**UNIVERSITY OF WAIKATO**

**Hamilton**
**New Zealand**

# Utility in WTP space: a tool to address confounding random scale effects in destination choice to the Alps

Riccardo Scarpa

Mara Thiene

Kenneth Train

**Department of Economics**

**Working Paper in Economics 15/06**

First version December 2006

Revised version August 2007

**Riccardo Scarpa**
Economics Department
University of Waikato
Private Bag 3105
Hamilton, New Zealand

Tel: +64 (0) 7-838-4045
Fax: +64 (0) 7-838-4331

Email: rscarpa@waikato.ac.nz
Web:
http://www.mngt.waikato.ac.nz

**Mara Thiene**
Department of Land and
Agriculture-Forestry Systems
University of Padua
Legnaro, Padova

Tel: +39049-827-2760
Fax: +39049-827-2703

Email: mara.thiene@unipd.it
Web:
http://www.agraria.unipd.it

**Kenneth Train**
University of California
Department of Economics
549 Evans Hall # 3880
Berkeley CA 94720-3880

Tel: +1-415-291-1023
Fax: +1-415-291-1020

Email: train@econ.berkeley.edu
Web:
http://elsa.berkeley.edu/~train/

**Abstract**

Destination choice models with individual-specific taste variation have become the presumptive analytical approach in applied nonmarket valuation. Under the usual specification, tastes are represented by coefficients of site attributes that enter utility, and the distribution of these coefficients is estimated. The distribution of willingness-to-pay (WTP) for site attributes is then derived from the estimated distribution of coefficients. Though conceptually appealing this procedure often results in untenable distributions of willingness to pay. An alternative procedure is to estimate the distribution of willingness to pay directly, through a re-parameterization of the model. We compare hierarchical Bayes and maximum simulated likelihood estimates under both approaches, using data on site choice in the Alps. We find that models parameterized in terms of WTP provide more reasonable estimates for the distribution of WTP, and also fit the data better than models parameterized in terms of attribute coefficients. This approach to parameterizing utility is hence deemed promising for applied nonmarket valuation.

**Keywords**

Mixed logit
Random utility parameters
Random willingness to pay
Travel cost method
Destination choice modeling

**JEL Classification**

C15; C25; Q26

**Acknowledgements**

We thankfully acknowledge the assistance of Tiziano Tempesta in the phase of survey design and data collection, comments from Timothy Gilbride, and the use of Gauss routines to assess convergence of the Gibbs sampler made available by Kelvin Balcombe. The usual disclaimer on the remaining errors applies.

# 1 Introduction

Nonmarket values of qualitative changes in sites for outdoor recreation are often investigated by estimating random utility models (RUMs) of site selection (Bockstael et al. 1987, Morey et al. 1993). Most recent applications address the issue of unobserved taste heterogeneity by using continuous (Train 1998, 1999) or finite mixing (Provencher et al. 2002, Scarpa & Thiene 2005) of individual taste distributions by means of panel mixed logit models. Such approaches are shown to produce more informative and realistic estimates of nonmarket values than models without taste heterogeneity and are now part of the state of practice in the profession. However, models with conveniently tractable distributions for taste coefficients, such as the normal and the log-normal, often obtain estimates that imply counter-intuitive distributions of *WTP*. This is due to the fact that the analytical expression for *WTP* involves a ratio where the denominator is the cost coefficient. Values of the denominator that are close to zero (which are possible under most standard distributions such as the lognormal) cause the ratio to be exceedingly large, such that the derived distribution of *WTP* obtains an untenably long upper tail. The mean and variance of the skewed distribution are both raised artificially by these implausibly large values.

One solution is to assume that the cost coefficient is constant and not random (e.g. Revelt & Train 1998, Goett et al. 2000, Layton & Brown 2000, Morey & Rossmann 2003). This restriction allows the distributions of willingness to pay (*WTP*) to be calculated easily from the distributions of the non-price coefficients, since the two distributions take the same form. For example, if the coefficient of an attribute is distributed normally, then *WTP* for that attribute, which is the attribute's coefficient divided by the price coefficient, is also normally distributed. The mean and standard deviation of *WTP* is simply the mean and standard deviation of the attribute coefficient scaled by the inverse of the (fixed) price coefficient. The fixed cost coefficient restriction also facilitates estimation. For example, Ruud (1996) suggests that a model specification with all random coefficients can be empirically unidentified, especially in datasets with few observed choices for each decision-maker (short panels). However, this restriction is counter-intuitive as there are very good theoretical and common-sense reasons as to why response to costs should vary across respondents according to factors that can be independent of observed socio-economic covariates.

Train & Weeks (2005) note on the topic that assuming a fixed price coefficient implies that the standard deviation of unobserved utility (i.e. the scale parameter) is the same for all observations. On the other hand, it is important to recognize that the scale parameter can, and in many situations clearly does, vary randomly over observations. Estimation practices that ignore such source of variation may lead to erroneous interpretation and policy conclusions. For example, in the context of destination choice modeling, if the travel cost coefficient is constrained to be fixed when in fact scale varies over observations, then the variation in scale will be erroneously attributed to variation in *WTP* for site attributes.

Another solution is to re-parameterize the model such that the parameters are the *WTP* for each attribute rather than the utility coefficient of each attribute. That is, instead of the usual approach of parameterizing the model in 'preference space' (i.e., coefficients in the utility), the model is parameterized in '*WTP* space'. This alternative procedure has recently been utilized to represent taste heterogeneity by Train & Weeks (2005) and Sonnier et al. (2007). However, the idea of specifying utility in the *WTP* space is not new. For example, the readers familiar with the analysis of discrete-choice contingent valuation data may recall the so-called *variation* function or *expenditure* function approach suggested in Cameron & James (1987) and in Cameron (1988), which as discussed in some more detail by McConnell (1995) in some cases boils down to a simple re-parameterization of the RUM model proposed by Hanemann (1984, 1989).

Train & Weeks (2005) and Sonnier et al. (2007) extended the approach by Cameron and James to multinomial choice models with random tastes, where distributional assumptions and restrictions can be placed on the coefficients of the *WTP*'s. They point out that the two approaches are formally equivalent because any distribution of coefficients translates into some derivable distribution of *WTP*'s, and vice-versa. However, the appeal of the approach is that it allows the analyst to specify and estimate the distributions of *WTP* directly, rather than deriving them indirectly from distributions of coefficients in the utility function. To researchers in nonmarket valuation this is an important advantage.

Comparisons of estimates obtained from the two parameterizations on an identical dataset have already been investigated using stated preference (SP) data. Train and Weeks compared the estimates of the two approaches and the implied *WTP* for attributes related to cars with different fuel (fossil, hybrid and electric). Sonnier et al. (2007) investigate the same issues in the context of stated preference data for car brand choice and photographic cameras. Both results use hierarchical Bayes (HB) estimators and find similar results. In particular, they found that the specifications in the preference space fit their data better but produce less reasonable distributions of *WTP* than specifications in the *WTP* space.[1]

We apply these concepts to revealed-preference (RP) data, the first such application to our knowledge. In order to ensure that results are not dependent on the estimation method, we estimate our models by both HB and maximum simulated likelihood (MSL). To our knowledge, this is the first application of MSL to random coefficient models in *WTP* space. We find, like Train & Weeks (2005) and Sonnier et al. (2007), that models in *WTP* provide far more reasonable distributions of *WTP* than models in preference space. However, unlike Train & Weeks (2005) and Sonnier et al. (2007), we find that the models in *WTP* space also fit the data better than the models in preference space. This improved fit arises with both HB and MSL estimation. Our findings indicate that, with our RP data, there is no tradeoff between goodness of fit and reasonableness of results: the model in *WTP* space outperforms on both criteria.

## 2 Specification

In this section we start with the conventional specification of utility in the preference space, and describe the implications for correlation of utility coefficients and implied *WTP*s. We then

[1] Importantly for the practice of RUM estimation, Train and Weeks emphasize how assuming independence across utility coefficients in the presence of a scale parameter which varies across visitors implies dependence (correlation) across implied *WTP* distributions, and vice-versa. This issue may escape the attention of analysts, and it is worth bearing in mind for its consequences in interpretation of results, because in general neither marginal *WTP*s for attributes nor their taste intensities are independently distributed, and hence correlation matrices should be estimated whenever the data allow it, regardless of the choice of utility specification.

reparameterize the model in *WTP* space and discuss the implications. Throughout, the notation and language is adapted for our application to Alpine site choice.

Day trippers are indexed by $n$, destination sites by $j$, and choice situations by $t$. To ease the illustration, we specify utility as separable in price, $p$, and a vector of non-price attributes, $x$:

$$U_{njt} = -\alpha_n p_{njt} + \theta_n' x_{njt} + \epsilon_{njt} \tag{1}$$

where $\alpha_n$ and $\theta_n$ vary randomly over day visitors and $\epsilon_{njt}$ is Gumbel distributed. The variance of $\epsilon_{njt}$ is visitor-specific: $Var(\epsilon_{njt}) = \mu_n^2(\pi^2/6)$, where $\mu_n$ is the scale parameter for day visitor $n$. Since utility is ordinal one can divide equation (1) by the scale parameter to obtain its scale-free equivalent. This division does not affect behavior and yet it results in a new error term that has the same variance for all decision-makers:

$$U_{njt} = -(\alpha_n/\mu_n)p_{njt} + (\theta_n/\mu_n)' x_{njt} + \varepsilon_{njt} \tag{2}$$

where $\varepsilon_{njt}$ is i.i.d. type-one extreme value, with constant variance $\pi^2/6$. The utility coefficients are defined as $\lambda_n = (\alpha_n/\mu_n)$ and $c_n = (\theta_n/\mu_n)$, such that utility may be written:

$$U_{njt} = -\lambda_n p_{njt} + c_n' x_{njt} + \varepsilon_{njt} \tag{3}$$

Note that if $\mu_n$ varies randomly, then the utility coefficients are correlated, since $\mu_n$ enters the denominator of each coefficient. Specifying the utility coefficients to be independent implicitly constrains $\mu_n$ to be constant. If the scale parameter varies and $\alpha_n$ and $\theta_n$ are fixed, then the utility coefficients vary with *perfect* correlation. If the utility coefficients have correlation less than unity, then $\alpha_n$ and $\theta_n$ are necessarily varying in addition to, or instead of, the scale parameter. Finally, even if $\mu_n$ does not vary over visitors (e.g., the standard deviation in unobserved factors over sites and trips is the same for all visitors), utility coefficients can be correlated simply due to correlations among tastes for various attributes.

The specification in equation (3) parameterizes utility in 'preference space'. The implied *WTP* for a site attribute is the ratio of the attribute's coefficient to the price coefficient: $w_n = c_n/\lambda_n = \theta_n/\alpha_n$. Using this definition, utility can be rewritten as

$$U_{njt} = -\lambda_n p_{njt} + (\lambda_n w_n)' x_{njt} + \varepsilon_{njt}, \tag{4}$$

which we name 'utility in *WTP* space', while Sonnier et al. (2007) called it the 'surplus model'. In a context in which scale can vary over people—such as in our alpine destination choice—this specification is very useful for distinguishing *WTP* variation (i.e. the distributional features of $w_n$) from variation in scale. To what extent this distinction affects the derived welfare estimates remains an empirical question, and one of the objectives of our investigation. We note that, although any coefficient can be used as the base that incorporates scale, the reason to focus on the travel cost coefficient in this case is that the scale-free terms can be directly interpreted as *WTP*s, which are easy to rationalize. This utility specification is distinctive for another reason as it gives a nonlinear-in-the-parameter utility function, which poses some computational challenges in the context of MSL estimation (and is probably the reason MSL has not been previously used for models in *WTP* space. In contrast, nonlinearity is readily accommodated in HB estimation.

The utility expressions are behaviorally equivalent and any distribution of $\lambda_n$ and $c_n$ in (3) implies a distribution of $\lambda_n$ and $w_n$ in (4), and vice-versa. The general practice in nonmarket valuation and elsewhere has been to specify distributions in preference space, estimate the parameters of those distributions, and derive the distributions of *WTP* from these estimated distributions in preference space (Train 1998). While fully general in theory, this practice is usually limited in implementation by the use of computationally convenient distributions for utility coefficients. However, empirically tractable distributions for coefficients do not necessarily imply convenient, or reasonable, distributions for *WTP*, and vice-versa. For example, if the travel cost coefficient is distributed log-normal and the coefficients of site attributes are normal, then *WTP* is the ratio of a normal term to a log-normal term. Similarly, in (4), normal distributions for *WTP* and a log-normal for the (negative of) travel cost coefficient imply that the utility coefficients are the product of a log-normal variate and a normal one: $\lambda_n \times w_n$.

A similar asymmetry exists for the placement of restrictions on patterns of correlations (independence). In the travel cost site selection literature it is fairly common for researchers to specify uncorrelated utility coefficients. However, this restriction implies that scale is constant, as stated above, and moreover that *WTP* is correlated in quite a particular way via the common variation in the price coefficient. Researchers might not be aware of such implications of their choice of specification, as few papers discuss its consequences. Symmetrically, specifications assuming uncorrelated *WTP* imply a pattern of correlation in utility coefficients that is difficult to implement in preference space. We know of only one other application of travel cost RUMs that assumes a random scale parameter, but in that case the authors do not explicitly address correlation across *WTP* estimates (Breffle & Morey 2000).

The issue becomes: does the use of convenient distributions and restrictions in preference space or *WTP* space result in more accurate and reasonable models? The answer is necessarily situationally dependent, since the true distributions differ in different applications. However, some insight into this issue can be obtained by comparing alternative specifications on a given dataset under alternative estimators. Description of our data is the topic of the next section.

# 3 Data

## 3.1 Respondents data

The data for our estimates were collected with a survey administered to a sample of 858 members of the local (Veneto Region) chapter of the CAI (Italian Alpine Club), who reported on their mountain visits for the year 1999. The total number of trips reported was 9,221, and some descriptive statistics are reported in Table I. The most visited sites are Piccole Dolomiti, Asiago, Lessini-Baldo, which are located in the pre-Alps, and Civetta, Pale S.Martino and Tre Cime, all of which are in the Dolomites. Unsurprisingly the most frequently attended sites are those closest to the urban centers located in the plains. The interviewers contacted the CAI members at club meetings taking place in the municipalities of the Veneto region. The various parts of the questionnaire were explained to a group of respondents, and then each member of the group filled out the questionnaire on their own. Respondents were asked questions about their mountaineering abilities and experience (i.e. when they started mountain recreation, whether they attended mountaineering training courses, and the kind of activities they usually undertook at the sites etc.). Importantly for this application they were asked the total number of days out they took to each of the 18 sites in the last twelve months. Finally, they provided the interviewers with socio-economic information about themselves and their households.

Round-trip distance from own residence to each of the destinations in the choice set was calculated using the software package "Strade d'Italia e d'Europa". These data were used to estimate the individual travel cost for each trip. Distance costs were converted into monetary values using a figure of €0.35 per km, which was the car running cost at the time. Each reported trip was a 'day out', as is customary for this generic form of local outdoor recreation. The eighteen mountain destinations differ substantially from both a morphological and mountaineering point of view, but they can provide both specialist and non-specialist outdoor recreation, and so are all destinations for local visitors.

## 3.2 Site attribute data

Data on attributes of mountain destinations have mostly been provided by means of a Geographical Information System and some of them were coded according to the knowledge of a panel of experts in local hiking features. Two broad geographically-determined groups can be distinguished. Destinations 1-6 (Table I) belong to the Prealps, which are mountains with gentler slopes and lower peaks separating the plane from the proper Alps. Because of their distinct nature the Prealps are the final destination of many trips with different recreational objectives from those trips taken to the Alps. Destinations 7-18 are in the Northeastern Alps, in the mountain chain of the Dolomites, which is an extended rocky area mostly made of dolomite rocks. This rare and distinguished rock type is geologically well-defined as it originates from coral reefs. Mountains made of this rock are scenically quite attractive as they tend to show orange-pink reflections at sunset.

Some of the recreational attributes describe the land use of the sites and some others provide specific information about hiking by means of an index. *Degree of difficulty* is a score taking up to 3 ordinal values and describing the degree of technical difficulty of trailing itineraries available at destination. That is, taking into account not only the total length of the trails network, but also the average degree of adversity of the mountain environment at destination; *Ferrata* is the number of trails equipped so as to allow visitors to secure themselves onto a safety rope in the ascent towards hard-to-reach vantage points; *Alpine shelters* is the number of equipped alpine shelters accessible in the destination area.

The recreational attractiveness of a destination to days out visitors is also described on the basis of the percent of total length of 'easily' walkable trails (*% of Easy trails* ). These are those requiring lower than average physical effort and are selected on the basis of a composite set of measurements, such as width, incline and accessibility. At the other extreme of the spectrum we use the percent of total length made-up of 'hard' walkable trails (*% of Hard trails* ), which are those requiring higher than average physical effort, and therefore degree of fitness. Percentages are worked out of the total existing trail network at destination. Finally, because the Prealps offer an experience distinctively different from the Dolomites, the trips to the former are associated with a alternative-specific constant.

# 4 Method

Revelt & Train (1998) derived the mixed logit specification in the context of repeated choices by individuals with continuous taste distributions, the so-called panel mixed logit. In our alpine destination choice context, visitor $n$ faces a choice among $J$ destination alternatives in each of $T_n$ trips taken over an outdoor season. $J$ in our case is 18 while we have a maximum of $T_n$ =40 which represents a reasonable maximum number of days out over a year. We have an unbalanced panel since the number of trips vary across individuals, hence the subscript $n$.

To assure a negative price coefficient, we define $\lambda_n = -\exp(v_n)$, where $v_n$ can be considered the latent random factor underlying the price coefficient. Let $\beta_n$ denote the random terms entering utility, which are $v_n$ and $c_n$ for the model in preference space, (equation 3), and $\lambda_n$ and $w_n$ for the model in *WTP* space, (equation 4). Similarly, let utility be written $U_{njt} = V_{njt}(\beta_n) + \varepsilon_{njt}$, with $V_{njt}(\beta_n)$ being defined by either equation (3) or (4), depending on the parameterization.

Visitor $n$ chooses destination $i$ in period $t$ if $U_{nit} > U_{njt}\ \forall j \neq i$. Denote the visitor's chosen destination in choice occasion $t$ as $y_{nt}$, the visitor's sequence of choices over the $T_n$ choice occasions as $y_n = \langle y_{n1}, \ldots, y_{nT_n}\rangle$. Conditional on $\beta_n$, the probability of visitor $n$'s sequence of choices is the product of standard logit formulas:

$$L(y_n \mid \beta_n) = \prod_{t=1}^{t=T_n} \frac{e^{V_{ny_{nt}t}(\beta_n)}}{\sum_j e^{V_{njt}(\beta_n)}}.$$

The unconditional probability is the integral of $L(y_n \mid \beta_n)$ over all values of $\beta_n$ weighted by its density:

$$P_n(y_n) = \int L(y_n \mid \beta_n) g(\beta_n) d\beta_n. \tag{5}$$

where $g(\cdot)$ is the density of $\beta_n$ which depends on parameters to be estimated. This unconditional probability is called the mixed logit choice probability, since it is a product of logits mixed over a density of random factors reflecting tastes.

## 4.1 Mixed logit estimation via hierarchical Bayes

Because MSL estimation of mixed logit models is well-documented (Train 2003, e.g.), in this section we mostly focus on HB estimation. For the MSL estimation we just mention that to deal with non-linearity of $V_{nit}$ we used BIOGEME (Bierlaire 2002, 2003) and the algorithm CFSQP (Lawrence et al. 1997) so as to avoid the problem of local optima. All MSL estimates were obtained using 100 quasi-random draws via Latin-hypercube sampling (Hess et al. 2006).

The Bayesian procedure for estimating the model with normally distributed coefficients was developed by Allenby (1997) and implemented by Sawtooth Software (1999). This estimation method was also applied by Rigby & Burton (2006) to derive transforms that address mass distribution at zero (indifference to attributes) of utility coefficients (not *WTP* coefficients) for choice over GM food products in the U.K. Related methods for probit models were developed by Albert & Chib (1993), McCulloch & Rossi (1994), Allenby & Rossi (1999). Layton & Levine (2005) made a contribution in the context of sequential learning from previous applications. A review of applications to marketing methods is found in Rossi et al. (2005).

We specify the density of $\beta_n$ to be normal with mean $b$ and variance $\Omega$, denoted $g(\beta_n \mid b, \Omega)$. Although terminology differs over authors and fields,[2] we call $b$ and $\Omega$ 'population parameters' since they describe the distribution of visitor-level $\beta_n$'s in the population. With this usage, the distribution $g(\beta_n \mid b, \Omega)$ is interpreted as the actual distribution of tastes for the recreational attributes of destination sites in the population of the regional branch of the Italian Alpine Club, from which we drew the sample. Note that, given the expression above for the price coefficient, the specification of normal $\beta_n$ implies that the price coefficient is lognormally distributed.

In Bayesian analysis, a prior distribution is specified for the parameters. We lack previous information on the type of visitors in our sample[3] and therefore specify the prior on $b$ to be a diffuse normal, denoted $N(b \mid 0, \Theta)$, which has zero mean and a sufficiently large variance $\Theta$ such that the density is essentially flat from a computational perspective. A normal prior on $b$ has a computational advantage since it provides a conditional posterior on $b$ (*i.e.*, conditional on $\beta_n \forall n$ and $\Omega$) that is also normal and hence easy to draw from, while the large variance ensures that the prior has minimal (effectively no) influence on the posterior, reflecting the absence of a-priori knowledge, especially in the presence of large samples, such as in our case. The standard diffuse prior on $\Omega$ is inverted Wishart with low degrees of freedom. This specification is also computationally advantageous as it provides a conditional posterior on $\Omega$ that is also Inverted Wishart and hence easy to draw from. The conditional posterior on $\beta_n \forall n$ , given $b$ and $\Omega$, is

$$\Lambda(\beta_n \mid, b, \Omega) \propto \prod_n L(y_n \mid \beta_n) \cdot g(\beta_n \mid b, \Omega). \tag{6}$$

Information about the posterior is obtained by taking draws from the posterior and calculating relevant statistics, such as moments, over these draws. Draws from the joint posterior are obtained by Gibbs sampling (Casella & George 1992). In particular, a draw is taken from the conditional posterior of each parameter, given the previous draw of the other parameters. The sequence of draws from the conditional posteriors converges, after a sufficient number of iterations (called 'burn-in'), to draws from the joint posterior. Technical information about the algorithm can be found in Train & Sonnier (2005) and Train (2003).[4]

[2]In Bayesian applications $b$ and $\Omega$ tend to be called hyper-parameters, with the $\beta_n$'s themselves being the parameters of interest. Sometimes, however, the $\beta_n$'s are called nuisance parameters, to reflect the concept that they are incorporated into the analysis to facilitate estimation of $b$ and $\Omega$.

[3]The only other study we know of on the region is Scarpa & Thiene (2005) and it focussed on rock-climbers and not generic day-out visitors.

[4]For the HB models in preference space, we used the GAUSS code that is available on K. Train's website at http://elsa.berkeley.edu/ train/software.html. We adapted this code appropriately for the HB models in *WTP* space.

It is worth reminding the reader not familiar with Bayesian estimation that the Bernstein-von Mises theorem states that, under quite unrestrictive conditions, the mean of the Bayesian posterior of a parameter is a classical estimator that is asymptotically equivalent to the maximum likelihood estimator of the parameter. Similarly, the variance of the posterior distribution is the asymptotic variance of this estimator. See Train (2003) for an extended explanation with citations. Hence, the results obtained by Bayesian procedures can be interpreted from a purely classical perspective. In the tables below, results are presented in the way that is standard for classical estimation, giving the estimate and standard error for each parameter. These statistics are the mean and standard deviation, respectively, of the draws from the posterior for each parameter.

# 5 Estimation results

## 5.1 Preference space

### 5.1.1 Model estimates

The HB estimates for models in the preference space (i.e., equation 3) with uncorrelated coefficients are reported in the top part of Table II, and estimates with correlated coefficients are reported in the bottom part. Allowing for full correlation amongst coefficients increases the log-likelihood simulated at the posterior means from –20,773.59 to –20,383.65. Table III reports similar estimates obtained by MSL, while the estimates of the Choleski matrix associated with the correlated model are reported in Table IV. Again, allowing for correlation increases the value of the simulated log-likelihood from –20,469.86 to –20,147.91.

In interpreting the figures in Tables II and III, recall that the coefficient for travel cost is log-normally distributed, such that the estimated mean and standard deviation are the mean of the latent normally distributed random factor underlying the travel cost coefficient. The other coefficients were all normally distributed, such that their means and standard deviations are estimated directly. The estimated mean and standard deviation together determine the proportion of the population implied to have coefficients of each sign; the implied share with negative coefficients is reported in the last column of these two Tables.

The estimated means have the same signs and ordering of magnitudes across models (with and without correlation) and estimators (HB and MSL). The signs are plausible considering that the population of reference are the members of the Italian Alpine Club selecting days out in the Alps. A negative mean is observed for the degree of technical difficulty. To tackle technically difficult sites requires rigorous training and experience, and it is expected that in general visitors are not attracted by technically challenging destinations. The negative mean for the number of ferrata seems reasonable when one bears in mind that the number of ferrata is mostly a consequence of strategic access for the military, established during the World War I period against invading Austrians, and not necessarily designed to facilitate tourist access to such vantage points.

Destinations with many alpine shelters tend to be liked more than those with few. Alpine shelters are often themselves the destinations of days out in the Alps and offer opportunities to encounter other visitors and eat local specialities, as well as providing shelter for unexpected bad weather. Everything else equal, one would be more inclined to plan a day out to a destination with shelters.

Sites with higher percent of easily walkable trails and hard walkable trails are, on the average, both liked by visitors from the Alpine Club, but with large estimated taste variation. Trail-walking is still the most popular activities in the Alps because it is cheap and attracts visitors of all ages and abilities. These results indicate that visitors like destinations with easy as well as more challenging trails and that there is considerable heterogeneity in visitors' response to trails' features. For example, we note that the MSL estimate imply that nearly fifty percent of the population do not like hard trails. Perhaps the nature of trails helps in sorting the composition of the visiting party or the purpose of the recreational visit.

#### 5.1.2 Implied *WTP* distributions

Using the estimates for the means of the latent normal variables and their variance-covariance matrices, one can simulate the implied distribution of *WTP* in the population of visitors. The means, medians and standard deviations are given in Table VI. The implied distribution of *WTP* is highly skewed, as evidenced by the absolute values of the mean *WTP* being considerably larger than those of the median for all attributes. Importantly, the estimates imply a fairly large proportion of visitors have implausibly large *WTP* for certain attributes, such as the degree of difficulty of excursions, the number of ferrata and the percentage of hard trails. For example, the MSL model in preference space implies that ten percent of visitors are *WTP* over €20 to avoid 1 extra level of difficulty, five percent are *WTP* more than €3 to avoid a ferrata, and ten percent are willing to pay over €30 to have 10% more difficult trails. Similarly implausible results are reported in many applications in which the price coefficient is allowed to vary across agents, and indeed it often motivates the assumption of a fixed travel cost coefficient.

The correlation matrices across *WTP*s obtained by simulating the population distribution of the utility parameters according to these estimates are reported in the lower triangular part of Table V, with the top part of the Table showing the HB estimates, and the bottom the MSL ones. These estimates mostly concord in signs across estimators with only 2 out 15 correlations being different. A large positive correlation is found between *WTP* for the number of Ferrata at destination and the degree of difficulty, which is very plausible, and similarly plausible is the strong negative correlation between *WTP* for alpine shelters and the degree of difficulty.

### 5.2 $WTP$ space

A salient feature of the *WTP* space model is that estimated parameters are also the parameters of the implied *WTP* distributions. These are therefore discussed jointly in the same subsection.

#### 5.2.1 Model estimates and implied *WTP* distributions

In Table VII we report HB estimates of models parameterized in *WTP* space, i.e., according to equation (4). Estimates for the model without correlation are reported in the top part of the table, while the one with full correlation is in the bottom part of the table. The simulated log-likelihood is higher for the models in *WTP* space than in preference space: –20,470.89 versus –20,773.59 for uncorrelated terms, and –20,325.55 compared to –20,383.65 for models with correlated terms. This result, which differs from the findings of Train & Weeks (2005) and Sonnier et al. (2007) on SP data, indicates that it is possible for models in *WTP* space to outperform models in preference space. A similar improvement is found for the MSL estimates reported in Table VIII. The associated estimates for the CHoleski matrix are reported in Table IX.

The MSL estimates imply smaller *WTP* variation than the HB ones for all attributes, but means have identical signs and very similar magnitudes. Models with correlation also uniformly imply smaller *WTP* variation in the population, with exclusion of the Prealps ASC in the MSL model. Examining the upper triangular sections of Table V we note that estimated correlation match perfectly in sign between the HB (upper part of the Table) and MSL estimates.

The estimated standard deviations of *WTP* are uniformly lower for the models in *WTP* space than the models in preference space. For example, in the HB models with correlated terms, the standard deviation of *WTP* for Alpine shelters is 1.29 for the model in preference space and 0.51 for the model in *WTP* space. However, the estimated means are not consistently higher or lower under either parameterization: with correlated terms, the HB model in *WTP* space gives a higher mean than the model in preference space for three attributes and a lower mean for the other three. The share of implausibly high values for *WTP* is far less with the models in *WTP* space than with the models in preference space. For example, the correlated preference space HB model implies that five percent of the population is willing to pay at least €1.41 for one percent increase in easy trails.[5] In contrast, the correlated model in *WTP* space implies a more plausible €0.60.

This point is visually described in figure 1 obtained with the SM package in R (Bowman & Azzalini 1997). Here we plot the kernel smoothing with cross-validated bandwidth of a simulation of 100,000 draws from each model's *WTP* for an extra alpine shelter at destination. The densities implied by the models in *WTP* space are much 'tighter' than those implied by the models in preference space. As a result, the shares above implausibly high values for *WTP* are much smaller for the models in *WTP* space than those in preference space.

# 6 Policy implications and conclusions

This study investigated destination choices of an inherently diverse population of visitors to alpine destinations in the North-East of Italy: those members of the local (Veneto) chapter of the alpine club visiting the Alps for days out. Using a panel dataset of 858 respondents who took a total of 9,221 day-out trips we estimate *WTP* distributions for key site attributes using models parameterized in preference space and in *WTP* space. Because parameters enter non-linearly in the model in *WTP* space and the number of parameters is large when correlations

[5]The distribution of $\widehat{WTP}$ was simulated with 100,000 draws from the distributions evaluated at the estimated location and scale parameters.

are allowed, previous studies used hierarchical Bayes estimation procedures, which are computationally much faster than maximum simulated likelihood for models of this form. In this study we contrast HB and MSL estimates and found them to be producing similar results, with the latter implying smaller variation of taste and hence of values. However, we note that MSL estimates are much more time consuming to derive. Even when iterations are started at the convergence values of the HB procedure the *WTP* space model with correlation took four days to run using BIOGEME with the CFSQP algorithm in a 3GHz pc with 2 G-bytes of RAM. The equivalent HB model was estimated in GAUSS using 500,000 draws for burn-in and a further 200,000 after burn-in, of which every 50-th draw was retained for averaging and run overnight. The convergence of the sampler was evaluated both visually and formally using the test suggested by Geweke (1992) and Koop (2003).

Our results confirm previous findings obtained by Train & Weeks (2005) and Sonnier et al. (2007) that the models in *WTP* space provide more reasonable estimates of the distribution of *WTP* than the models in preference space. However, unlike these previous studies, which used stated preference data, we find that, on our revealed preference data, the specification in *WTP* space statistically outperforms that in preference space. This means that practitioners need not face a trade-off between plausibility of *WTP* estimates and model fit to the data, as was previously suggested.

Although the main objective of the paper is methodological, the estimation results from the MSL model in *WTP* space with correlated terms—which gives the most behaviorally plausible results and also fits the data best—provide some interesting implications. About 83 percent of day visitors are estimated to dislike sites with high difficulty of tracking activities. Only about 17 percent show a positive *WTP* value for this attribute. Similarly, a large number of ferrata at the site is attractive to only about 16 percent of the population of day-out visitors. The presence of alpine shelters is preferred by the vast majority of visitors: only five percent of visitors prefer sites without the shelters. For most members of the Italian Alpine Club, the site becomes more attractive as the percent of trails that are classified as easily walkable and hard walkable (as opposed to those with mixed classification) rises. Finally, visitors are found to be willing to pay more to visit the Dolomites than the Prealps, which–given the popularity of these sites–is a perhaps foregone conclusion, but is nevertheless confirmed by the negative sign of the alternative specific constant for Prealps.

# References


Albert, J. & Chib, S. (1993), 'Bayesian analysis of binary and polychotomous response data', *Journal of the American Statistical Association* **88**, 669–679.

Allenby, G. (1997), 'An introduction to hierarchical Bayesian modeling', Tutorial notes, Advanced Research Techniques Forum, American Marketing Association.

Allenby, G. & Rossi, P. (1999), 'Marketing models of consumer heterogeneity', *Journal of Econometrics* **89**, 57–78.

Bierlaire, M. (2002), 'An introductory tutorial to BIOGEME. Federal Polytechnic School of Lausanne, Switzerland'. http://rosowww.epfl.ch/mbi/biogeme.

Bierlaire, M. (2003), 'BIOGEME: a free package for the estimation of discrete choice models, 3rd Swiss Transport Research Conference Monte Verita, Ascona, March 2003'.

Bockstael, N. E., Haneman, W. M. & Kling, C. L. (1987), 'Estimating the value of water quality improvements in a recreational demand framework', *Water Resources Research* **23**, 951–960.

Bowman, A. W. & Azzalini, A. (1997), *Applied Smoothing Techniques for Data Analysis: the Kernel Approach withS-Plus Illustrations*, Oxford University Press, Oxford, U.K.

Breffle, W. S. & Morey, E. R. (2000), 'Investigating preference heterogeneity in a repeated discrete-choice recreation demand model of Atlantic salmon fishing', *Marine Resource Economics* **15**, 1–20.

Cameron, T. (1988), 'A new paradigm for valuing non-market goods using referendum data: Maximumlikelihood estimation by censored logistic regression', *Journal of Environmental Economics and Management* **15**, 355–379.

Cameron, T. & James, M. (1987), 'Efficient estimation methods for closed-ended contingent valuation survey data', *Review of Economics and Statistics* **69**, 269–276.

Casella, G. & George, E. (1992), 'Explaining the Gibbs sampler', *The American Statistician* **46**, 167–174.

Geweke, J. (1992), Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments, *in* J. Bernardo, J. Berger, A. Dawid & F. Smith, eds, 'Bayesian Statistics', Oxford University Press, New York, pp. 169–193.

Goett, A., Train, K. & Hudson, K. (2000), 'Customer choice among retail energy suppliers: the willingness-to-pay for service attributes', *Energy Journal* **21**, 1–28.

Hanemann, W. M. (1984), 'Welfare evaluations in contingent valuation experiments with discrete response data', *American Journal of Agricultural Economics* **66**, 332–341.

Hanemann, W. M. (1989), 'Welfare evaluations in contingent valuations experiments with discrete response data: a reply', *American Journal of Agricultural Economics* (71), 1057–1061.

Hess, S., Train, K. E. & Polak, J. W. (2006), 'On the use of a modified latin hypercube sampling (MLHS) method in the estimation of a mixed logit model for vehicle choice', *Transportation Research B* **40**, 147–167.

Koop, G. (2003), *Bayesian econometrics*, Wiley.

Lawrence, C., Zhou, J. & Tits, A. (1997), User's guide for CFSQP version 2.5: A C code for solving (large scale) constrained nonlinear (minimax) optimization problems, generating iterates satisfying all inequality constraints, Technical Report TR-94-16r1, Institute for Systems Research, University of Maryland, College Park, MD 20742, 1997.

Layton, D. F. & Brown, G. (2000), 'Heterogeneous preferences regarding global climate change', *The Review of Economics and Statistics* **82**(4), 616–624.

Layton, D. & Levine, R. (2005), Bayesian approaches to modeling stated preference data, *in* R. Scarpa & A. Alberini, eds, 'Applications of simulation methods in environmental and resource economics', Springer Publisher, Dordrecht, The Netherlands, chapter 10, pp. 187–208.

McConnell, K. (1995), 'Consumer surplus from discrete choice models', *Journal of Environmental Economics and Management* **29**, 263–270.

McCulloch, R. & Rossi, P. (1994), 'An exact likelihood analysis of the multinomial probit model', *Journal of Econometrics* **64**, 207–240.

Morey, E. & Rossmann, K. (2003), 'Using stated-preference questions to investigate variations in willingness to pay for preserving marble monuments: Classic heterogeneity, random parameters, and mixture models', *Journal of Cultural Economics* **27**(3/4), 215–229.

Morey, E., Rowe, R. & Watson, M. (1993), 'A repeated nested-logit model of Atlantic salmon fishing', *American Journal of Agricultural Economics* **75**, 578–592.

Provencher, B., Barenklau, K. & Bishop, R. C. (2002), 'A finite mixture model of recreational angling with serially correlated random utility', *American Journal of Agricultural Economics* **84**(4), 1066–1075.

Revelt, D. & Train, K. (1998), 'Mixed logit with repeated choices', *Review of Economics and Statistics* **80**(4), 647–657.

Rigby, D. & Burton, M. (2006), 'Modeling disinterest and dislike: A bounded Bayesian mixed logit model of the UK market for GM food', *Environment and Resource Economics* **33**, 485–509.

Rossi, P. E., Allenby, G. & McCulloch, R. (2005), *Bayesian Statistics and Marketing*, Wiley and Sons.

Ruud, P. (1996), 'Simulation of the multinomial probit model: An analysis of covariance matrix estimation', Working Paper, Department of Economics, University of California.

Sawtooth Software (1999), 'The CBC/HB module for hierarchical Bayes', Technical Paper available on the web site of Sawtooth Software.

Scarpa, R. & Thiene, M. (2005), 'Destination choice models for rock climbing in the North-eastern Alps: a latent-class approach based on intensity of preference', *Land Economics* **85**(3), 426–44.

Sonnier, G., Ainslie, A. & Otter, T. (2007), 'Heterogeneity distributions of willingness-to-pay in choice models', *Quantitative Marketing Economics* **DOI 10.1007/s11129-007-9024-6**.

Train, K. (1998), 'Recreation demand models with taste differences over people', *Land Economics* **74**, 185–194.

Train, K. (1999), Mixed logit models for recreation demand, *in* J. Herriges & C. Kling, eds, 'Valuing Recreation and the Environment', Edward Elgar, Northampton, MA.

Train, K. (2003), *Discrete Choice Methods with Simulation*, Cambridge University Press, New York.

Train, K. & Sonnier, G. (2005), Mixed logit with bounded distributions of correlated partworths, *in* R. Scarpa & A. Alberini, eds, 'Applications of simulation methods in environmental and resource economics', Springer Publisher, Dordrecht, The Netherlands, chapter 7, pp. 117–134.

Train, K. & Weeks, M. (2005), Discrete choice models in preference space and willing-to-pay space, *in* R. Scarpa & A. Alberini, eds, 'Applications of simulation methods in environmental and resource economics', Springer Publisher, Dordrecht, The Netherlands, chapter 1, pp. 1–16.

Table I: Site-specific data.

| | *Descriptive Statistics of Trips* | | | | *Attributes* | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *Destination sites* | Mean | St. Dev. | Visits | Percent | Degree of Difficulty | Ferratas | Easy Trails | Shelters | Hard Trails |
| 1. Vette Feltrine | 0.7 | 1.5 | 642 | 7.0 | 3 | 3 | 0.61 | 25 | 0.07 |
| 2. P. Dolomiti-Pasubio | 2.1 | 4 | 1808 | 19.6 | 1 | 4 | 0.54 | 13 | 0.17 |
| 3. Alpago-Cansiglio | 0.5 | 1.7 | 414 | 4.5 | 3 | 4 | 0.86 | 10 | 0.08 |
| 4. Asiago | 1.5 | 2.8 | 1318 | 14.3 | 1 | 0 | 1 | 13 | 0 |
| 5. Grappa | 0.9 | 2.1 | 757 | 8.2 | 1 | 1 | 0.99 | 5 | 0.01 |
| 6. Baldo-Lessini | 1.2 | 3.6 | 1045 | 11.3 | 1 | 2 | 0.76 | 18 | 0.02 |
| 7. Antelao | 0.3 | 0.7 | 244 | 2.6 | 3 | 0 | 0.68 | 6 | 0.08 |
| 8. Pelmo | 0.3 | 0.6 | 243 | 2.6 | 3 | 0 | 0.66 | 9 | 0.04 |
| 9. Cortina | 0.3 | 0.8 | 220 | 2.4 | 2 | 22 | 0.53 | 32 | 0.11 |
| 10. Duranno-Cima Preti | 0.1 | 0.3 | 44 | 0.5 | 3 | 0 | 0.33 | 4 | 0.09 |
| 11. Sorapis | 0.1 | 0.5 | 128 | 1.4 | 3 | 4 | 0.36 | 9 | 0.23 |
| 12. Agner-Pale S.Lucano | 0.1 | 0.5 | 112 | 1.2 | 3 | 2 | 0.51 | 7 | 0.14 |
| 13. Tamer-Bosconero | 0.2 | 0.6 | 188 | 2.0 | 3 | 0 | 0.3 | 6 | 0.06 |
| 14. Marmarole | 0.2 | 0.7 | 161 | 1.7 | 2 | 1 | 0.51 | 9 | 0.07 |
| 15. Tre Cime-Cadini | 0.6 | 1.2 | 547 | 5.9 | 2 | 4 | 0.6 | 9 | 0.08 |
| 16. Civetta-Moiazza | 0.7 | 1.3 | 561 | 6.1 | 2 | 4 | 0.34 | 16 | 0.11 |
| 17. Pale S.Martino | 0.7 | 1.3 | 564 | 6.1 | 2 | 11 | 0.46 | 14 | 0.14 |
| 18. Marmolada | 0.3 | 0.7 | 225 | 2.4 | 3 | 2 | 0.21 | 13 | 0.25 |

Table II: HB estimates. Coefficients for preference space models

| *Prefer. parameters* | Statistics of posterior distribution | | | |
|---|---|---|---|---|
| $\hat{v}$ and $\hat{c}$ | Mean | St. err. | St. dev. | St. err. |
| $\hat{v}$ | –1.29 | 0.04 | 0.73 | 0.25 |
| Degree of difficulty | –0.76 | 0.04 | 0.72 | 0.24 |
| Ferrata | –0.12 | 0.01 | 0.09 | 0.03 |
| % of easy trails | 0.02 | .002 | 0.06 | .001 |
| Alpine shelters | 0.11 | .005 | 0.08 | .001 |
| % of hard trails | 0.09 | 0.01 | 0.10 | 0.03 |
| Prealps ASC | –1.54 | 0.10 | 1.28 | 0.46 |
| Uncorrelated: $\ln \mathcal{L}^*$ at means of post. dist. –20,773.59 | | | | |
| $\hat{v}$ | –1.22 | 0.05 | 0.88 | 0.28 |
| Degree of difficulty | –1.16 | 0.07 | 1.17 | 0.39 |
| Ferrata | –0.19 | 0.01 | 0.23 | 0.06 |
| % of easy trails | 0.04 | .004 | 0.11 | 0.03 |
| Alpine shelters | 0.15 | 0.01 | 0.18 | 0.05 |
| % of hard trails | 0.14 | 0.01 | 0.19 | 0.06 |
| Prealps ASC | –2.74 | 0.16 | 2.84 | 0.94 |
| With correlation: $\ln \mathcal{L}^*$ at means of post. dist. –20,383.65 | | | | |

Table III: MSL estimates. Coefficients for preference space models

| *Prefer. parameters* $\hat{v}$ and $\hat{c}$ | Mean | St. err. | St. dev. | St. err. |
|---|---|---|---|---|
| $\hat{v}$ | –1.41 | 0.06 | 0.71 | 0.06 |
| Degree of difficulty | –0.51 | 0.04 | 0.48 | 0.06 |
| Ferrata | –0.07 | 0.01 | 0.02 | 0.01 |
| % of easy trails | 0.01 | .001 | 0.01 | .002 |
| Alpine shelters | 0.07 | 0.01 | 0.03 | 0.01 |
| % of hard trails | 0.05 | .005 | 0.07 | .005 |
| Prealps ASC | –0.98 | 0.11 | 0.98 | 0.09 |
| Uncorrelated: $\ln \mathcal{L}^*$ at convergence –20,469.86 | | | | |
| $\hat{v}$ | –1.43 | 0.07 | | |
| Degree of difficulty | –0.67 | 0.12 | 0.73 | |
| Ferrata | –0.10 | 0.01 | 0.11 | |
| % of easy trails | 0.01 | .002 | 0.01 | |
| Alpine shelters | 0.09 | 0.01 | 0.08 | |
| % of hard trails | 0.07 | 0.01 | 1.95 | |
| Prealps ASC | –1.62 | 0.25 | 0.07 | |
| With correlation: $\ln \mathcal{L}^*$ at convergence –20,147.91 | | | | |

Table IV: Choleski matrix from MSL estimates in preference space

| *Parameters* | $\hat{v}$ | Degree of difficulty | Ferrata | % of easy trails | Alpine Shelters | % of hard trails | Prealps ASC |
|---|---|---|---|---|---|---|---|
| $\hat{v}$ | 0.92 | | | | | | |
| | (20.4) | | | | | | |
| Degree of diff. | –0.19 | 0.70 | | | | | |
| | (3.9) | (19.7) | | | | | |
| Ferrata | –0.06 | 0.05 | –0.08 | | | | |
| | (5.5) | (6.5) | (7.3) | | | | |
| % of easy trail | 0.001 | 0.002 | 0.002 | 0.01 | | | |
| | (0.4) | (1.3) | (1.0) | (0.7) | | | |
| Alpine shelters | 0.06 | –0.02 | 0.06 | –0.001 | –0.004 | | |
| | (8.1) | (3.5) | (9.6) | (0.1) | (0.7) | | |
| % of hard trail | 0.01 | –0.01 | –0.02 | 0.001 | –0.03 | 0.06 | |
| | (2.8) | (2.2) | (2.0) | (0.9) | (6.1) | (10.8) | |
| Prealps ASC | –1.29 | 0.92 | –0.34 | –0.07 | –0.02 | 1.08 | –0.01 |
| | (7.3) | (8.2) | (2.4) | (0.5) | (4.0) | (14.8) | (0.04) |

($|z$-values$|$ in brackets)

Table V: *WTP* correlations

| *Site attributes* | | | HB estimates | | | |
|---|---|---|---|---|---|---|
| Degree of diff. | 1 | 0.60 | –0.35 | –0.40 | –0.59 | 0.73 |
| Ferrata | 0.43 | 1 | –0.30 | –0.80 | –0.42 | 0.61 |
| % of easy trail | –0.13 | –0.12 | 1 | 0.04 | 0.68 | –0.51 |
| Alpine shelters | –0.20 | –0.48 | 0.04 | 1 | 0.27 | –0.40 |
| % of hard trail | –0.32 | –0.27 | 0.34 | 0.14 | 1 | –0.46 |
| Prealps ASC | 0.63 | 0.48 | –0.14 | –0.38 | –0.21 | 1 |
| | | | MSL estimates | | | |
| Degree of diff. | 1 | 0.80 | –0.80 | –0.66 | –0.73 | 0.71 |
| Ferrata | 0.57 | 1 | –0.52 | –0.93 | –0.46 | 0.83 |
| % of easy trail | 0.16 | –0.07 | 1 | 0.41 | 0.68 | –0.64 |
| Alpine shelters | –0.38 | –0.97 | 0.11 | 1 | 0.33 | –0.75 |
| % of hard trail | –0.21 | –0.02 | –0.04 | 0.02 | 1 | –0.32 |
| Prealps ASC | 0.63 | 0.70 | –0.01 | –0.67 | 0.31 | 1 |

Upper triangular from *WTP* space

Lower triangular from preference space

Table VI: Statistics of simulated *WTP*s from models in preference space in €.

| *Statistics* | Medians | | Means | | St. Dev. | |
|---|---|---|---|---|---|---|
| *Correlated* | No | Yes | No | Yes | No | Yes |
| *Estimator* | Simulated from HB estimates | | | | | |
| Degree of difficulty | –2.35 | –3.04 | –3.62 | –4.52 | 5.44 | 8.77 |
| Ferrata | –0.39 | –0.48 | –0.58 | –0.67 | 0.77 | 1.65 |
| % of easy trails | 0.06 | 0.09 | 0.11 | 0.18 | 0.35 | 0.84 |
| Alpine shelters | 0.34 | 0.36 | 0.51 | 0.40 | 0.65 | 1.29 |
| % of hard trails | 0.28 | 0.35 | 0.44 | 0.53 | 0.73 | 1.44 |
| Prealps ASC | –4.83 | –6.93 | –7.34 | –7.87 | 10.07 | 19.52 |
| *Estimator* | Simulated from MSL estimates | | | | | |
| Degree of difficulty | –1.65 | –2.08 | –2.99 | –3.12 | 6.49 | 7.10 |
| Ferrata | –0.21 | –0.31 | –0.40 | –0.29 | 1.22 | 1.08 |
| % of easy trails | 0.03 | 0.05 | 0.06 | 0.09 | 0.79 | 0.16 |
| Alpine shelters | 0.22 | 0.26 | 0.42 | 0.21 | 1.42 | 0.83 |
| % of hard trails | 0.16 | 0.21 | 0.32 | 0.34 | 2.18 | 0.70 |
| Prealps ASC | –3.31 | –4.72 | –5.75 | –2.67 | 10.10 | 20.77 |

Table VII: HB estimates for *WTP* space models in €.

| *WTP Parameters* | Statistics of posterior distribution | | | |
|---|---|---|---|---|
| $\hat{v}$ and $\hat{w}$ | Mean | St. err. | St. dev. | St. err. |
| $\hat{v}$ | –1.41 | 0.04 | 0.74 | 0.24 |
| Degree of difficulty | –2.80 | 0.16 | 2.24 | 0.83 |
| Ferrata | –0.37 | 0.02 | 0.21 | 0.08 |
| % of easy trails | 0.07 | 0.01 | 0.09 | 0.03 |
| Alpine shelters | 0.35 | 0.01 | 0.17 | 0.06 |
| % of hard trails | 0.30 | 0.02 | 0.23 | 0.08 |
| Prealps ASC | –4.54 | 0.32 | 4.60 | 1.72 |
| Uncorrelated: $\ln \mathcal{L}^*$ at means of post. dist. –20,470.89 | | | | |
| $\hat{v}$ | –1.81 | 0.05 | 0.74 | 0.25 |
| Degree of difficulty | –5.59 | 0.34 | 5.87 | 2.25 |
| Ferrata | –0.60 | 0.05 | 0.74 | 0.28 |
| % of easy trails | 0.16 | 0.02 | 0.27 | 0.09 |
| Alpine shelters | 0.53 | 0.04 | 0.51 | 0.19 |
| % of hard trails | 0.56 | 0.05 | 0.70 | 0.26 |
| Prealps ASC | –7.37 | 0.78 | 13.78 | 5.13 |
| With correlation: $\ln \mathcal{L}^*$ at means of post. dist. –20,325.55 | | | | |

Table VIII: MSL estimates for *WTP* space models in €.

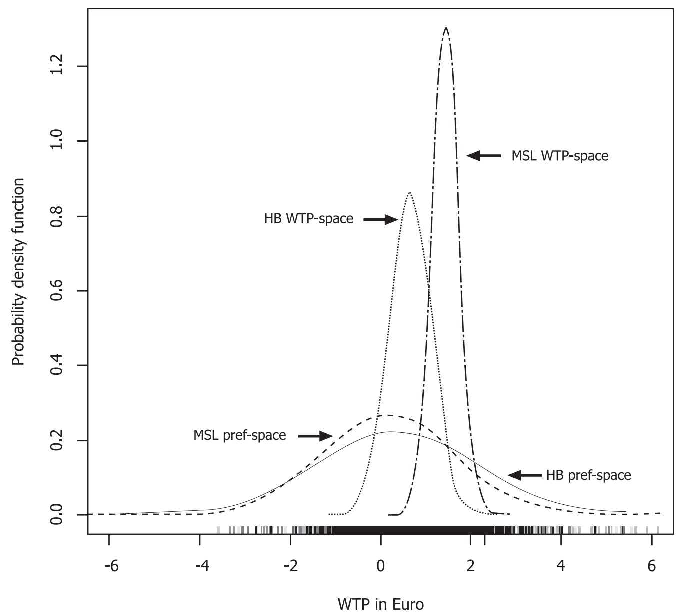
| *WTP parameters* $\hat{v}$ and $\hat{w}$ | Mean | St. err. | St. dev. | St. err. |
|---|---|---|---|---|
| $\hat{v}$ | –1.22 | 0.06 | 0.67 | 0.05 |
| Degree of difficulty | –1.99 | 0.20 | 2.19 | 0.33 |
| Ferrata | –0.31 | 0.03 | 0.06 | 0.04 |
| % of easy trails | 0.07 | 0.01 | 0.03 | 0.01 |
| Alpine shelters | 0.32 | 0.02 | 0.12 | 0.02 |
| % of hard trails | 0.28 | 0.03 | 0.16 | 0.01 |
| Prealps ASC | –4.39 | 0.46 | 3.97 | 0.39 |
| Uncorrelated: $\ln \mathcal{L}^*$ –20,419.91 | | | | |
| $\hat{v}$ | –1.16 | 0.04 | | |
| Degree of difficulty | –2.85 | 0.16 | 2.98 | |
| Ferrata | –0.37 | 0.02 | 0.37 | |
| % of easy trails | 0.10 | 0.01 | 0.08 | |
| Alpine shelters | 0.36 | 0.02 | 0.23 | |
| % of hard trails | 0.37 | 0.02 | 0.38 | |
| Prealps ASC | –5.76 | 0.36 | 2.57 | |
| With correlation: $\ln \mathcal{L}^*$ –20,068.04 | | | | |

Table IX: Choleski matrix from MSL estimates in *WTP* space

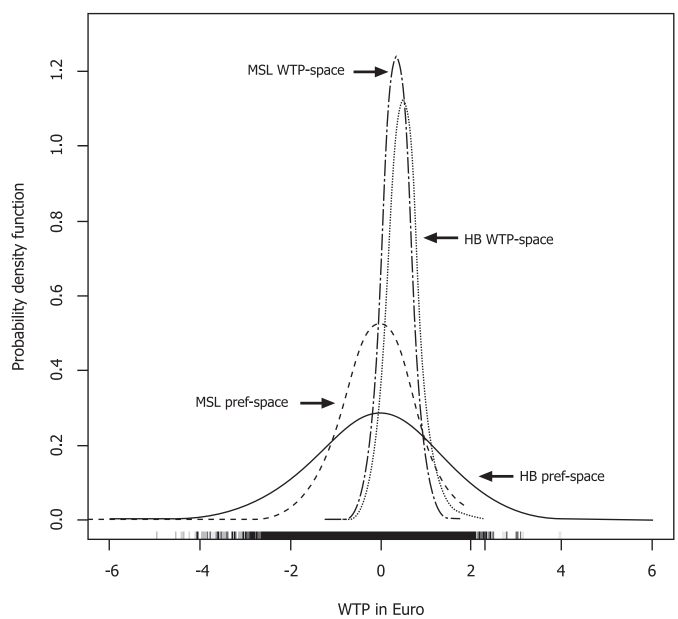
| *Parameters* | $\hat{v}$ | Degree of difficulty | Ferrata | Easy trails | Alpine Shelters | Hard trails | Prealps ASC |
|---|---|---|---|---|---|---|---|
| $\hat{v}$ | –0.043 | | | | | | |
| | (21.5) | | | | | | |
| Degree of diff. | 0.193 | –2.977 | | | | | |
| | (1.7) | (19.4) | | | | | |
| Ferrata | 0.067 | –0.291 | 0.220 | | | | |
| | (2.9) | (11.1) | (9.3) | | | | |
| % of easy trail | –0.007 | 0.060 | 0.015 | –0.043 | | | |
| | (1.1) | (7.5) | (1.3) | (12.5) | | | |
| Alpine shelters | –0.037 | 0.148 | –0.149 | –0.003 | –0.081 | | |
| | (2.2) | (8.8) | (8.5) | (0.3) | (7.0) | | |
| % of hard trail | 0.011 | 0.279 | 0.070 | –0.038 | 0.024 | –0.244 | |
| | (0.5) | (11.2) | (2.2) | (4.3) | (2.1) | (10.5) | |
| Prealps ASC | 2.520 | –4.517 | 2.449 | 1.605 | –0.014 | –1.312 | 2.490 |
| | (7.9) | (11.4) | (7.2) | (5.3) | (1.6) | (4.2) | (14.2) |

($|z$-values$|$ in brackets)

Figure 1: Distributions of *WTP* for one additional alpine shelter at destination.




(a) Models with no correlation.




(b) Models with correlation.