APPLYING THE TRAVEL COST METHOD TO FIFTY ONE MINORCA BEACHES. SOME POLICY RESULTS

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Introduction

Valuation methods can be applied for several purposes. For instance to land management based on social recreational values, or for Natural Resource Damage Assessment. These are only two examples where both revealed and stated preference valuation methods can be used. Within revealed preferences, the Travel Cost Method (TCM) is particularly suitable for valuing coastal recreational uses.

TCM can take different forms. The first variant of TCM applied was the so-called Zonal Travel Cost Method. The original idea was given by Harold Hotelling (1949) in a letter dated June 1947 to the US National Park Service, answering a request for ideas on how to measure the value of parks. Hotelling made the connection between average frequentation from a given zone and the average cost of the visit depending on how close or how far the zone was from the park, and briefly described how the consumer surplus could be derived. This idea was later applied by Clawson (1959) and Clawson and Knetsch (1966), with much influence on future studies.

With the development of econometrics, TCM was able to capture variations in cost and frequentation at individual level instead of relying on zonal averages, giving way to the individual travel cost method (Brown and Nawas 1973). This required that the researcher addresses the problems of selection and truncation of the trips per user, which is the typical dependent variable in the individual travel cost approach (Bockstael et al. 1987a). This was feasible with truncated normal distributions, or more conveniently with count data models (Smith 1988). Thus, the number of visits per period of the individuals is regressed against the cost of the visit and other explanatory co-variables. Then the average individual consumer surplus can be estimated (Creel and Loomis 1990). This is probably the most applied TCM variant.

With the introduction of the Random Utility Model (RUM) and its econometric treatment (McFadden 1974), another TCM variant appeared. It was based on the observation of choices made by individuals (Bockstael et al. 1987b). For instance, an individual wanting to spend a recreational day in a beach may have several to choose from. Each beach might have some different characteristics and the cost associated to travelling to each beach might also differ. Observing choices made and characteristics of each beach in the choice set allows the researcher to apply a discrete choice model consistent with RUM (Haab and McConnell 2002). The nice theoretical properties and practical applicability of the RUM make it widely used.

This chapter illustrates the use of a discrete choice TCM to estimate the recreational value of visitors to the beaches of the Minorca Island, in Spain. It also illustrates its policy use in the context of natural resource damage assessment. Next section develops the theoretical and econometric modeling. It is followed by an explanation of the case study and the results estimated. It ends with some conclusions.

The model

The analysis is based on a RUM model, where participants choose among a set of alternatives, which in this application are the beaches of Minorca. Each beach has different levels of attributes. For the empirical analysis, the choice corresponds to the beach the recreationist went to on the day of the interview. Choices are conditional in the sense that the participants choose which beach to visit, given that they do visit a beach. A "do-nothing" alternative, such as staying at home, is not included in the choice set, since participants are surveyed on-site, i.e. at the beach.

The conditional logit model (McFadden 1974) is commonly used in recreational valuation. It begins by specifying individual random utility for each of the alternatives as a function of the characteristics of the alternatives, u_{ij}, j=1,…,J for individual i, and breaks these utilities into a deterministic and random component: $u_{ij} = v_{ij} + \varepsilon_{ij}$ where v_{ij} are the deterministic components of utility and ε_{ij} are random components, distributed type I extreme value independently across alternatives and individuals. The deterministic components depend on the attributes of the alternatives that affect the utility. These are derived by considering the income given up to reach the alternative and the attributes of alternatives that people enjoy. We denote the attributes for alternative j, individual i as $X_{ij}\beta$ so that we can write $u_{ij}=X_{ij}\beta$. This model gives the probability that individual i chooses alternative j as a function of attributes that vary by alternative and unknown parameters (Haab and McConnell 2002).

A feature of the conditional logit model is the possibility of including variables that differ among alternatives and respondents. It is the case of the cost attribute in our empirical application. The cost attribute varies among alternatives; the cost may differ for individuals for a given alternatives. It is feasible to allow individuals from different locations to select their best alternative from different choice sets. However, in our application individuals may choose from all of the island's beaches, regardless of their initial location. Random utility models applied to recreational choices typically assume that the impact of a change in cost is constant both with respect to increasing costs and among different alternatives. This is a consequence of assuming a constant marginal utility of income in the random utility model.

Let X_{ij} denote the vector of attributes of site *j*. The probability that individual *i* chooses alternative *j* is

$$\Pr_i(j) = \frac{e^{X_{ij}\beta}}{\sum_{k=1}^{J} e^{X_{ik}\beta}},$$

where β is a vector of unknown parameters to be estimated and *J* the number of alternatives.

Unlike in the multinomial logit model, individual characteristics, such as age or gender, cannot be directly included in the model, as they do not vary among alternatives. It is however possible to interact those with beach characteristics, or the alternatives, to check, for instance, whether men attach a different importance to the orientation of the beach than women. To do so we would interact the personal characteristics with attributes that vary across alternatives.

We are interested in estimating the welfare impact of a variety of beach closures on Minorca. To estimate the loss of welfare implied by the closure of several sites, we calculate a representative WTP. Stated purely in behavioural terms, the value of lost access to a beach *j* for the individual *i* would be

$$WTP_{ij} = -\ln(1 - \Pr_i(j)) / \beta_y,$$

where WTP_{ij} corresponds to the willingness to pay of individual *i* for beach *j*, $\Pr_i(j)$ the probability for the individual to choose beach *j* and β_y the marginal utility of income. When several sites are involved, the WTP for each beach cannot be added up to obtain the total WTP, since substitution among sites needs to be considered. The following formula may however be used (Haab and McConnell 2002):

$$WTP_{iJ*} = -\ln(1 - \sum_{h=1}^{J*} \Pr_i(h)) / \beta_y, \qquad [1]$$

where *J**, is a subset of the *J* beaches. For example, to assess the loss of access to a group of five beaches (say some west-facing group), the welfare loss for individual *i* would correspond to

$$WTP_{i5} = -\ln(1 - \Pr_i(1) - \Pr_i(2) - \Pr_i(3) - \Pr_i(4) - \Pr_i(5)) / \beta_y .$$

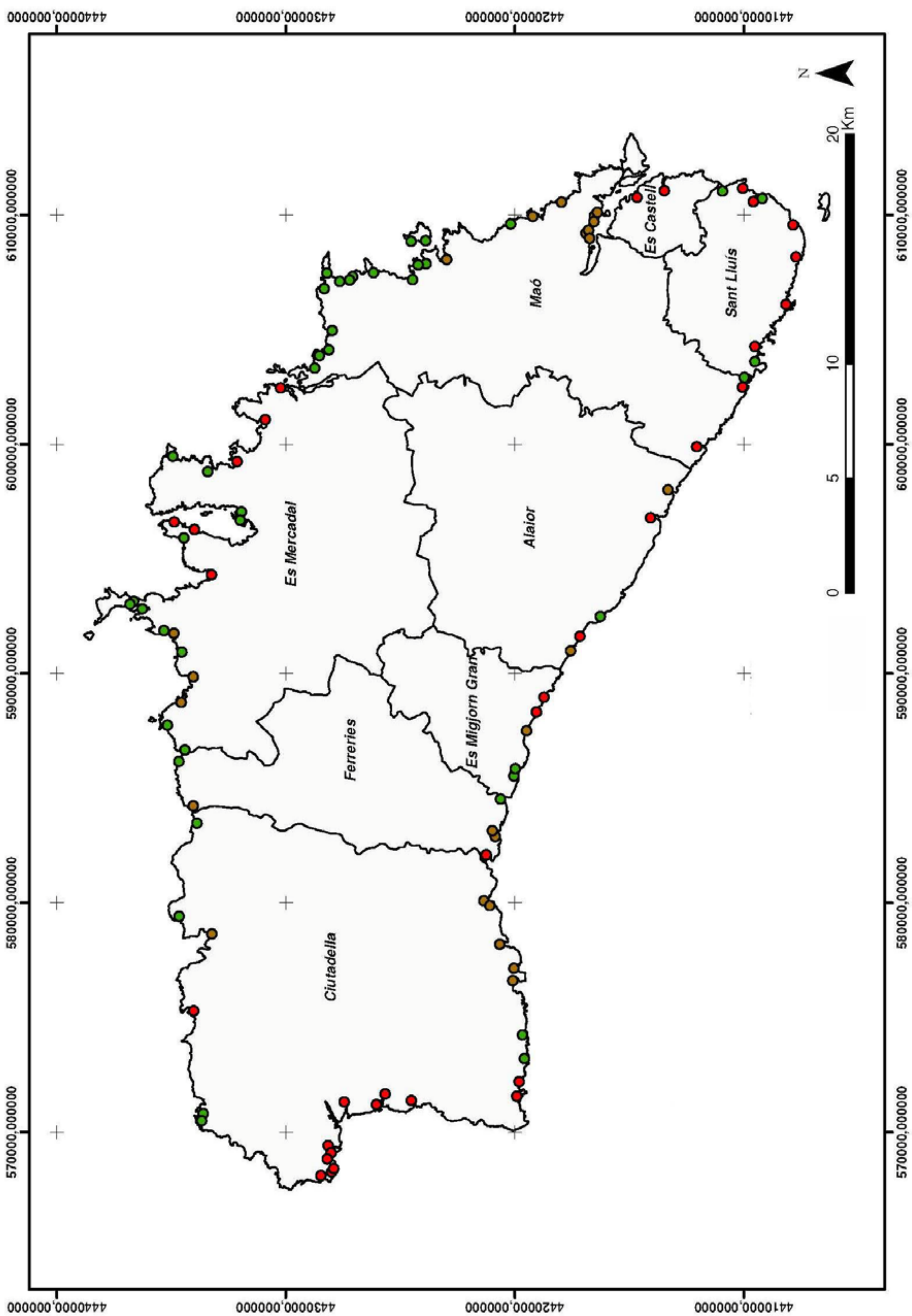
This represents the willingness to pay to avoid loss of access for a given individual. The individual probabilities naturally vary, and when some respondents live close to the sites being lost they will suffer greater losses. This expression in willingness to pay reveals the higher losses as the probabilities get bigger.

Case study

In the summer of 2008 we surveyed users of Minorca beaches. Minorca is a Balearic island in the western part of the Mediterranean Sea, belonging to Spain. Its surface is of circa 700 square kilometers, with a length of 53 kilometers and a perimeter of 216 kilometers. The combination of nature, beaches and sunny weather makes it a popular tourist attraction in the summer months. With a bit more than 80 thousand permanent residents, its population went up to 150 thousand in July 2008 and reached an average of 175 thousand people present in the island during the month of August. Tourism is the main economic activity of the island, accounting for near two thirds of its GDP. According to the Consell Insular de Menorca counts, an average of circa 25000 people enjoyed the beaches of Minorca during a peak season day, in August of 2008.

Figure 1 shows a map of Minorca with the municipalities and the location of the beaches. A common classification used in the island to group beaches goes from type A, with an urbanized environment to type C, or unspoiled beaches only reachable by foot, with type B being reserved to non-developed beaches with car access to its vicinity.

Figure 1. Municipal map of Minorca Island with the points indicating the location of beaches


Ciutadella
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The sample followed a distribution based on the frequency of past visitation. For beaches of type A and B, which are the most frequented, the sample was representative of the number of visitors at beach level. Some contiguous beaches that are often considered separately from an ecological perspective were pooled together because they were perceived as a single beach for the purposes of sampling in the study. Thus, 20 type A and 22 type B beaches were taken into account. For C beaches, the least frequented were pooled together in one representative beach, because there was much less than one person per beach to be interviewed according to sample proportionality. A total of 9 type C beaches were sampled. Altogether, 573 individuals were surveyed in 51 beaches. Interviews were performed face-to-face, on-site, with an average duration of 15 minutes each. The survey instrument gathered user data concerning limited household characteristics and alike. In addition, the origin of the trip was recorded. No particular implementation problems were found.

The questionnaire was designed for a travel cost method exercise. It asked questions about the origin of the trip, the means of transportation, party composition, socioeconomic characteristics, and attitudinal questions on different beach attributes and leisure activities. Also interviewers had to complete a questionnaire with beach characteristics. Table 1 shows some of the variables collected –the ones that were found most significant in the econometric analysis, as will be explained later.

Table 1. Variables of interest

VARIABLES [a]	Description	Mean	Standard Deviation
COST	Travel cost, including time of travelling at 5 Euros per hour (in 2008 Euros)	13.467	5.778
EAST	East facing beach	0.176	0.381
SOUTH	South facing beach	0.510	0.500
WEST	West facing beach	0.098	0.297
BLUE_FLAG [b]	Beach awarded blue flag quality	0.196	0.397
NUDISTS	Presence of nudists	0.373	0.483
URBAN	Beach at an urban environment (type A)	0.235	0.424
CLEANING	Beach cleaned periodically	0.490	0.500

TOILET	Toilets available nearby the beach	0.294	0.456
DRINK	Drinks sold nearby the beach	0.412	0.492
TEMPERATURE	Average water temperature (Degrees Celsius)	25.235	1.214
CROWDED	Beach crowded	0.627	0.483
ALGAE	Presence of algae	0.118	0.322
CALM	Sea usually calm	0.725	0.446
LIFE_GUARD	Presence of lifeguard	0.627	0.483
THIN_SAND	Presence of thin sand (thick sand - reference level)	0.843	0.364

[a] All variables but travel cost and temperature are indicators variables, taking the value 1 when the statement about the beach is true.
[b] Blue flags are awarded following criteria dealing with water quality, environmental education and information, environmental management, and safety and other services. The *Blue Flag Programme* is run by the Foundation for Environmental Education.

The cost of the trip was estimated by means of transportation software. Origin and destination were entered in the trip planning software of Via Michelin web site (http://www.viamichelin.com). The software accounts for speed limits in the different types of roads. The output provided the estimated road distance, time and cost of the trip. The walking distance, e.g. from the parking lot to the beach, was estimated using Google maps (http://maps.google.com).

Travel cost is composed of fuel cost, tolls and the value of travel time. Travel time was calculated accounting for the different speed limits of the road involved. Walking time was calculated at an average speed of 4 kilometers per hour. We would expect that individuals would have the opportunity of their travel time to depend on household characteristics. However, the typical characteristics are not available in this survey. Consequently the value of time was set to 5 euros per hour for all respondents. The cost variable accounts for the round trip.

The data was organized in a panel manner. It was assumed that the individual that chose the particular beach could have gone to any other beach of the island. Travelling to any beach of the island is doable within a recreational day. We have structured problem such that each interview with an individual forms a choice, with the beach where the individual is interviewed being the beach chosen and all of the other beaches comprising the rest of the choice set. Each interview creates a choice occasion, with the data represented by 51 alternatives with alternative-specific data. The survey completed 573 interviews. 17 interviews were dropped, due to non-recorded or misreported origin of the trip. The 556 remaining interviews create the equivalent of 28356 observations (51X556).

Results

The conditional logit model is estimated with NLOGIT 4.0 statistical software. Three models are reported, starting with a more general one. Results are shown in Table 2. The likelihood function is the standard RUM likelihood. Because we have sampled in proportion to the population of users, it is not necessary to weight individual probabilities by the onsite weights.

The most general model included all the variables from table 1. The signs of the significant variables are in accordance with a priori expectations. The COST variable has the expected negative sign —equivalent to the negative value of the marginal utility of income. As is usual in random utility models, the travel cost coefficient is highly significant. We classified beaches based on their orientation—facing north east, south or west. The three included orientations, facing east, south and west, are all negative and significant. This implies the north facing beach, the excluded alternative, has a positive effect. The impact of facing north probably embeds some landscape characteristics, being remarkably divers and attractive. Other covariates are also significant. A good environmental and educational quality denoted by a blue flag, with lifeguards, the sand being thin, nudism present at the beach, periodical cleaning, and toilets and drink selling facilities all contribute positively to the utility of the alternative. Also, warmer waters are preferred. On the other hand urban beaches, crowded beaches and presence of algae contribute negatively to the utility. Finally people seem to prefer beaches with surf to calm waters, although variable CALM is not significant at 10 percent level of significance.

Table 2. Results of the Conditional Logit Model Estimation

VARIABLES	Model I COEFFICIENTS (STANDARD ERRORS)	Model II COEFFICIENTS (STANDARD ERRORS)	Model III COEFFICIENTS (STANDARD ERRORS)
COST	-0.190***	-0.190***	-0.190***

	0.012	0.011	0.011
EAST	-1.224*** 0.205	-1.268*** 0.202	-1.384*** 0.196
SOUTH	-0.357** 0.167	-0.468*** 0.134	-0.428*** 0.131
WEST	-1.973*** 0.258	-2.017*** 0.259	-1.957*** 0.255
BLUE_FLAG	0.456*** 0.136	0.400*** 0.129	0.456*** 0.126
NUDISTS	0.433*** 0.112	0.416*** 0.110	0.407*** 0.108
URBAN	-.692*** 0.184	-0.658*** 0.180	-0.695*** 0.160
CLEANING	0.358*** 0.110	0.326*** 0.108	0.390*** 0.098
TOILET	0.305** 0.129	0.261** 0.116	0.243** 0.112
DRINK	0.710*** 0.147	0.721*** 0.138	0.691*** 0.131
TEMPERATURE	0.188*** 0.050	0.202*** 0.049	0.209*** 0.047
CROWDED	-0.284* 0.145	-0.259* 0.140	-0.299** 0.137
ALGAE	-0.266* 0.160	-0.242 0.155	
THIN_SAND	0.286* 0.169	0.247 0.171	
CALM	-0.216 0.172		
LIFE_GUARD	0.073 0.119		
Log-Likelihood	-1789.833	-1790.621	-1792.571
Pseudo R2	0.181	0.181	0.180
N	28356	28356	28356

* 10% significance level; ** 5% significance level; *** 1% significance level two-tailed tests.

The second model excludes the two variables that were not significant at 10 percent level in the first model, calm waters and the presence of lifeguards. There was no change in the signs of the remaining variables, although two of them were no longer significant, the presence of algae and the beach having thin sand. The change in the log-likelihood value from the first to the second model was not statistically significant, with a likelihood ratio test statistic of 1.58 whereas the critical value for 0.05 level and 2 degrees of freedom is 5.99.

A third model was estimated excluding the two non-significant variables from the previous one. This rendered with all variables significant at 0.01 level, except for crowded beaches, significant at 0.05.

There was no change in the signs of the coefficients and only small changes in their magnitude. The likelihood ratio test of the third model with respect to the second one and to the first one indicates no significant change in the model fit. Furthermore, moving from the first general model to the most restricted one has almost no impact on the estimates of the significant variables. In particular, the COST coefficients vary at the fourth decimal only. Thus, being the most parsimonious, we choose the third model for welfare estimates.

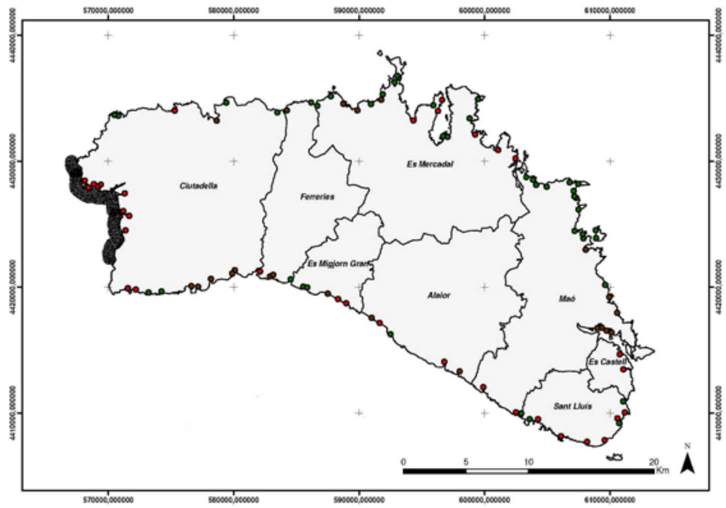
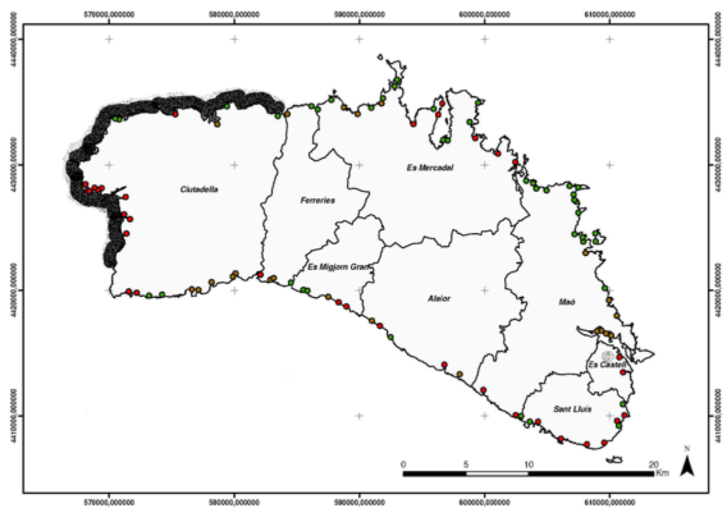
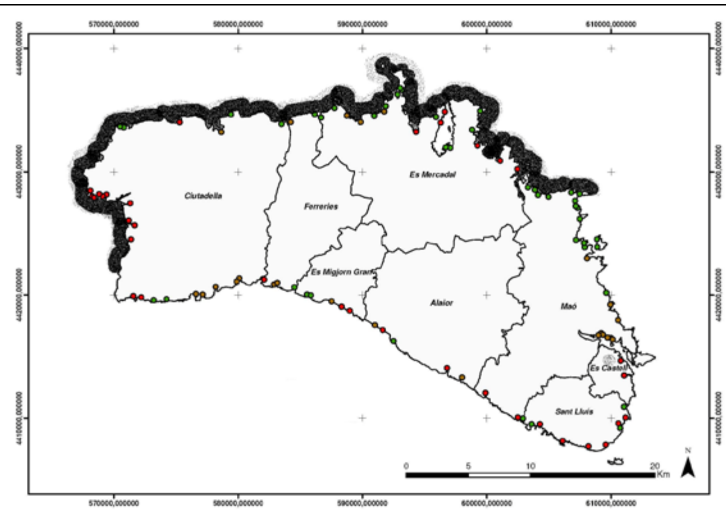
One of the clear advantages of the RUM is their flexibility in modeling welfare changes. Researchers can investigate the welfare effects of changes in the attributes at a single site or a group of sites. The welfare implications of closing various sites can also be computed in a straightforward way with the RUM. The manner in which the RUM handles substitution among alternatives makes it an attractive approach to computing welfare. The recreationist is assumed to be fully informed about all sites, and can switch from one to another by paying only the difference in travel costs to the different sites. In practice, individuals are driven to an extent by habits. They find a beach they like and visit it repeatedly. As a consequence, the welfare estimates tend to be quite low, reflecting easy substitution. In the absence of formal models of inertia or habit formation, this might represent the longer run welfare loss, when the individuals have had time to learn about alternatives. In the Menorca case, where the recreationists are tourists, there may be less inertia, and so the direct estimates might give a more accurate measure of welfare gains and losses.

To illustrate the welfare estimation with the discrete choice travel cost method, assume an environmental damage, e.g. caused by an oil spill, results in the closure of the beaches of the west coast, around the city of Ciutadella (see Figure 2, scenario 1). The probability of visiting these beaches is 0.043 and the WTP to avoid the recreational loss is of 24 cents of euro, in 2008 values, per daily beach visit on the island, which are 25000 during the peak period. At aggregate level, this implies a total daily welfare loss of 6000 euros (table 3). This represents the daily welfare loss to users of the beaches. It does not include losses to vendors of beach services—bars umbrella rentals, etc.

Table 3. Welfare loss associated with closing different beaches from an oil spill in three simulated scenarios

Scenario	Beaches	Probability of visiting	WTP/visit to avoid loss of the sites (euros of 2008)	Total welfare loss per day during peak season (euros of 2008)
1	West	0.045	0.24	6000
2	West and Ciutadella North	0.084	0.46	11500
3	West and North	0.280	1.73	43250

Figure 2. Municipal map of Minorca Island with the points indicating the location of beaches and the dark coastal ribbon indicating the extend of the effect of an oil spill in three simulated scenarios

Scenario 1 West oil spill	
Scenario 2 West and Ciutadella North oil spill	
Scenario 3 West and North oil spill	

Assume next that the oil spill spreads northwards to affect the northern beaches of the municipality of Ciutadella (Figure 2, scenario 2). The probability of visiting the beaches would then be 0.08, and the welfare loss would be of 46 cents per beach recreationist. If the accident happened during peak season, it would daily decrease the aggregate welfare in 11,500 euros per day.

Finally, suppose the oil spreads farther, to the rest of the north beaches (Figure 2, scenario 3). The probability of visiting the west and north beaches would go up to 0.28, and the average individual welfare loss would be 1.73 euros per day, or a total of 43.250 euros per day during peak season.

Conclusions

Discrete choice travel cost is becoming more popular, being rooted in the RUM model and requiring relatively little information. A case study of this TCM variant has been presented involving the beaches of the Minorca Island, in the Mediterranean Sea. A large dataset (more than 28 thousand lines of observation) gave way to stable conditional logit model results. The results can be used to estimate the welfare loss from natural resource damages. To illustrate it, a simulation of closing some of the beaches has been presented. If only the west beaches were affected, the daily welfare loss would be 6000 euros; if the oil spill extends to the northern beaches of Ciutadella, the loss would go up to 11500 euos; and if western and northern Minorca beaches had to close, the estimated daily recreational loss would be 43250 euros.

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