Employing Travel Costs to Compare the Use Value of Competing Cultural Organizations

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Abstract. Since recently, a number of studies have applied non-market valuation techniques to measure the value of cultural goods. All studies are single case applications and rely mostly on stated preferences, such as contingent valuation techniques. We compare the relative value of multiple, competing goods and show how revealed preferences, in particular travel costs, may be used for this. In addition, we account for heterogeneity. Using a unique transaction database with the visiting behavior of 80,821 Museum Cardholders to 108 Dutch museums, we propose a latent class application of a logit model to account for the different distances of museums to the population and for differences in willingness-to-travel.

Key words: museums, non-market valuation, revealed preferences, travel cost method.

1. Introduction

An important area in cultural economics is determining the social value of cultural goods, in particular vis-à-vis government subsidy. A number of studies have tried to justify the use of public funding by investigating the value people place on particular cultural goods. Latest development in this field has been the use of non-market valuation techniques. Applications have covered a variety of national issues such as a general willingness to support the arts (Thompson et al., 2002) or television programming (Finn et al., 2003; Papandrea, 1999), as well as a number of single site cases, such as the Bosco di Capodimonte park (Willis, 2002) and Napoli Musei Aperti (Santagata and Signorello, 2000) in Italy, Lincoln Cathedral in England (Pollicino and Maddison, 2001), a historic shipwreck state park in North Carolina, United States (Whitehead and Finney 2003), or the Royal Theatre of Copenhagen in Denmark (Bille Hansen, 1997). In reviewing this development, three observations can be made:

Firstly, almost all applications are based on stated preferences (*see also* Navrud and Ready 2002). Main advantage of stated preference techniques is that they can capture both use value and non-use value of a cultural good. The validity of the respondent's answer to a hypothetical question, however, has raised considerable debate (*see* Noonan, 2003; Throsby 2003). Also, subtle, seemingly irrelevant changes in the information about the good, the response format, or the question sequence can have substantial effects on the elicited willingness to pay (*e.g.,* Green et al., 1994). Revealed preferences, such as travel costs, have the advantage of modeling actual behavior in real life situations. We believe that for measuring use value, either as a single component (Forrest et al., 2000) or as part of estimating total value (Martin, 1994), these techniques merit more research interest than has been the case so far in cultural economics[1].

Secondly, all applications of non-market valuation techniques in cultural economics have been limited to single case applications. Navrud and Ready (2002) voice the general concern that single case studies may be biased; the measured WTP may reflect the respondent's general attitude to all similar goods rather than the particular good in question. If estimates of social value are to represent realistic values, one needs to introduce choice options in the measurement process; especially since choice among complementary or substitute alternatives are an important aspect of consumers' valuation of cultural goods. So far, applications with choice options have consisted only of choices within one site or organization (*e.g.,* Alberini et al., 2003; Finn et al., 2003; Whitehead and Finney, 2003). There have been no attempts to determine the relative value of an organization or site in comparison to competition.

Thirdly, with the exception of Morey and Rossmann (2003), non-market valuation studies into cultural goods so far have not considered differences in preferences. However, several recent studies in cultural economics have shown that there is substantial heterogeneity in preferences, with groups of people differing in their patronage behavior (e.g., *cinema:* Cuadrado and Frasquet, 1999; *music:* Prietro-Rodríguez and Fernández-Blanco, 2000; *theatre:* Corning and Levy, 2002; Urrutiaguer, 2002; *general cultural market:* López-Sintas and García Álvarez, 2002). Morey and Rossmann (2003), too, find segments that differ in their willingness to pay. Hence, it seems likely that there are segments that differ in how they rank competing cultural organizations in their utility.

The aim of this study is to show how *revealed* preferences, in this case travel costs[2], can be used to compare the use value of *multiple, competing* cultural organizations. In particular, we show the importance of accounting for the different probabilities in visiting these organizations, given the consumers' relative distance to the various sites. In addition, we show that the market is heterogeneous in how cultural organizations are ranked in their utility.

The remainder of this study is organized as follows. First, we introduce the Dutch National Museum Card organization and their data on the visiting behavior of their cardholders. Using the revealed preferences of 80,821 cardholders for 108 museums across The Netherlands, we show that two simpler forms of ranking, total number of visits and average travel time of visitors, reveal very different rankings of museums due to the different distributions of people and museums across the country. For this reason, we argue that a site choice logit model is more appropriate as it accounts for the likelihood of visiting a particular museum. We then develop a latent class application of a logit model and show that there are segments of museum patrons that differ in their willingness to pay travel costs. We conclude with a discussion of the results and limitations and suggest directions for future research.

2. The Dutch National Museum Card

In The Netherlands, an important tool in promoting museum attendance is the National Museum Card, issued by the Dutch Museum Association (NMV). In return for an annual fee of € 25 for adults or € 12.50 for anyone younger than 26 years, cardholders get free access to 442 museums in this country; the only remaining cost per visit being the cost of traveling. At the 150 largest participating museums, cardholder visits are logged electronically. These data are collected and stored on a central server to aid reimbursement to the museums. The Dutch Museum Association supplied us with the transaction data of the visits to these 150 museums for the period March 2000 – January 2003.

Fields in the dataset provided are the customer number, type of card (youth or adult), the museum, the date and time of the visit and the zip codes of both museum and visitor. Using a commercial GIS database that contains travel distance and travel time by road for every zip code combination in The Netherlands, travel distance and travel time were added to the dataset for each recorded visit. As the choice for some museums may differ across seasons, we selected the visits of one full year (2002) from this dataset, so that all seasons are represented equally. Furthermore, not all 150 museums had provided visiting data in all twelve months. Some of the museums are not open all year round and some museums faced incidental closure due to major refurbishments. To avoid distortion of the results by these temporal closures, only museums that were able to provide data for all twelve seasons were retained. This subset of 108 museums shows substantial variation in size, type of collection and location. Table I presents the key figures of the resulting dataset:

Table I. Overview of the dataset

Number of museums participating	108
Number of cardholders in the dataset	80,821
Number of visits recorded in dataset	346,978
Average number of visits per cardholder	4.3
Average number of different museums visited per cardholder	3.3
Average travel time in minutes	44.9

As shown in Table I, cardholders on average made 4.3 visits to 3.3 of the 108 museums in our dataset; i.e., occasionally, museums were visited more than once. Note that the average of 4.3 visits is not caused by a lack of choice. A preliminary analysis of the dataset reveals that within the common willingness to travel of 44.9 minutes, the average cardholder has 29.5 out of the 108 museums to choose from. The museums visited are therefore likely to reflect a real utility to the cardholder.

3. Comparing museums by use value

3.1 Ranking by key indicators

In museum management practice two key indicators seem prevalent in analyzing and reporting the value the general public places on the museum. The first and foremost is "number of visitors". It is the most readily available statistic on museums and allows for easy measurement and communication of success. The second key indicator often used is "average travel time" or "service area", measured in questionnaires by asking zip codes or nationality. The ability to attract visitors from all places seems equally suitable in communicating a certain position in the field. Furthermore, data on "average travel time" or "service area" is tightly connected to strategic choices in the level of communication efforts or the level at which private or public funding can be attracted (i.e., local, regional or national). Sometimes, this is communicated as an economic value, as tourists may result in additional spending in that area (*cf.* economic impact studies).

Popular perception is that large or "Superstar" museums attract many visitors and from further away (e.g., Frey, 1998), whereas smaller museums attract much fewer visitors and have a smaller service area. In this view, either "number of visitors" or "average travel time" as measurement of use value would likely result in a similar ranking. As both seem readily available and are easily calculated from the transaction data, the question arises why – if our only aim is to compare museums in their use value – we cannot simply use either variable for ranking. However, as shown in Table II, the two variables lead to a very different ranking of museums:

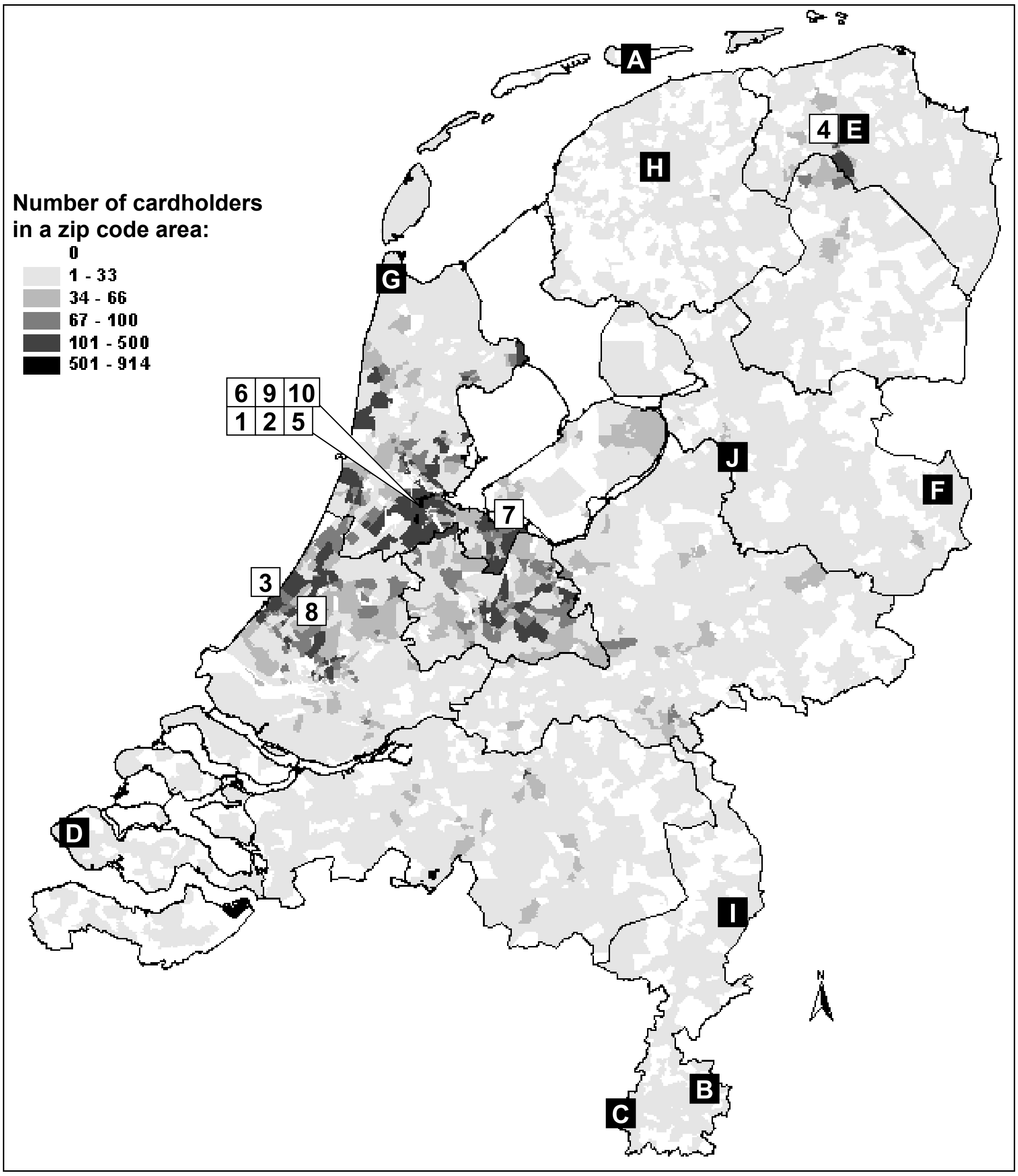
Table II.
Top ten museums by total number of cardholder visitors and by average travel time of visiting cardholders

Museum	# visitors
1. Rijksmuseum Amsterdam	34,236
2. Stedelijk Museum Amsterdam	23,067
3. Haags Gemeentemuseum	22,250
4. Groninger Museum	18,527
5. Van Gogh Museum	17,301
6. Cobra Museum Amstelveen	12,540
7. Singer Museum	11,343
8. Mauritshuis	10,173
9. Amsterdams Historisch Museum	9,580
10. Joods Historisch Museum	8,695

Museum	Avg. travel time in min.
A. Natuurcentrum Ameland	233.1
B. Industrion	130.3
C. Bonnefantenmuseum	119.6
D. Zeeuws Biologisch Museum	117.8
E. Groninger Museum	101.7
F. Natura Docet Natuurmuseum	95.9
G. Marinemuseum	86.1
H. Fries Museum	80.4
I. Limburgs Museum	78.6
J. Hannema-De Stuers Fundatie	78.0

When the relative value of a museum is judged by its number of cardholder visits, the Rijksmuseum Amsterdam is by far the most valued museum. However, when the relative value of a museum is judged by the average travel time of the visiting cardholders, the Natuurmuseum Ameland is the most valued museum. In other words, museums that attract the most visitors are not necessarily the museums that attract people from a greater area and vice versa. In table 2, only the Groninger Museum scores high in both types of ranking. Explanation for the different outcomes of the two variables can be found in the different distributions of people and museums across the country, shown in Figure I:

Figure I.
Number of Museum cardholders per 4-digit zip code area with locations of the museums in either top ten ranking



As can be seen in Figure I, the ten museums ranking highest in number of visits are all located in or near the “Randstad”, the most densely populated area of The Netherlands, formed by the four largest cities of the country and their suburbs. In fact, six out the top ten museums ranked by number of visits (1, 2, 5, 6, 9, 10) are located in the capital city of Amsterdam. With also so much more cardholders living in their direct vicinity, it is not surprising that these museums find it easier to attract a larger crowd. Museums that are located in more rural areas are therefore at a disadvantage when value is measured in terms of number of visitors. On the other hand, however, the ten museums ranking highest in average travel time are all located in the periphery of the country. A peripheral location allows for a greater travel time, with the largest possible distance from one border to another border as its maximum. Note that the maximum travel distance possible for a museums located in the centre of the country is only half this distance. Museums that are located centrally are therefore at a disadvantage when value is measured by average travel time of their visitors. This is particularly true in The Netherlands, where all distances back and forth can be covered in a single day.

Straightforward modeling of use value by “number of visitors” or “average travel distance” of visitors is only appropriate when all people and museums are distributed equally. However, as shown, museums differ in the number of people in their vicinity and maximum travel distance by which visitors can show the utility they perceive. As a simple model to compare multiple sites in their use value, either of these two variables seems inappropriate.

3.2 ACCOUNTING FOR SPATIAL DISTRIBUTIONS OF PEOPLE AND MUSEUMS: SITE CHOICE MODELS

Site choice models try to estimate which of several sites will be preferred and chosen by an individual on a given occasion. Visitors will have several sites to choose from on a given occasion. Each site offers different levels of utility to the visitor as well as different travel costs. The utility is inferred by comparing visitation patterns with the probability that a visitor would have chosen particular cultural goods. As the preceding discussion underlines, a travel cost method for determining the relative use value of various museums would be enhanced substantially if it accounts for the different probabilities of visiting a particular museum. This is precisely what site choice models do. So far, there have been no applications of site choice models in cultural economics.

The most common form of site choice modeling is the multinomial logit model. McFadden (1974, 1981) provides a choice theoretic foundation for this model on which the following discussion is based. Assume that the utility for respondent *j* of visiting museum *i* equals:

$$u_{ji} = \alpha_i + \beta d_{ij} + \mu \varepsilon_{ji} \tag{1}$$

In this equation d_{ji} is the distance from consumer *j* to museum *i*, ε_{ij} is the realization of a random variable and α, β and μ are parameters. The expression $\mu\varepsilon_{ij}$ is accordingly referred to as the random part of the consumer's utility, whereas the other two terms on the right-hand-side constitute the systematic part. The utility in (1) should be interpreted as the net utility of visiting museum *i* for consumer *j*. The gross utility equals $\alpha_i + \mu\varepsilon_{ij}$ and it indicates the value consumer *j* attaches to visiting museum *i* if he would not have to travel. The random part of the utility is assumed to have expectation 0 and α_i can therefore be interpreted as the expected value of the utility of visiting museum *i*. Note that (ticket) price is not part of our formulation, since we analyze cardholders, who have free access to all museums in the dataset.

The difference between gross and net utility is the disutility caused by traveling from one's home to the museum. According to (1) this disutility is proportional to the distance d_{ji}, which is measured as travel time. The linearity of (1) implies that there is a simple trade-off between the utility of a museum and the disutility of traveling. Indeed, it is easy to verify that the maximum distance d_i* a visitor is willing to travel to realize a gross utility α_i is equal to:

$$d_i{}^* = -\frac{\alpha_i}{\beta} \tag{2}$$

If we know the value of time (*vot*), the monetary value *V* of a museum can be determined as the product of the *vot* and the maximum travel time d_i*:

$$V_i = -vot\, d_i\, ^* \tag{3}$$

We can, of course, only compute the value of the museums if we can estimate the parameters of the utility functions. In order to be able to do this, one should derive the behavioral implications from (1) and assume that the consumer chooses to visit the museum that gives him the highest net utility. If we make the standard assumption that all ε_{ij} s are identical and independent extreme value type I distributed, the probability $p_{j,i}$ that an individual chooses museum *i* is:

$$p_{ji} = \frac{e^{v_{ji}}}{\sum_m e^{v_{jm}}} \tag{4}$$

with:

$$\begin{aligned} v_{ji} &= \frac{\alpha_i}{\mu} + \frac{\beta}{\mu} d_{ji} \\ &= a_i + b\, d_{ji} \end{aligned} \tag{5}$$

The variables v_{ji} that appear in the choice probabilities are therefore equal to the ratio between the systematic part of the consumer's utility and μ. The parameter μ is proportional to the variance of the random part of the utility. If this variance is small, the consumers tend to choose the museum with the highest systematic utility with probability 1, whereas a large variance of the random part tends to make all choice probabilities equal. We can only estimate a_i and b, but not the underlying parameters α, β and μ. In fact, we can only estimate the differences (a_i-a_r) for an (arbitrary) reference museum r[3]. These standard identification issues for the multinomial logit model imply that we are unable to estimate V_i, but we can estimate the difference between the values of any two museums[4]:

$$\begin{aligned} V_i - V_{i'} &= -vot\left(d_i * - d_{i'} *\right) \\ &= -vot\left(\frac{\alpha_i}{\beta} - \frac{\alpha_{i'}}{\beta}\right) \\ &= -vot\left(\frac{a_i - a_r}{b} - \frac{a_{i'} - a_r}{b}\right) \end{aligned} \tag{6}$$

Since we can estimate the numerator and the denominator of the two expressions appearing in brackets in (6), we can compute the difference between the values of any two museums. Note that the parameter *b*, which refers to the disutility of traveling, is crucial in this computation. This shows that the logit model formulated here offers a generalization to the travel cost method.

Many individuals in our sample make more than one trip to some museum and in order to deal with this phenomenon we introduce some additional notation. We use the index *k* to distinguish these trips from each other and let *i*(*k*) denote the alternative chosen for the *k*-th trip. For all these trips, the choice probabilities are assumed to be given by (4), which means that different realizations of the random variables are relevant for each choice. This is in accordance with our interpretation of the random part of utility as referring to idiosyncrasies of the choice situation. Let *K*(*j*) be the total number of trips made by individual *j*. The probability *P* of observing the specific combination of choices made by individual *j* is:

$$P(j) = \prod_{k=1}^{K(j)} p_{j,i(k)} \tag{7}$$

The likelihood *L* is the product of these probabilities:

$$L = \prod_{j} P(j) \tag{8}$$

The logarithm of this likelihood is:

$$
\begin{aligned}
LL &= \sum_{j} \ln(P(j)) \\
&= \sum_{j} \sum_{k=1}^{K(j)} \ln(p_{j,i(k)}) \\
&= \sum_{j} \sum_{k=1}^{K(j)} \left(v_{j,i(k)} - \ln\left(\sum_{m} e^{v_{j,m}} \right) \right)
\end{aligned} \tag{9}
$$

Maximization of this likelihood function results in the estimates of the standard logit model. We have (arbitrarily) chosen the Groninger Museum as our reference. Table III shows the results of the top ten museums with highest estimated parameter a_i-a_r, expressing the attractiveness of the museum (relative to the Groninger Museum).

Table III. Top ten museums by estimated parameter

Museum	a_i - a_r	Ranking by # visitors	Ranking by avg travel dist.
Groninger Museum	0	4	E
Rijksmuseum Amsterdam	-1.12540	1	-
Natuurmuseum Ameland	-1.19554	-	A
Haags Gemeentemuseum	-1.29904	3	-
Stedelijk Museum Amsterdam	-1.52027	2	-
Bonnefantenmuseum	-1.62294	-	C
Van Gogh Museum	-1.80791	5	-
Paleis Het Loo Nationaal Museum	-2.06020	-	-
Mauritshuis	-2.11333	8	-
Zuiderzeemuseum	-2.13590	-	-

As our base reference, the Groninger museum, is also the most attractive museum, all parameters of other museums are negative. More interestingly, the ranking includes both museums that scored high in number of visits, as well as museums that scored high in average travel distance of its visitors (Table II), with the only museum that scored high on both variables as the most attractive museum.

Although this application of a general site choice model is fair in that it accounts for the different probabilities of visiting particular museums, it does not take into account the individual differences in willingness to travel caused by the different contexts of visits. Museum visits are likely to be part of a multi purpose trip. Differences in such contexts may lead to a different willingness to travel. For instance, one segment may prefer to visit museums in combination with any of the other attractions a large city has to offer. Another segment may like to visit museums as part of a short holiday break in that region. The nature of the trip is likely to influence the cardholder’s willingness to travel. By looking for segments that differ in their willingness to travel, we may find segments with different rankings of museums that are typical for the different contexts. Note that the resulting rankings would then also be fairer in comparing relative use value of each museum, as the museums are compared within a similar context.

3.3 ACCOUNTING FOR DIFFERENCES IN WILLINGNESS TO TRAVEL

Many simple approaches to heterogeneity in economics treat it as identifiable from the effects of exogenous variables. That approach is overly restrictive. Other early approaches treated heterogeneity as a nuisance; fixed effects models were applied, in which individual-level constants were included in the model, which could be estimated directly. Later, conditional likelihood approaches were used in which the choice model was formulated conditional upon sufficient statistics for the individual-level parameters, eliminating the individual level constants from the models and simplifying the estimation task. Heckman and Singer (1984) first approximated the distribution of those individual level constants by S support points and probability masses. Their specification leads to a multinomial distribution of the mixing distribution of the intercept. Then, economists recognized that heterogeneity is of fundamental interest by itself. See the *Journal of Econometrics* for a recent discussion, e.g. Allenby and

Rossi (1999) and Wansbeek, Wedel and Meijer (2001). First, the support point approach was extended to all parameters in the choice model, which results in a finite mixture model as used in the present paper. These models have received considerable attention in marketing and transportation research, since they have an elegant interpretation in terms of market segments underlying consumer choice. A technical advantage is that the maximum likelihood estimation is straightforward. Developments on finite mixture models have been reviewed recently by, for example, McLachlan and Peel (2000) and Wedel and Kamakura (2000). The assumption of a (multivariate) normal mixing distribution for the coefficients, leads to random coefficient logit models, or mixed logit models. Such models have been widely applied to microeconomic problems. While the models themselves are identical, they are often referred to as Hierarchical Bayes models (Allenby and Lenk 1994) when estimated with the Markov Chain Monte Carlo Methods, and as Mixed Logit (Revelt and Train 1998) when estimated by simulated likelihood. This is the approach to Contingent Valuation used by Morey and Rossman (2003). In both MCMC and simulated likelihood inference the possibly high dimensional integrals in the likelihood are approximated through sampling. While current empirical evidence favors neither the continuous nor the discrete representation of heterogeneity (Andrews, Ansari and Currim 2002), in this paper we choose to focus on the finite mixture MNL model. Next to simplicity of estimation an important advantage of this class of models dealing with heterogeneity of subjects, is that they connect elegantly to theories of market segmentation, that postulate the existence of groups in the population with different behavior (Wedel and Kamakura 2000).

The latent class model assumes that consumers are heterogeneous in the sense that there are two or more groups (or segments) with different preferences (*see* Wedel et al., 1993; Wedel and DeSarbo, 1995). For each group, behavior is described by a standard logit model, as discussed above. However, the parameters a_i and b are different for each group. Let q_k be the probability that an actor belongs to group k. In the simplest case, in which there are two groups, the probability that individual j chooses museum i at his or her k-th trip will be denoted as $pl^2_{j,i(k)}$ and is equal to:

$$pl^2_{j,i(k)} = q_1 p^1_{j,i(k)} + q_2 p^2_{j,i(k)} \tag{10}$$

where $p^n_{j,i(k)}$ denotes the logit choice probabilities for latent class n. The probability of observing the particular combination of choices made by individual j is:

$$PL^2(j) = q_1 \prod_{k=1}^{K(j)} p^1_{j,i(k)} + q_2 \prod_{k=1}^{K(j)} p^2_{j,i(k)} \tag{11}$$

This formula takes into account that all choices made by this individual are based on the same preferences (i.e. each individual belongs always to the same class, which is a constraint that is needed for model identification). The logarithm of the likelihood is:

$$\begin{aligned} LL &= \sum_j \ln(PL^2(j)) \\ &= \sum_j \ln\left(q_1 \prod_{k=1}^{K(j)} p^1_{j,i(k)} + q_2 \prod_{k=1}^{K(j)} p^2_{j,i(k)} \right) \end{aligned} \tag{12}$$

The probability that an individual belongs to class 1 must lie between 0 and 1 and it is therefore convenient to specify it in such a way that this is guaranteed. For this reason, we use the following reparameterization:

$$q_1 = \frac{1}{1+e^{c_1}} \tag{13}$$

The latent class model gives a non-parametric approach to the heterogeneity in the sample of respondents and it is often found that a limited number of mass points give a good fit to the data (*see* Heckman and Singer, 1984). We estimated models with 2, 3 and 4 latent classes. Estimation of the model with 5 latent classes was impossible because of (almost) perfect separation[5]. Information about the estimation results of the various models is provided in Table IV:

Table IV. Some statistics of estimated models

Number of latent classes	Ln(Likelihood)	Number of parameters	AIC	CAIC	BIC
1	-1.262.999	107	2.526.213	2.527.315	2.527.208
2	-1.226.545	215	2.453.520	2.455.735	2.455.520
3	-1.213.065	320	2.426.769	2.430.065	2.429.745
4	-1.207.557	427	2.415.967	2.420.365	2.419.938

The log-likelihood increases at a decreasing rate when more classes are distinguished. For each group we estimate 106 attractiveness parameters, one distance decay parameter and one parameter referring to the relative size of the group[6]. The Akaike Information Criterion (AIC) is equal to $-2\ln(L)+2p$ where L denotes the likelihood of the model and p the number of estimated parameters. Model selection can be based on this criterion by choosing the one with the lowest value. Table IV shows that this suggests to select the model with 4 classes. Related to the AIC are the Bayesian Information Criterion (BIC) and the Consistent Akaike Information Criterion (CAIC) (Schwartz, 1978; Bozdogan, 1987), which put a higher penalty on adding coefficients to the model. These criteria also point at selection of the model with four classes. The top 10 rankings of each of the four latent classes are shown in Table V:

Table V. Top ten museums by estimated parameter for each latent class

Group 1 (size = 45.1%)	$a_i - a_r$	Group 2 (size = 19.4%)	$a_i - a_r$
Groninger Museum	0	Natuurmuseum Ameland	3.914736
Rijksmuseum Amsterdam *(R)*	-0.54747	Groninger Museum	0
Haags Gemeentemuseum *(R)*	-0.6983	Bonnefantenmuseum	-2.83072
Van Gogh Museum *(R)*	-1.15019	Noordelijk Scheepvaartmuseum	-4.21262
Stedelijk Museum Amsterdam *(R)*	-1.16435	Natuurmuseum Groningen	-4.24441
Mauritshuis *(R)*	-1.47307	Industrion	-4.73062
Singer Museum *(R)*	-1.4885	Fries Museum	-5.04448
Bonnefantenmuseum	-1.51818	Princessehof Leeuwarden	-5.47349
Cobra Museum Amstelveen *(R)*	-1.72125	Rijksmuseum Twenthe	-6.52019
Joods Historisch Museum *(R)*	-1.81393	Fries Natuurmuseum	-7.07272

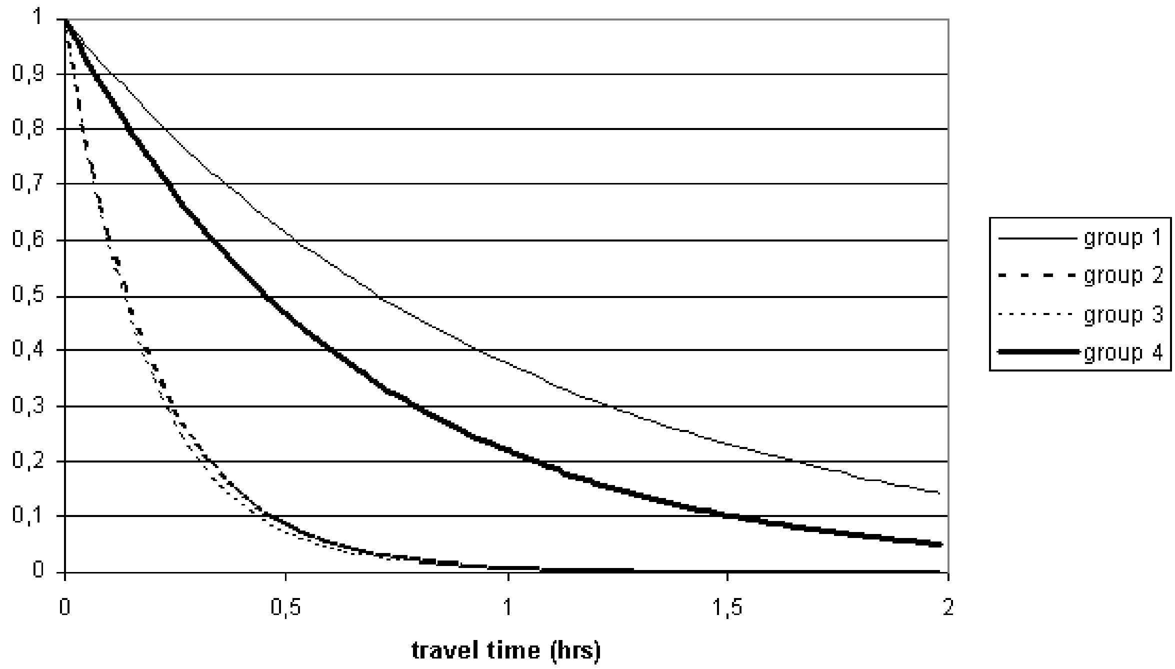
Group 3 (size = 17.8%)	$a_i - a_r$	Group 4 (size = 17.7%)	$a_i - a_r$
Zeeuws Biologisch Museum	1.012599	Groninger Museum	0
Zuiderzeemuseum *(R)*	0.709294	Zuiderzeemuseum	-0.08942
Rijksmuseum Amsterdam *(R)*	0.605999	Paleis Het Loo	-0.14705
Naturalis *(R)*	0.558438	Naturalis *(R)*	-0.29998
Museon *(R)*	0.026191	Natuurmuseum Ameland	-0.37013
Amsterdams Historisch Museum *(R)*	0.012279	Bonnefantenmuseum	-0.90283
Groninger Museum	0	Museon *(R)*	-1.03953
Rijksmuseum voor Volkenkunde *(R)*	-0.20559	Ned. Spoorwegmuseum *(R)*	-1.09757
Tropenmuseum *(R)*	-0.227	Ecodrome	-1.22266
Ned. Spoorwegmuseum *(R)*	-0.23201	Industrion	-1.22477

(R) = located in or very near to the Randstad

Although a few museums appear in the top ten of multiple segments, overall the four segments differ substantially in their ranking. The top ten museums in Group 1 are mostly large art museums, located in the large cities in the Randstad (indicated by an *R*), the most densely populated area of The Netherlands. In Group 2's top ten, eight museums are located in the (far) north of the country and comprise a mix of regional museums, three of which are concerned with local nature. The top ten museums of Group 3 are mostly large well-known museums in the Randstad with a variety of collections. Finally, the top ten museums in Group 4 are larger museums located away from the Randstad, again with a variety of collections.

Also, the four groups differ in their sensitivity to distance. The coefficients *b* are equal to -0.98, -4.92, -5.28 and -1.52, for group 1, 2, 3 and 4, respectively. For groups 2 and 3 the friction caused by distances appears to be much larger than for the other two groups. This is illustrated in Figure II, which pictures the distance decay functions $\exp(b\, d_{ij})$:

Figure II. Distance decay functions



The curves in this figure show the ratio between the probability that a particular museum will be visited if the distance to that museum is given by the value on the horizontal axis and the probability at distance 0 [7]. All curve start at the value 1, but the curves for groups 2 and 3 decline much faster than those for groups 1 and 4. Respondents belonging to groups 2 and 3 will hardly ever visit a museum for which they have to travel more than one hour. For respondents belonging to group 1, one hour travel time decreases the probability of visiting a museum by approximately 60%. Although this is still a substantial effect, it implies that museums that are sufficiently attractive still have a relatively large probability of being chosen. The position of group 4 is in between that of group 1 and groups 2 and 3. Although the segments differ in their willingness to travel and where to, they are very similar in where they live, in terms of their distribution across the twelve counties in The Netherlands, as shown in Table VI:

Table VI. Ranking of the county of residence for each latent class

Group 1	Group 2	Group 3	Group 4
Noord-Holland	Noord-Holland	Noord-Holland	Noord-Holland
Zuid-Holland	Zuid-Holland	Zuid-Holland	Zuid-Holland
Utrecht	Utrecht	Utrecht	Utrecht
Noord-Brabant	Gelderland	Gelderland	Gelderland
Gelderland	Noord-Brabant	Noord-Brabant	Noord-Brabant
Groningen	Groningen	Overijssel	Groningen
Overijssel	Overijssel	Groningen	Overijssel
Drenthe	Drenthe	Friesland	Drenthe
Friesland	Friesland	Drenthe	Friesland
Limburg	Limburg	Limburg	Limburg
Zeeland	Zeeland	Flevoland	Flevoland
Flevoland	Flevoland	Zeeland	Zeeland

For all four classes, most of the cardholders live in Noord-Holland and the least number of cardholders live in Flevoland or Zeeland. The logit model does account for differences in where cardholders live and where museums are located. Apparently, the differences in how far and where to people are willing to travel are caused by other reasons. Transaction data hold no direct information about motivations or reasons. However, in light of the previous discussion on multi purpose trips and the influence of different contexts on willingness to travel, it is interesting to note that most of the museums in the top 10 of segment 1 and 3 are located in the major cities, suggesting that other amenities available in such urban areas may have influenced willingness to travel. Museums in the top 10 of segment 2 and 4, on the other hand, are mostly located in rural areas, with particularly the museums in the top 10 of segment 2 being typical destinations that are part of short holidays in the country. Without additional survey based research we cannot be sure whether the latent class application has adequately addressed the issue of multi purpose trips, and the tendencies to engage in them by these segments. However, as the latent groups clearly differ in how the museum visits could have been combined (with city attractions or with a holiday in the country), we believe that this at least constitutes an interesting avenue for further research.

Using the few variables available in the dataset, we can further illustrate some of the different backgrounds of the four segments (Table VII):

Table VII. Profiles of the different latent classes

	Group 1	Group 2	Group 3	Group 4
Avg # of visits	**4.8**	**4.5**	3.7	3.3
Avg travel distance in min.	**56.6**	29.7	24.3	**52.5**
% of youth cards in group	10.5	11.3	**20.3**	**28.9**
% of visits in (primary) school holidays	29.3	29.2	32.4	**40.6**
Type of collection:				
Art	**50.4**	**49.1**	**33.3**	**13.7**
Historical	0.6	0.3	1.0	0.4
Cultural history	38.8	33.9	32.5	40.2
Science	**2.0**	**5.6**	**10.3**	**18.2**
Transport and Technique	**3.8**	**5.9**	**8.7**	**11.9**
Ethnographic	1.8	3.2	6.6	6.5
Maritime	1.7	0.9	3.3	5.2
Other	0.8	1.1	4.2	4.0
Total	100.0	100.0	100.0	100.0

The four groups seem to differ most on the average travel distance in minutes versus the percentage of youth cardholders. Groups 1 and 2 have a very similar profile on most variables, but the willingness to travel of Group 2 is about half as large as that of Group 1. This may perhaps have to do with age, a variable that unfortunately is not registered in the dataset. Group 3 and 4 are also reasonably similar on a number of variables, but differing substantially in their willingness to travel. In addition, Group 4 has a higher percentage of youth cards, a subsequently higher percentage of visits during school holidays, and less likely to visit art museums, particularly in comparison to Group 1 and 2. Where the four groups seem to be equally spread out over the country, the profiles suggest that the four groups have very different backgrounds and interests.

4. Discussion

The aim of this study was to show that the use value of multiple organizations can be compared using travel costs, but that one needs to account for the different probabilities in visiting the museums, given the consumers' relative distance to the various sites. Secondly, the willingness to travel depends on a number of individual and situational differences and the market is thus heterogeneous in the utility function. We have developed a latent class logit model to address these two issues and have shown its application. We think that this approach has much to offer in valuing cultural goods such as museums, in particular since it shows the *relative* use value of competing museums. An important aspect of government subsidy for arts organizations is that multiple organizations contend for the same, limited budget. The summed social value of all potential arts beneficiaries is likely to exceed available budget and choices will have to be made. Modeling relative use value may be of help in justifying the distributing limited governmental resources. In addition, because it provides valuation for segments in the population, which enables museums to position themselves to specifically appeal to those segments in the population (Wedel and Kamakura, 2000).

4.1 LIMITATIONS

The data set used in this research has the distinct advantage that it captures a wide range of different museums, locations, competitive situations and travel distances. As such, we believe it is an excellent starting point for exploring the willingness to travel and the factors influencing this willingness. However, there are, of course, also limitations to our approach. Firstly, although the latent class application seems an interesting idea to address the issue of multi purpose visits at least in part, much more research is required to determine how the context of a visit influences the willingness to travel and how the context may be derived from travel costs. Advances in this area would contribute significantly to an important shortcoming of all travel costs applications. Mixture modeling such as our latent class application may be an interesting perspective.

Furthermore, the database does not register which parts of the museum have been visited by the cardholders; whether they come for one exhibition in particular or just for the main collection. Particularly blockbuster exhibitions can have a substantial influence on attendance and willingness to travel and are not captured as such in our model. With the trend towards temporary exhibitions (Hutter, 1998), this is a shortcoming of the present study. However, one might argue that to some extent, variables such as museum size or prestige partly account for this effect. It will be the larger, more prestigious museums that have larger exhibitions and therefore become more prestigious or grow in renown.

Finally, the annual fee of the National Museum Card roughly equals four to five times the average admission charge for a museum in The Netherlands. Subscribers are therefore likely to be museum visitors who anticipate going more often and for whom the card is a financially attractive option (although, as pointed out by Nunes (2000), this does not mean that these subscribers actually go that often). Other segments, such as tourists or non-cardholders may be less willing to travel or their willingness may be influenced differently. For instance, for these segments a museum's prestige or renown may be more important in influencing their willingness to travel. Furthermore, the museums in the database are the 150 largest museums in The Netherlands. Although these museums show a considerable range in popularity, types of museums and location characteristics, they are not representative of all museum types. Particularly museums such as small local archeological or cultural history exhibits may attract a different audience of local inhabitants and occasional tourists.

4.2 Suggestions for further research

Although a survey will be limited in covering the number and range of museums, it may be an attractive next step in further research. The factors in our model have been inferred from the limited user variables in the database. The survey would allow further investigation of the segments and the use of other variables such as socio-demographics, type of transport or the role of particular exhibitions. The results of the present study can be a starting point in the design of such a study. This would enable us to combine the sources of stated and revealed preferences in a single model, to obtain even more accurate insights into the valuation of cultural goods by consumers.

Notes

[1] Epstein (2003) argues that revealed preferences, too, may be called into question. As Epstein correctly points out, exchange value is not the same as use value; it is only a minimum bound. However, our aim is not to determine the absolute use value, but the relative value of organizations in comparison to others. Assuming that the average difference between exchange value and use value is the same for all museums, this issue seems negligible here. In addition, Epstein argues that choices may in hindsight be regretted and therefore not truly reflect preferences. Assuming that such erroneous choices are not structural, this would be captured in the error term in our model. Given that we base our estimation on 80,821 people making 346,978 choices, we believe that such errors are unlikely to influence our results.

[2] Another type of revealed preferences, hedonic pricing, is not discussed here. In hedonic price techniques, market goods have different levels of a non-market good as add-on benefit. By comparing the different prices for the different levels of the non-market good attached to the market goods, one can infer the marginal implicit price for this non-market good. An example mentioned by Navrud and Ready (2002) is the influence of cultural heritage goods on house prices. Such techniques seem more appropriate for monuments than museums, the subject of this study.

[3] The reason is that the choice probability in (4) does not change if we add an arbitrary constant to all v_{ji}s.

[4] An easy way to check this derivation is to simplify the bottom line, substitute (2) and finally use (3).

[5] The parameters in one group ‘exploded’: their absolute values became vary large.

[6] The latter parameter is not estimated when all respondents are considered as a single group. When two or more groups are distinguished, a small number of parameters had to be fixed in order to prevent them to attain very large negative numbers, thereby causing numerical problems. This happened for the attractiveness parameters of some museums with a relatively small number of visitors. Note that all museums included in the estimation procedure have at least 250 visitors. The model suggests therefore that some museums are unattractive for some groups. For these museums the attractiveness parameters have been set equal to –20. The implied choice probability is virtually equal to 0.

[7] Strictly speaking this statement is only approximately true. It ignores the fact that a change in the distance to one museum does not only change the nominator of the left-hand-side of (4), but also the denominator.

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