thus, the variables assumed to shift the market wage are age (serving as a proxy for experience), education, and gender.

The SVLT for the ith individual is specified as:

$$\rho_i = \rho(M, T, \boldsymbol{s}_1) = \rho(w \cdot h + A, T' - h, \boldsymbol{s}_1)$$
$$= (w \cdot h_i + A_i) \cdot \exp(\beta \cdot \boldsymbol{s}_{1i})/(T_i' - h_i) + \varepsilon_i, \quad \forall i = 1,\ldots,N,$$

where $\mathbf{s}_{1i}$ is the individual's SVLT shifters, and ε_i is a normally distributed disturbance term. The function is positive-valued and increasing at an increasing rate in hours worked, indicating that the marginal value of non-work time increases as the individual works more. Several recent studies provide evidence that the SVLT is conditional on demographic variables such as gender and household size.[11]

The errors, e_i and ε_i, are assumed to be bivariate-normally distributed disturbances each with zero means and standard deviations, σ_e and σ_ε, respectively, and a correlation coefficient r. Given the stochastic assumptions and equilibrium conditions in the labor market, the probability of observing a flexible schedule worker (L_1), non-worker (L_2), overemployed worker (L_3), or underemployed worker (L_4) can be calculated and are presented in table 1. With the exception of L_1, the probabilities are written in terms of the standard normal cumulative distribution function (Φ) and probability density function (ϕ). The component of the log-likelihood function associated with the labor supply model is:

$$LL^{HFS} = \sum_{i=1}^{N} \sum_{k=1}^{4} D_{ki} \cdot \ln(L_{ki}), \tag{7}$$

where D_{ki} is 1 if the ith individual is in the kth labor class and 0 otherwise, where $k = 1, 2, 3, 4$, corresponding to flexible hours, non-workers, overemployed, and underemployed, respectively.

A Repeated Nested Logit Model of Participation and Site Choice

Beach users' values for recreation are revealed through two choices made on each choice occasion: whether or not to visit a beach (the participation decision) and which beach to visit (site choice decision). These decisions depend upon the (time and money) costs of visiting each beach, the features of the beaches that are important to their recreation experience, and the non-beach recreation opportunities available. This two-stage decision process can be modeled over the season using a repeated nested multinomial logit (RL) model (Morey, Rowe, and Watson 1993). This is an extension of the commonly used nested multinomial logit model (NMNL).[12]

In contrast to previous NMNL models of recreational participation and site choice, in this application the SVLT is treated as stochastic in the recreation decision. Lew and Larson (2005a) showed that ignoring the stochastic nature of unobserved opportunity costs of time in discrete-choice recreation demand models

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[11] See Lew (2002) and Larson, Shaikh, and Layton (2004).
[12] Morey (1999) provides a detailed description of NMNL models.

Table 1
Probabilities of Observing Types of Labor Classes

Labor Classification	Probability
Flexible schedule worker	$L_{1i} = \frac{1}{2\pi} \cdot \left|\det(\Sigma)\right|^{-1/2} \cdot \exp\left(-\frac{1}{2} \cdot \boldsymbol{D} \cdot \Sigma^{-1} \cdot \boldsymbol{D}'\right),$
where	$\boldsymbol{D}' = \left[\left(\frac{\exp(\boldsymbol{\alpha}'\mathbf{s}_{2i}) \cdot h_i + A_i}{T_i' - h_i} \cdot \exp(\boldsymbol{\beta}'\mathbf{s}_{1i}) - \alpha' s_{2i}\right), \mathbf{w}_i - \exp(\boldsymbol{\alpha}' \cdot \mathbf{s}_{2i})\right],$
	$\Sigma = \begin{bmatrix} B_i^{\,2} \cdot \sigma_e^2 + \sigma_\varepsilon^2 - 2 \cdot B_i \cdot r \cdot \sigma_e \cdot \sigma_e & B_i \cdot \sigma_e^2 - r \cdot \sigma_e \cdot \sigma_e \\ B_i \cdot \sigma_e^2 - r \cdot \sigma_e \cdot \sigma_e & \sigma_e^2 \end{bmatrix}$, and
	$B_i = \left[1 - \frac{h_i \cdot \exp(\beta' s_{1i})}{T_i' - h_i}\right]$
Non-worker	$L_{2i} = \Phi\left(\frac{\frac{A_i}{T_i'} \cdot \exp(\beta \cdot \mathbf{s}_{1i}) - \alpha'\mathbf{s}_{2i}}{\sqrt{\sigma_e^2 + \sigma_\varepsilon^2 - 2 \cdot r \cdot \sigma_e \cdot \sigma_\varepsilon}}\right)$
Overemployed	$L_{3i} = \Phi\left(\frac{\frac{\exp(\alpha'\mathbf{s}_{2i}) \cdot h_i + A_i}{T_i' - h_i} \cdot \exp(\beta \cdot \mathbf{s}_{1i}) - \alpha'\mathbf{s}_{2i}}{\sqrt{B_i^2 \cdot \sigma_e^2 + \sigma_\varepsilon^2 - 2 \cdot B_i \cdot r \cdot \sigma_e \cdot \sigma_\varepsilon}}\right) - \Phi\left(\frac{\frac{A_i}{T_i'} \cdot \exp(\beta \cdot \mathbf{s}_{1i}) - \alpha'\mathbf{s}_{2i}}{\sqrt{\sigma_e^2 + \sigma_\varepsilon^2 - 2 \cdot r \cdot \sigma_e \cdot \sigma_\varepsilon}}\right)$
	$\times\, \phi\left[\frac{w_i - \exp(\alpha' s_{2i})}{\sigma_e}\right]$
Underemployed	$L_{4i} = \left[1 - \Phi\left(\frac{\frac{\alpha'\mathbf{s}_{2i} \cdot h_i + A_i}{T_i' - h_i} \cdot \exp(\beta \cdot \mathbf{s}_{1i}) - \alpha'\mathbf{s}_{2i}}{\sqrt{B_i^2 \cdot \sigma_e^2 + \sigma_\varepsilon^2 - 2 \cdot B_i \cdot r \cdot \sigma_e \cdot \sigma_\varepsilon}}\right)\right] \times \phi\left(\frac{w_i - \exp(\alpha' s_{2i})}{\sigma_e}\right)$

leads to biased parameter estimates, and, hence, biased welfare estimates. In this article, labor market information and recreational choice decisions are combined to estimate stochastic SVLT value functions when multiple recreation choices are made during the course of a season.

The season is divided into T choice occasions, during each of which the individual chooses to participate by visiting one of J beach sites, or to not participate.[13] In the participation decision, we specify the conditional utility for the ith individual

[13] In our application, $T = 60$ to allow for daily visits to the beach during a two-month period, as was observed in a small fraction of the sample.

not going to any beach in the tth choice occasion as U_{i0t}.[14] This utility is assumed to be the sum of a deterministic component, $V_{i0t} = \alpha_0 + \delta \cdot z_{it}$,[15] which is a function of a vector of observable individual-specific characteristics (z_{it}), and a disturbance term, ξ_{i0t}, that represents the variation in utility that is unobservable to the researcher, but known to the individual.

The decision to participate in beach recreation on a given occasion depends both on U_{i0t} and on the anticipated satisfaction of visiting beaches. We define the conditional indirect utility for the ith individual visiting the jth beach site on the tth choice occasion as:

$$U_{ijt} = U_{ijt}(c_{ijt}, \mathbf{q}_{jt}; u_{ijt}) = V_{ijt}(c_{ijt}, \mathbf{q}_{jt}) + x_{ijt} = \theta \cdot c_{ijt} + \mathbf{g} \cdot \mathbf{q}_{jt} + x_{ijt}, \tag{8}$$

where θ and γ are parameters to be estimated, c_{ijt} is the "full price" of visiting the jth beach ($j = 1,\ldots,J$) by the ith individual ($i = 1,\ldots,N$) on the tth choice occasion ($t = 1,\ldots,T$), $\mathbf{q}_{jt}$ is a vector of site attributes for the jth site at time t, and ξ_{ijt} is the econometric error.[16] The full price of a visit to the beach includes both the time cost and the out-of-pocket money cost and is written as $c_{ijt} = p_{ijt} + \rho_i \cdot t_{ijt}$, where p_{ijt} is the money cost of visiting beach j by individual i, t_{ijt} is the time required to visit site j by the ith individual at time t, and ρ_i is the money cost of the time spent for the ith individual; *i.e.*, his or her SVLT.

For this two-level nested choice, the error associated with the ith individual's conditional indirect utility of the jth beach if choosing to visit a beach in time t, ξ_{ijt}, is assumed to follow a generalized extreme value (GEV) distribution. For any individual and choice occasion (and dropping the individual and time notation, i and t, to simplify the exposition), the probability of choosing the jth beach is:

$$\begin{aligned}\Pr(\text{choose } j) &= \Pr(\text{visit beach}) \cdot \Pr(\text{choose } j \mid \text{visit beach}) = \pi_j \\ &= \exp(V_j/d) \cdot (\textstyle\sum_k \exp(V_k/d))^{d-1} \cdot [\exp(V_0) + (\textstyle\sum_k \exp(V_k/d))^d]^{-1}\end{aligned}$$

and the probability of not visiting a beach is:

$$\Pr(\text{do not visit beach}) = \pi_0 = \exp(V_0) \cdot [\exp(V_0) + (\textstyle\sum_k \exp(V_k/d))^d]^{-1},$$

where d is the dispersion parameter of the distribution.[17] The parameter d is also known as the inclusive value parameter and measures the degree of substitutability between the non-participation and site-choice decisions. It is the presence of these

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[14] U_{i0t} is a reference level of utility for the individual, which does not vary across beach choices. It does, however, vary over individuals, and possibly time, which is why it is modeled as a function of individual characteristics.

[15] The linear conditional indirect utility assumption is widespread in the literature.

[16] The unconditional indirect utility function can be obtained from the maximum indirect utility from each choice occasion. Letting j_t^* be the utility-maximizing beach on choice occasion t and I_t be a dummy variable that takes the value $I_t = 1$ if the person actually goes to a beach on that choice occasion (with $I_t = 0$ otherwise), the occasion-t expected indirect utility is $V_{it} = I_t \cdot (\theta \cdot c_{ij_t^*t} + \gamma \cdot q_{j_t^*t}) + (1 - I_t) \cdot (\alpha_0 + \delta \cdot z_{it})$. The expected indirect utility function with T choices in a season is:

$$V_i = \textstyle\sum_{t=1}^T V_{it} = \theta \cdot \sum_{t=1}^T I_t \cdot c_{ij_t^*t} + \gamma \cdot \sum_{t=1}^T I_t \cdot q_{j_t^*t} + \alpha_0 \cdot (T - \sum_{t=1}^T I_t) + \delta \cdot \sum_{t=1}^T (1 - I_t) \cdot z_{it}.$$

So long as θ is negative, equation (8) satisfies the usual theoretical restrictions imposed by consumer theory.

[17] When $0 \le d \le 1$, this cumulative density function is globally well defined and thus is consistent with stochastic utility maximization (McFadden 1978).

inclusive value parameters that relaxes the restrictive IIA property of the multinomial logit model (MNL) across nests. Note that if $d = 1$, the NMNL model reduces to the MNL model.

Our estimation approach uses the additional information provided by labor market decisions to estimate the SVLT jointly with the recreation site choice decision, explicitly recognizing that the SVLT is observed with error in both the labor market and recreational choice decisions.

A principal concern with the NMNL approach is that it implies no correlation among choices within nests, which in this case would mean that the site choice probabilities exhibit the IIA property. A common way of relaxing this restrictive property in conditional logit models is to let the parameters of the model be random (Train 1998). Explicitly modeling the stochastic SVLT in the beach choice model and jointly estimating it with the labor supply choice is another way of introducing random parameters, so that the choice probabilities do not suffer from IIA.

In this joint estimation model, the recreational choice probabilities are conditional upon the realized SVLT value for each individual. Thus, to estimate it, the probabilities must be evaluated over the distribution of SVLT values, resulting in a form of the mixed logit model.[18] The individual-specific probabilities to be estimated for each choice occasion thus take the form:

$$\pi_j^s = \int \exp\left[V_j(\rho) / d\right] \cdot \left\{\Sigma_k \exp\left[V_k(\rho) / d\right]\right\}^{d-1}$$
$$\cdot\left[\exp(V_0) + \left\{\Sigma_k \exp\left[V_k(\rho) / d\right]\right\} d\right]^{-1} \cdot f(\rho \mid \Omega) d\rho,$$
$$\forall j = 1,\ldots,J$$

$$\pi_0^s = \int \exp(V_0) \cdot \left[\exp(V_0) + \left\{\Sigma_k \exp\left[V_k(\rho) / d\right]\right\}^{d}\right]^{-1} \cdot f(\rho \mid \Omega) d\rho,$$

where the conditional indirect utilities are functions of each individual's stochastic SVLT, and $f(\rho \mid \Omega)$ is the probability density function of the SVLT function with parameters Ω. The beach choice model can be estimated using simulated maximum likelihood to maximize the simulated log-likelihood function:

$$LL^s = \Sigma_n \Sigma_t [d_{nt0} \cdot \ln(\pi_{nt0}^s) + \Sigma_j d_{ntj} \cdot \ln(\pi_{ntj}^s)], \quad (9)$$

where d_{ntj} equals 1 when the nth individual chooses the jth beach in time t and 0 otherwise, d_{nt0} equals 1 when the *nth* individual chooses not to visit a beach in the tth time period and 0 otherwise.

Combining the results from (7) and (9), respectively, the log-likelihood for the combined labor market-recreation choice model is $LL = LL^{HFS} + LL^s$.

Data

A telephone-mail-telephone survey was conducted on a sample of randomly chosen households in San Diego County during the period from January 2000 through March 2001. A preliminary phone interview was used to identify beach users who

[18] See Brownstone and Train (1999) and Train (1998).

had gone recently (in the most recent two weeks) or were planning to go to the beach in the upcoming two weeks from the time of the interview. This one-month window of time was chosen to improve the respondents' recall about their recent beach experiences. Persons satisfying this requirement were asked whether they would participate in a follow-up interview that collected detailed information on recent beach experiences. Those who agreed were mailed a booklet that contained questions and information to prepare them for the follow-up phone interview.

Out of the 3,740 initial interviews completed,[19] 1,105 were qualified beach users, who had visited a San Diego beach or were planning an upcoming trip within the one-month window. Only 8% of those initially interviewed were non-users who had not visited a San Diego County beach, or were not planning a future beach visit. Of the qualified beach users, 74% agreed to participate in the follow-up interview. Unless reached before then, these individuals were called at least fifteen times (and up to 20 times) at varying times of the day for the follow-up interview after being sent the booklet. A total of 607 follow-up interviews were completed from this group. Of the 428 who did not complete follow-up interviews, there were 83 refusals, 2 partial interviews, and the remainder could not be contacted for a variety of reasons (*e.g.*, invalid numbers).[20] Of the 607 beach users completing the follow-up interview, 494 provided sufficient information to be used to estimate the economic model. Table 2 provides a summary of several important characteristics of the sample.

The data set contains information on respondents' trips to San Diego County bay or coastal beaches over the two-month period. The 31 San Diego County beach areas used for the analysis are listed in table 3, which also shows the number of trips taken to each beach area. Pacific, Mission, and Ocean Beaches, all in the City of San Diego, were the most popular, accounting for about 37% of all beach trips in the sample. The mean number of trips taken by a respondent during the two-month period was 17.92, with an average of 3.77 beaches visited. Fifteen respondents indicated visiting the beach everyday, and the most beaches visited by any individual during the two-month period was 15.

Table 2
Descriptive Statistics for San Diego Beach Users Sample (N = 494)

Variable	Unit	Mean	Standard Deviation	Min.	Max.
Income	$/year	$62,698	$41,761	$2,500	$200,000
Average hourly income	$/hour	$18.38	$22.48	$0.00	$291.67
Educational attainment	Years completed	14.91	2.35	3.5	18
Gender	1 = male, 0 = female	0.51	0.50	0	1
Household size	Persons	2.82	1.43	1	8
Hours	Hours per week worked	32.32	19.12	0	100
Age	Years	39.58	13.38	18	88

[19] In total, 3,740 screener interviews were completed, 2,296 refused, and the remaining cases could not be contacted for a variety of reasons (*e.g.*, phone number no longer in service). Given that 83 partial interviews were completed, the total number of individuals successfully contacted was 6,119. Since 3,740 completed the preliminary screening interview to identify qualified beach users, the cooperation rate was 61%.

[20] The cooperation rate, defined as the number of completed interviews (607) over the total number of cases successfully contacted (692), is 88%.

Table 3
San Diego County Beach Sites and Sample Visitation (*J* = 31 beaches)

Beach Name	Number Beach Visits	Percent of Total Trips
San Onofre State – Camp Pendleton Beaches	97	1.10
Oceanside Beaches	714	8.07
Carlsbad Beaches	491	5.55
South Carlsbad State Beach	169	1.91
Ponto Beach	52	0.59
North Encinitas Beaches	215	2.43
Moonlight Beach	237	2.68
Boneyard Beach	21	0.24
Swami’s Beach	136	1.54
San Elijo State Beach	112	1.27
Cardiff State Beach	137	1.55
Tide Beach Park	18	0.20
Fletcher Cove Park	48	0.54
Seascape Surf – Del Mar Shores Beaches	183	2.07
Del Mar City Beach	204	2.30
Torrey Pines State Beach	398	4.50
Black’s Beach	187	2.11
La Jolla Shores Beach	618	6.98
Scripps Park Beaches	232	2.62
Marine Street Beach	68	0.77
Windansea Beach	121	1.37
Pacific Beach	1,265	14.29
Mission Beach	1,178	13.31
Ocean Beach	842	9.51
Coronado Beach	457	5.16
Silver Strand State Beach	132	1.49
Imperial Beach	230	2.60
Border Field State Beach	13	0.15
Mission Bay	170	1.92
San Diego Bay	16	0.18
Sunset Cliffs – Point Loma Beaches	92	1.04
Total Trips	8,853	100

Both the distances traveled and time required to visit each beach were calculated for each individual using geographic information systems.[21] Across the sample, the mean round-trip travel time for the most recent trip taken was 0.79 hours, or about 47 minutes. The monetary travel costs depended upon the mode of travel and the distance traveled. For those who drove to the beach (~85%), the cost per mile for vehicle travel was calculated using figures on costs per mile collected by the Southern California branch of the American Automobile Association.[22] The money costs per mile for non-automotive modes of travel are assumed to be zero, except for travel by boat (<1%), which is assumed to have the same cost per mile as driving.

[21] The travel times and distances were calculated using the Network Analyst module within ArcView GIS assuming a distance minimization criterion.
[22] The AAA cost per mile estimate accounts for gas and oil, maintenance, and tires. For 2001, the AAA cost per mile was 14.6 cents.

Those who walk (~12%) or bike (~2%) to the beach accrue time costs of travel, but are assumed to have no out-of-pocket expenses. The travel costs were calculated for each beach area for each beach user.

Respondents were asked about their labor status, for use in modeling their labor market choices. Almost three-quarters of the sample were full- or part-time workers. Together with self-employed workers, about 80% of the sample indicated they worked, with the majority being full-time workers. The remaining 99 people, who categorized themselves as temporarily unemployed, students, homemakers, retired, or disabled and unable to work, are non-workers. With respect to the labor categories used in the empirical labor supply model, over a third (167 or 33.81%) of the sample had flexible work schedules. Almost half of all respondents (228 or 46.15%) faced fixed work schedules and were thus classified as either overemployed (95 or 19.23%) or underemployed (133 or 26.92%).

Results

Welfare estimates in random utility models can be sensitive to choice set considerations, particularly the aggregation of smaller sites into larger sites (Parsons and Needleman 1992; Feather 1994; Haener *et al.* 2004). This is potentially an important issue in modeling beach recreation in areas like Southern California, where beach areas are often contiguous and multiple beach sites may be accessible on a single beach trip. To assess the effect of aggregating beach sites, two models were estimated that differ in the definition of the beach choice set. The *full sites model* uses all 31 beach sites enumerated in table 3, and the *aggregate sites model* uses a smaller set of sites where contiguous beach areas are combined into single sites, resulting in a choice set of 16 beach areas. Beaches lying within the city limits of the following municipalities were aggregated: Carlsbad, Encinitas, Solana Beach, Del Mar, La Jolla,[23] and San Diego.

The models were estimated using maximum simulated likelihood in GAUSS. The conditional indirect utility associated with site choices is assumed to depend upon the full price of travel to each beach and physical and managerial attributes of each beach including its length; the presence or absence of lifeguards (both stationed and mobile); managed activity zones (*e.g.*, swimming-only areas); availability of free parking; and whether its surface suffers from cobblestoning, a seasonal loss of sand that exposes cobblestones and pebbles. The factors assumed to affect participation decisions are the individual's gender, age, educational level, and household size. Table 4 presents the parameter estimates and associated asymptotic t-values for each model.[24]

The estimated conditional utility parameters of the recreational choices (site choice and participation) are similar for both models.[25] In the conditional site utility

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[23] Although part of San Diego proper, La Jolla was treated as a distinct area due to the physical separation of La Jolla beaches from other San Diego beaches.

[24] Because it is not known when individuals took trips within the two-month time period, time-dependent characteristics of sites, such as daily temperature or water quality, cannot be incorporated in the model. Similarly, for this reason and because accurate beach visitor counts are not generally available, congestion measures could not be included. The literature on congestion in recreation demand finds that the effect of congestion is highly variable depending on the characteristics of both the area visited and the visitors themselves. A good recent summary is in Schuhmann and Schwabe (2004).

[25] This lack of any significant difference in parameter estimates for the two models may be due to inclusion of the beach length variable, which helps account for the size effect in conditional indirect utility (Haener *et al.* 2004).

Table 4
Model Estimates (N = 494)

Parameter	Full Sites Model Estimate	Aggregate Sites Model Estimate
Price	–0.01523** (–2.18717)	–0.01386** (–2.25429)
On-beach lifeguard dummy	0.15963** (2.58544)	0.30499** (2.24507)
Mobile lifeguard dummy	0.05475* (1.73096)	0.10615** (2.34231)
Activity zone dummy	0.08956** (2.29122)	0.12593** (2.66056)
Free parking lot dummy	0.09857** (2.26691)	0.15044** (2.47014)
Free street parking dummy	0.12603 (1.58629)	0.02022 (0.29119)
Cobblestone dummy	–0.04647 (–1.54935)	0.00408 (0.12994)
Length	0.04097** (2.28605)	0.02810 (1.41402)
Length squared	–0.00272** (–2.38622)	–0.00219* (–1.80857)
Constant	5.36634** (3.81222)	5.17281** (4.02514)
Gender	–0.22628 (1.57948)	–0.20527 (–1.49287)
Age	–0.02215 (–0.75315)	–0.02112 (–0.75122)
Education	–0.49200** (2.77472)	–0.43767** (–2.74597)
Household size	0.32137* (1.77704)	0.26893 (1.58924)
Age squared	0.00036 (1.33387)	0.00033 (1.10074)
Education squared	0.01463** (2.32196)	0.01264** (2.19995)
Household size squared	–0.02440 (–0.93350)	–0.01847 (–0.74520)
Inclusive value (d)	0.14992** (2.67274)	0.13555** (2.62708)
SVLT – Constant	0.86073* (1.87970)	1.28747** (5.30816)
SVLT – Gender	–0.42094 (–1.41604)	–0.41040** (–2.37600)
SVLT – Household size	–0.24283 (–0.98428)	–0.38521** (–2.70934)
SVLT – Household size squared	0.03452 (1.30116)	0.04684** (2.53622)
SVLT – Standard deviation	6.29956** (10.46162)	6.18774** (12.34223)
Wage – Constant	1.33465 (0.81863)	1.54120 (1.44680)
Wage – Gender	–0.06496 (–0.18318)	–0.05126 (–0.25411)
Wage – Age	0.06339 (1.28367)	0.05145 (1.58274)
Wage – Age squared	–0.00077 (–1.26338)	–0.00056 (–1.45169)
Wage – Education	0.06328 (0.30391)	0.02143 (0.17615)
Wage – Education squared	–0.00308 (–0.31655)	0.00009 (0.01761)
Wage – Standard deviation	11.65255** (13.47333)	11.17289** (16.07339)
Correlation	0.39985** (2.88870)	0.25136* (1.86297)
Mean simulated log-likelihood	–90.8331	–72.2494
Recreation demand model component	–86.2546	–67.8236
Labor supply model component	–4.57850	–4.42580
LRI	0.5852	0.6738

Notes: Asymptotic t-values in parentheses; ** and * denote statistical significance at the 5% and 10% levels, respectively.

function, the price coefficient is negative and statistically different from zero, as expected, suggesting the probability of visiting a site diminishes with increased travel costs. The length coefficients in the full sites model are significant and of opposite sign, implying that utility increases with beach length at a decreasing rate, all else being equal. In the aggregate sites model, the signs of the length coefficients imply the same thing, though only the squared beach length parameter is statistically significant. The inclusive value index in both models is positive, significantly different from both zero and one, and in the range of values for which the model is consistent with stochastic utility maximization.

In the indirect utility function for non-participation, the constant, education, and education squared parameters are statistically different from zero at the 5% level in both models. The signs of these coefficients suggest that, *ceteris paribus*, individuals with less education or larger families are more likely to not visit the beach in any given choice occasion. In the full sites model, household size is positive and statistically significant at the 10% level, indicating that individuals from larger households are less likely to visit the beach, while household size is not statistically significant in the aggregate sites model. Gender and age are not significant in either model.

The results for the labor supply model component are qualitatively similar across the models. In both models, the constants and standard deviation in the SVLT function is statistically different from zero at least at the 10% level. Although similar in signs and magnitudes, the two models differ markedly in the significance of demographic effects on SVLT. In the full sites model, household size and gender are insignificant. In the aggregate sites model, gender and household size coefficients are statistically different from zero at conventional levels.

In both models, only the standard deviations are statistically significant in the market wage function. Gender, age, and education do not seem to be statistically related to the market wage. The correlation coefficient, r, however, is statistically different from both zero and one in both models (0.40 in the full sites model and 0.25 in the aggregate sites model). This suggests that the SVLT and market wage errors are positively correlated, although not perfectly.

Although both models predict the same signs and similar magnitudes for common statistically significant coefficients, the model results are not identical. Several parameters that are not significant in the full sites model are significant in the aggregate sites model, and the Likelihood Ratio Index (LRI), which measures goodness-of-fit, for the aggregate sites model (0.674) exceeds the LRI for the full sites model (0.585).

Welfare Estimates

A goal of this article is to estimate the value of a beach day using the model of repeated beach participation and site choice decisions.[26] To this end, define $V(\boldsymbol{c}, \boldsymbol{q})$ as the individual's expected utility in a given time period for a given vector of costs and quality attributes. In the NMNL model, this is:

$$V(\boldsymbol{c}, \boldsymbol{q}) = \ln\left[\exp(V_0) + \left\{\Sigma_i \exp\left[V_i(c, q) / d\right]\right\}^d\right] + 0.5772,$$

where 0.5772 is Euler's constant. The expected per-choice occasion compensating variation (ECV) associated with a change from price and quality levels ($\boldsymbol{c}^0$, $\boldsymbol{q}^0$) to new levels ($\boldsymbol{c}^1$, $\boldsymbol{q}^1$) is defined implicitly by the identity $V(\boldsymbol{c}^0, \boldsymbol{q}^0) \equiv V(\boldsymbol{c}^1 - ECV, \boldsymbol{q}^1)$. This measure of the value of a beach day accounts for the fact that an individual has the choice not to visit the beach on a given choice occasion. The seasonal expected compensating variation is calculated by summing the ECV over the T time periods

[26] Although not the main purpose of this article, the repeated nested logit model of recreation demand can be used to predict the number of trips taken during the study period. To generate an estimate of the number of trips taken during the 60-day period, the probability of visiting a beach in each choice occasion (a day) is calculated for each individual in the sample and multiplied by the length of the study period. Across the sample, the mean predicted number of beach days is 17.4, which is similar to the actual mean beach days taken by the sample of 17.9.

making up the season. When indirect utility is nonlinear in income, *ECV* must be calculated numerically, since it has no closed-form solution.

For the linear conditional indirect utility specification, indirect utility is linear in income and *ECV* has a closed-form solution, which reduces to:

$$ECV = -(1 / q) \cdot \Big\{ \ln\Big[\exp(V_0) + \big\{\Sigma_i \exp\big[V_i(c_i^1, q_i^1) / d\big]\big\}^d\Big] - \ln\Big[\exp(V_0) + \big\{\Sigma_i \exp\big[V_i(c_i^0, q_i^0) / d\big]\big\}^d\Big]\Big\}.$$

To determine the value of a beach choice occasion specifically, the change of interest is from ($\boldsymbol{c}^0$, $\boldsymbol{q}^0$) to (∞, $\boldsymbol{q}^0$); that is, we wish to evaluate the expected compensating variation associated with a change from the present trip prices to the prices that would choke demand to zero at all beaches. This leads to the following *ECV*:

$$ECV^{day} = -(1/\theta) \cdot \Big\{V_0 - \ln\Big[\exp(V_0) + \big\{\Sigma_i \exp\big[V_i(c_i^0, q_i^0) / d\big]\big\}^d\Big]\Big\}. \quad (10)$$

Note, however, that these welfare measures do not account for the fact that SVLT is stochastic. To calculate welfare measures consistent with our empirical model, equation (10) must be evaluated over the distribution of SVLT values; *i.e.*,

$$ECV^{day} = \int -(1/\theta) \cdot \Big\{V_0 - \ln\Big[\exp(V_0) + \big\{\Sigma_i \exp\big[V_i(c_i^0, q_i^0 | \rho) / d\big]\big\}^d\Big]\Big\} \cdot f(\rho | \Omega) d\rho, \quad (10')$$

which can be calculated numerically using equation (11):

$$ECV^{day} = R^{-1} \cdot \Sigma_r - (1/\theta) \cdot \Big\{V_0 - \ln\Big[\exp(V_0) + \big\{\Sigma_i \exp\big[V_i(c_i^0, q_i^0 \mid \rho^r) / d\big]\big\}^d\Big]\Big\}, \quad (11)$$

where R is the number of draws and ρ^r is the *r*th draw from the SVLT distribution. The ECV^{day} calculated from equation (11) for each model are reported in table 5, summarized across the sample of 494 beach users. The mean and median ECV^{day} across the sample using the full sites model estimates are \$22.93 and \$22.36, respectively, and for the aggregate sites model are \$22.08 and \$21.44. Extrapolating these to a two-month period (the timeframe used in the study), the value to residents of

Table 5
Per-Day Values of Beach Access (ECV^{day})

	Full Sites Model	Aggregate Sites Model
Sample mean ECV^{day}	\$22.93	\$22.08
Sample median ECV^{day}	\$22.36	\$21.44
Krinsky-Robb 90% Conf. Interval[a]	(\$12.57, \$74.15)	(\$11.33, \$76.01)
Krinsky-Robb 95% Conf. Interval[a]	(\$11.07, \$104.94)	(\$10.16, \$124.29)

[a] Based on 4,000 draws from the empirical distribution of the mean ECV^{day}.

beach access in San Diego County is in the range of $1,300–1,400 bimonthly. Confidence intervals for the mean ECV^{day} for each model are estimated from simulated distributions following Krinsky and Robb (1986). These confidence intervals clearly show the means have skewed distributions and also that they are not statistically different for the two models. Thus, aggregation of contiguous beaches had no appreciable effect on the value of a beach day in San Diego County.

Welfare impacts of individual site removal are presented in table 6. Because a "site" in the aggregate sites model is a group of 1-5 sites in the individual sites

Table 6
Compensating Variation of Individual and Aggregate Beach Site Closures

	Full Sites Model: Individual Site Removal		Full Sites Model: Aggregate Site Removal		Aggregate Sites Model: Aggregate Site Removal	
Beach Name	Mean	Median	Mean	Median	Mean	Median
San Onofre State – Camp Pendleton Beaches	–$0.04	–$0.03	–$0.24	–$0.14	–$0.42	–$0.27
Oceanside Beaches	–$0.19	–$0.09				
Carlsbad Beaches	–$0.07	–$0.04	–$0.19	–$0.12	–$0.34	–$0.22
South Carlsbad State Beach	–$0.08	–$0.05				
Ponto Beach	–$0.04	–$0.03				
North Encinitas Beaches	–$0.03	–$0.03	–$0.22	–$0.18	–$0.14	–$0.12
Moonlight Beach	–$0.11	–$0.09				
Boneyard Beach	$0.00	$0.00				
Swami's Beach	–$0.06	–$0.05				
San Elijo State Beach	–$0.03	–$0.03	–$0.03	–$0.03	–$0.15	–$0.13
Cardiff State Beach	–$0.04	–$0.03	–$0.04	–$0.03	–$0.05	–$0.04
Tide Beach Park	–$0.03	–$0.03	–$0.19	–$0.16	–$0.02	–$0.02
Fletcher Cove Park	–$0.06	–$0.05				
Seascape Surf – Del Mar Shores Beaches	–$0.09	–$0.08				
Del Mar City Beach	–$0.15	–$0.13	–$0.27	–$0.25	–$0.34	–$0.28
Torrey Pines State Beach	–$0.12	–$0.11				
Black's Beach	–$0.02	–$0.02	–$0.37	–$0.34	–$0.01	$0.00
La Jolla Shores Beach	–$0.26	–$0.24				
Scripps Park Beaches	–$0.05	–$0.04				
Marine Street Beach	–$0.02	–$0.01				
Windansea Beach	–$0.02	–$0.01				
Pacific Beach	–$0.30	–$0.28	–$1.13	–$1.04	–$0.20	–$0.19
Mission Beach	–$0.39	–$0.37				
Ocean Beach	–$0.28	–$0.27				
Coronado Beach	–$0.15	–$0.13	–$0.15	–$0.13	–$0.06	–$0.05
Silver Strand State Beach	–$0.03	–$0.03	–$0.03	–$0.03	–$0.05	–$0.04
Imperial Beach	–$0.12	–$0.09	–$0.12	–$0.09	–$0.04	–$0.03
Border Field State Beach	–$0.01	–$0.01	–$0.01	–$0.01	–$0.10	–$0.06
Mission Bay	–$0.05	–$0.05	–$0.05	–$0.05	–$0.19	–$0.19
San Diego Bay	–$0.08	–$0.07	–$0.08	–$0.07	–$0.48	–$0.42
Sunset Cliffs – Point Loma Beaches	–$0.06	–$0.06	–$0.06	–$0.06	–$0.18	–$0.17

model, three sets of calculations are presented for comparability. The first pair of estimates (mean, median) is for single site removal in the individual sites model, while the last pair is for removal of single sites in the aggregate sites model. The middle pair of estimates is for removing groups of sites in the individual sites model that correspond to individual sites in the aggregate sites model.

Three main points are illustrated. First, the welfare impact of removing a single site is relatively small, from –\$0.01 (for Border Field State Park) to –\$0.39 (for Mission Beach). Second, the welfare effects of removing a small group of sites is, in most instances, about the same as the sum of the individual site removal costs. The exception is for the highly valued Pacific, Mission, and Ocean Beach group near downtown San Diego, where removing all three beaches has a higher welfare cost (by about 15%) than the sum of the individual site removal costs. Third, there are some differences (most relatively small) in how the two models predict the welfare costs of removing small groups of beaches, a finding that has occurred regularly in the literature on aggregation in random utility recreation models.

Table 7 presents mean implicit prices and confidence intervals for beach attributes, which show the effects of attributes on the expected value of a beach day. Presence of lifeguards, designated activity zones, and free parking lots are valued positively, as expected, with the magnitude being somewhat greater in the aggregate sites model. Implicit prices for free street parking near the beach and presence of cobblestones on the beach are not significantly different from zero.

Table 7
Implicit Prices of Beach Attributes and Characteristics

Site Attribute	Full Sites Model	Aggregate Sites Model
On–beach lifeguard	\$2.92	\$5.65
	(\$1.57, \$6.92)	(\$2.26, \$11.47)
Mobile lifeguard	\$1.03	\$2.12
	(–\$0.32, \$2.56)	(\$0.70, \$5.14)
Activity zone	\$1.70	\$2.53
	(\$0.75, \$3.66)	(\$1.15, \$6.38)
Free parking lot	\$1.86	\$2.98
	(\$0.78, \$3.85)	(\$1.92, \$5.37)
Free street parking	\$2.31	\$0.41
	(–\$1.79, \$4.65)	(–\$7.22, \$2.73)
Cobblestoning	–\$0.88	\$0.08
	(–\$3.90, \$0.40)	(–\$1.78, \$2.63)

Note: 95% confidence intervals are in parentheses and based on 4,000 draws from the empirical distribution of the mean implicit price.

Conclusions

This article has developed and implemented a beach recreation model that jointly determines participation, site choices, and the SVLT. It extends the repeated nested multinomial logit model to include an endogenous, jointly estimated function identifying the latent value of time spent in beach recreation. The structure of two-constraint optimization models provides guidance for how to specify and incorporate the SVLT within the repeated NMNL consistent with the requirements of theory. Allowing for error in specification of the SVLT generates a random parameters logit which induces correlation among the alternatives within nests, so the model does not suffer from the IIA property.

The model was estimated using data collected from households in San Diego County on their use of county beaches during 2000–01. Two levels of aggregation are considered: a model with each of the 31 area beaches as a choice alternative, and a 16-beach model which aggregates nearby and contiguous beaches. Both models are highly significant with correct signs and significance on the key economic variables. Aggregation appears to help somewhat in the identification of the shadow wage equation, though not evidently in the market wage equation. It does not appear to impart a bias to welfare estimation, as the welfare estimates produced by the two models are not significantly different from one another.

The presence of a non-beach alternative in the model allows for the calculation of the per-day value of access to area beaches for county beach users. The compensating variation measure of this value is between \$21 and \$23 per day, which is a value per choice occasion (assumed to occur daily, as the sample included beach users who went daily).

The estimates of the value of a beach day in San Diego County fall within the (rather broad) range of previous beach values for California. Compared to the Lew and Larson (2005b) model based on a single (most recent) trip, which generated expected beach day values of about \$28, the repeated RUM model reported here that uses information on all trips generates values that are about 20% lower. Hanemann *et al*. (2004) cite several estimates of daily beach value for Los Angeles, Orange, and San Diego County beaches, a number of which were based on adaptations of studies from other areas, with a range of \$8 to \$81 per day. Their own estimate based on surveys conducted in Los Angeles County was \$11 per day. This latter estimate is the one most comparable to ours, since it was also based on original data collection and a repeated-RUM framework. It falls within the 95% confidence interval for both the full sites model and the aggregate sites model.[27]

While this article extends the repeated NMNL framework to better account for the opportunity cost of time devoted to recreation, it has some of the same limitations. For example, the number of choice occasions is specified arbitrarily (though in a way that is consistent with the observed patterns of beach visits), which seems inevitable given the unobservability of choice occasions. Also, as with other applications of the RL, it is assumed that there is no correlation between choice occasions. While this article shows how measurement error in the latent shadow value of leisure time generates the more flexible random parameters version of the MNL model, it should be possible to allow more key economic parameters, such as the marginal utility of income, to be random as well. Additionally, while there is an explicit role for (full) income in the shadow value of leisure time, linearity of indirect utility means that income drops out of the choice probabilities (even though the income effect is still present via the price coefficients). A role for incomes independent of price in the choice probabilities could be introduced through use of nonlinear indirect utility functions or (where appropriate) relaxing the assumption that everyone consumes one unit of the good being chosen.

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[27] The difference in magnitude of the Los Angeles versus San Diego estimates could easily be explained by differences in beach attributes and other factors.

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