Journal of Cultural Economics (2005) 29: 19–33

Employing Travel Time to Compare the Value of Competing Cultural Organizations

JAAP BOTER[1], JAN ROUWENDAL[2] and MICHEL WEDEL[3]

[1]*Department of Marketing, Faculty of Economics and Business Administration, Vrije Universiteit Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands;*
(E-mail: jboter@feweb.vu.nl)
[2]*Department of Spatial Economics, Faculty of Economics and Business Administration, Vrije Universiteit Amsterdam, The Netherlands*
[3]*Michigan Business School, University of Michigan, Ann Arbor, U.S.A.*

Abstract. A number of studies have applied non-market valuation techniques to measure the value of cultural goods. Virtually all of these 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 time, 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, particularly in relation to the level of 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. The 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. First, almost all of these applications are based on stated preferences (see also, Navrud and Ready, 2002). The 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 those in evidence in the distance or time traveled by visitors, 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; Poor and Smith, 2004) 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]

Second, virtually all of the 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.

Third, 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 segments 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). 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 revealed through willingness to travel,[2] can be used to compare the relative value of *multiple, competing* cultural organizations. In particular, we show the importance of accounting for the different probabilities of 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 travel. 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 to 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. Unfortunately, not all of these 150 museums had provided visiting data for all 12 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 temporary closures, only museums that were able to provide data for all 12 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.

As shown in Table I, on average cardholders 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

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

44.9 min, 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.

The size of this dataset 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 a good starting point to explore the visitors' willingness to travel and to compare museums in this respect. However, there are several disadvantages to using transaction data such as these that should not be left unnoted.

First, we have very limited socio-economic information on the visitors – only age as a dummy variable (youth card or adult card). Also, the size of the party is unknown; the system does not register whether some cardholders travel together. In conventional travel cost method applications, travel distance or time are multiplied by a percentage of the wage rate to estimate travel costs. Other socio-economic variables are often used as control variables (cf. Forrest et al., 2000; Poor and Smith, 2004). Because such information is unavailable here, we can only compare travel *time* and assume all visitors to be equal in their costs per travel unit.

Second, the dataset holds no background information on the nature of the trip. We do not know whether a particular part or exhibition of the museum was visited. Here, we assume this to be captured by the overall attractiveness of the museum. Of greater concern is that we do not know whether a visit was part of a multi-purpose trip and how travel time thus has to be valued. We will return to the issue of multi-purpose trips in the final stage of our model and suggest a possible solution to this issue.

Finally, museum card subscribers are likely to be museum visitors who anticipate going more often and for whom the card is a financially attractive option. Although the card enjoys broad popularity, we cannot assume the cardholders to be representative of all museum visitors. The results thus reflect the value for a large, but particular group of visitors.

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 a wide area seems equally suitable in communicating a certain position in the field. Furthermore, data on "average travel time" or "service area" are 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 increased tourism may result in additional spending in that area (cf. economic impact studies).

Popular perception is that large or "Superstar" museums attract many visitors from further away (e.g., Frey, 1998), whereas smaller museums attract fewer visitors and have a smaller service area. In this view, either "number of visitors" or "average travel time" as a 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 this ranking. However, as shown in Table II, the two variables lead to a very different ranking of museums.

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 for a single trip, 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 II, only the Groninger Museum scores high in both types of ranking. Note that the long average travel times for some of the museums in Table II also raise the question whether these are single purpose trips, an issue we will address later.

Explanation for the different outcomes of the two variables can be found in the different distributions of people and museums across the country. The 10 museums ranking highest in number of visits are all located in or near the "Randstad", the

Table II. Top 10 museums by total number of cardholder visitors and by average travel time of visiting cardholders

Museum	# Visitors	Museum	Average travel time in min (single trip)
1. Rijksmuseum Amsterdam	34,236	A. Natuurcentrum Ameland	233.1
2. Stedelijk Museum Amsterdam	23,067	B. Industrion	130.3
3. Haags Gemeentemuseum	22,250	C. Bonnefantenmuseum	119.6
4. Groninger Museum	18,527	D. Zeeuws Biologisch Museum	117.8
5. Van Gogh Museum	17,301	E. Groninger Museum	101.7
6. Cobra Museum Amstelveen	12,540	F. Natura Docet Natuurmuseum	95.9
7. Singer Museum	11,343	G. Marinemuseum	86.1
8. Mauritshuis	10,173	H. Fries Museum	80.4
9. Amsterdams Historisch Museum	9580	I. Limburgs Museum	78.6
10. Joods Historisch Museum	8695	J. Hannema-De Stuers Fundatie	78.0

most densely populated area of the Netherlands, formed by the four largest cities of the country and their suburbs. In fact, six of the top 10 museums ranked by number of visits (1, 2, 5, 6, 9, 10) are located in the capital city of Amsterdam (Figure 1). With so many 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

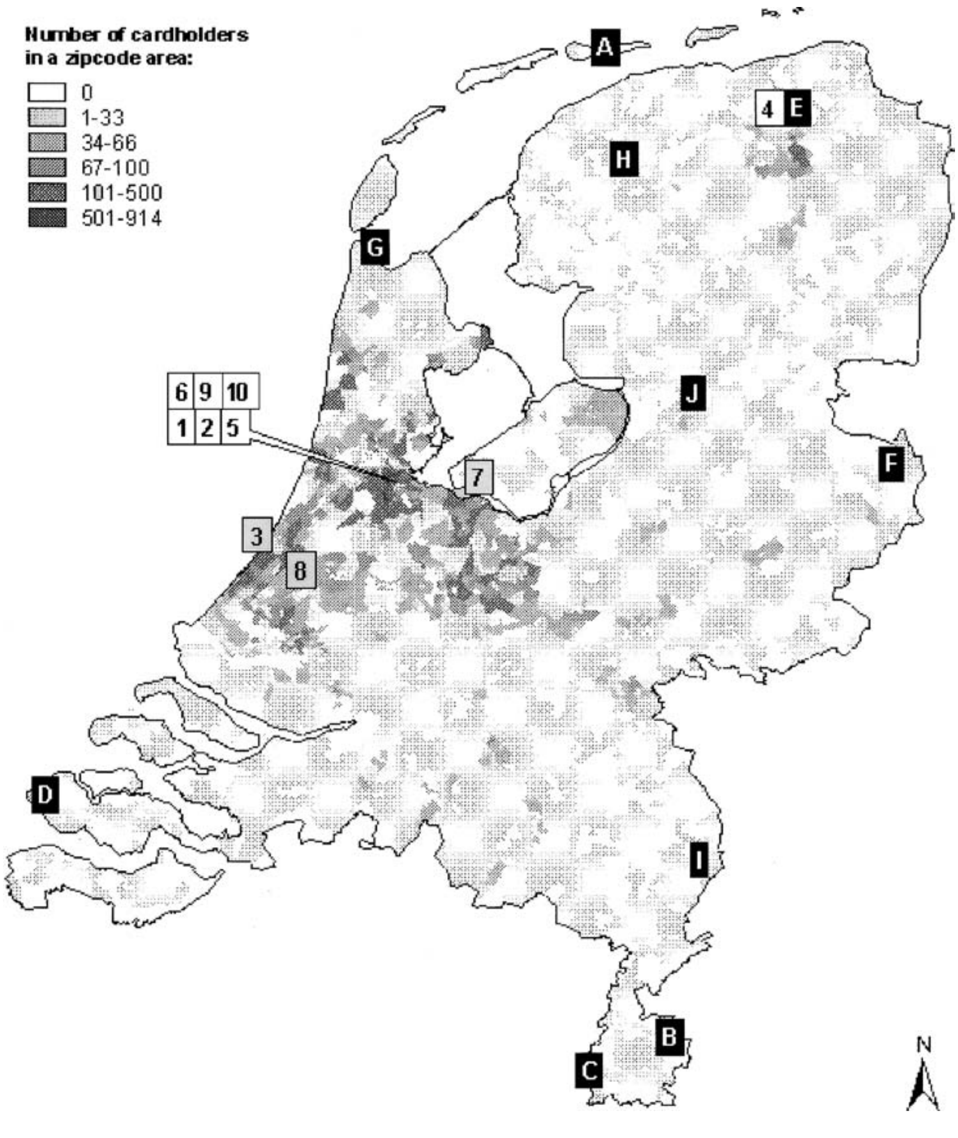

Figure 1. Number of Museum Cardholders by four-digit zip code area and locations of the museums in each top 10 ranking. Note: Numbers and letters refer to the museums in each top 10 ranking as tabulated in Table II.

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 10 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 museum located in the center 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 most 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 through which visitors reveal 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 THE SPATIAL DISTRIBUTION 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. Visitors will have several sites to choose from on a given occasion. Each site offers different levels of utility to the potential 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 method focusing on travel time 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. As far as we are aware, 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:

$$u_{ji} = a_i + b\,d_{ij} + \varepsilon_{ji} \tag{1}$$

In this equation d_{ji} is the distance from consumer *j* to museum *i*, ε_{ij} is the realization of a random variable, and a, and b are parameters. The term ε_{ij} is accordingly referred to as the random part of the consumer's utility, whereas the other two terms on the right-hand side of the equation 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 $a_i + \varepsilon_{ij}$ and it indicates the value consumer *j* would attach to visiting museum *i* if he did not have to travel. The random part of the utility is assumed to have exceptation 0, and a_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. Note that we cannot estimate the parameter α. In fact, we can only estimate the differences $(a_i - a_r)$ for an (arbitrary) reference museum r.[3] Maximization of the likelihood function under the standard assumption that the error term has an extreme value distribution results in the estimates of the standard multinomial logit (MNL) model.[4] We have (arbitrarily) chosen the Groninger Museum as our reference. Table III shows the results for the top 10 museums with highest estimated parameter $a_i - a_r$, expressing the attractiveness of the museum (relative to the Groninger Museum). 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 time of its visitors (Table II), with the only museum that scored high on both variables as the most attractive museum.

3.3. ACCOUNTING FOR DIFFERENCES IN WILLINGNESS TO TRAVEL

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 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

Table III. Top 10 museums by estimated parameter

Museum	$a_i - a_r$	Ranking by # visitors	Ranking by average travel distance
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 National Museum	−2.06020	–	–
Mauritshuis	−2.11333	8	–
Zuiderzeemuseum	−2.13590	–	–

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.

In this paper we choose to focus on the finite mixture MNL model. An important advantage of this class of models dealing with heterogeneity of subjects is the simplicity of estimation (Wedel and Kamakura, 2000). The latent class model assumes that consumers are heterogeneous in the sense that there are two or more segments with different preferences (see Wedel et al., 1993; Wedel and DeSarbo, 1995). For each segment, behavior is described by a standard logit model, as discussed above. However, the parameters a_i and b are different for each segment.[5] Estimation of the latent segments and the MNL models within each segment is done simultaneously by maximizing the likelihood function. 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 five latent classes was impossible because of (almost) perfect separation[6].

The log-likelihood increases at a decreasing rate when more classes are distinguished. For each segment we estimate 106 attractiveness parameters, one distance decay parameter, and one parameter referring to the relative size of the segment[7]. 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. Here, results suggest selecting the model with four latent 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 latent classes. The top 10 rankings of each of the four latent classes are shown in Table IV (upper half).

Although a few museums appear in the top 10 of multiple segments, overall the four segments differ substantially in their ranking. The top 10 museums in Segment 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 Segment 2's top 10, 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 10 museums of Segment 3 are mostly large well-known museums in the Randstad with a variety of collections. Finally, the top 10 museums in Segment 4 are larger museums located away from the Randstad, again with a variety of collections.

Table IV. Top 10 museums by estimated parameter for each segment

Segment 1 (45.1%)	$a_i - a_r$	Segment 2 (19.4%)	$a_i - a_r$	Segment 3 (17.8%)	$a_i - a_r$	Segment 4 (17.7%)	$a_i - a_r$
Groninger Museum	0	Natuurmus. Ameland	3.91	Zeeuws Biologisch Mus.	1.01	Groninger Museum	0
Rijksmus. Amsterdam (*R*)	−0.55	Groninger Museum	0	Zuiderzeemuseum (*R*)	0.71	Zuiderzeemuseum	−0.09
Haags Gemeentemus. (*R*)	−0.70	Bonnefantenmuseum	−2.83	Rijksmus. Amsterdam (*R*)	0.61	Paleis Het Loo	−0.15
Van Gogh Museum (*R*)	−1.15	Noord. Scheepvaartmus.	−4.21	Naturalis (*R*)	0.56	Naturalis (*R*)	−0.30
Sted. Mus. Amsterdam (*R*)	−1.16	Natuurmus. Groningen	−4.24	Museon (*R*)	0.03	Natuurmus. Ameland	−0.37
Mauritshuis (*R*)	−1.47	Industrion	−4.73	Amsterdams Hist. Mus. (*R*)	0.01	Bonnefantenmuseum	−0.90
Singer Museum (*R*)	−1.49	Fries Museum	−5.04	Groninger Museum	0	Museon (*R*)	−1.04
Bonnefantenmuseum	−1.52	Princessehof	−5.47	Rijksmus. Volkenkunde (*R*)	−0.21	Ned. Spoorwegmus. (*R*)	−1.10
Cobra Museum (*R*)	−1.72	Rijksmus. Twenthe	−6.52	Tropenmuseum (*R*)	−0.23	Ecodrome	−1.22
Joods Hist. Mus. (*R*)	−1.81	Fries Natuurmuseum	−7.07	Ned. Spoorwegmus. (*R*)	−0.23	Industrion	−1.22
Average travel distance in min	**56.6**		29.7		24.3		**52.5**
Average # of visits	**4.8**		**4.5**		3.7		3.3
% youth cards	10.5		11.3		**20.3**		**28.9**
% visits in school holidays	29.3		29.2		32.4		**40.6**
Type of collection visited:							
Art	**50.4**		**49.1**		**33.3**		**13.7**
Cultural history	39.4		34.2		33.5		40.6
Science/technique	**5.8**		**11.5**		**19.0**		**30.1**
Other	4.3		5.2		14.1		15.7
Total	100.0		100.0		100.0		100.0

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

Using the few variables available in the dataset, we can investigate some of the background of the four segments (Table IV bottom half). The four segments seem to differ most in their willingness to travel, the percentage of youth cardholders, and the type of collection visited. Segments 1 and 2 have a very similar profile on most variables, but the willingness to travel of Segment 2 is about half as large as that of Segment 1. This may perhaps have to do with age, a variable that unfortunately is not registered in the dataset. Segments 3 and 4 are also reasonably similar on a number of variables, but also differ substantially in their willingness to travel. In addition, Segment 4 has a higher percentage of youth cards, and a subsequently higher percentage of visits during school holidays; the visitors of this segment are less likely to visit art museums, particularly in comparison to Segments 1 and 2. Further analyses revealed that the segments are very similar in their distribution across the 12 counties in The Netherlands. The four segments simply have very different backgrounds and interests.

The four segments differ in their sensitivity to distance. The coefficients, b, are equal to -0.98, -4.92, -5.28 and -1.52, for Segments 1, 2, 3 and 4, respectively. For Segments 2 and 3 the friction caused by distances appears to be much larger than for the other two segments. This is illustrated in Figure 2, which pictures the distance decay functions $\exp(bd_{ij})$. 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. All curves start at the value 1, but the curves for Segments 2 and 3 decline much faster than those for Segments 1 and 4. Respondents belonging to

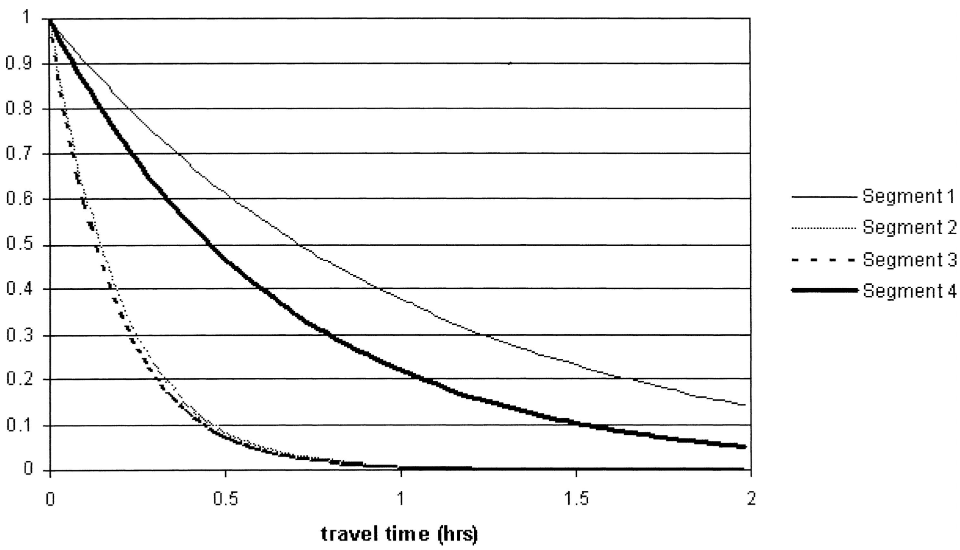

Figure 2. Distance decay functons.

Segments 2 and 3 will hardly ever visit a museum for which they have to travel more than 1 h. For respondents belonging to Segment 1, 1 h of 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 Segment 4 is in between that of Segment 1 and Segments 2 and 3.

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 Segments 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 Segments 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 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 segments 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.

4. Discussion

The aim of this study was to show that the use value of multiple organizations can be compared using travel time, but that one needs to account for the different probabilities in visiting the museums, given the consumers' relative distance to the various sites. Second, 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 the available budget and choices will have to be made. Modeling relative use value may be of help in justifying distributing limited governmental resources in particular ways.

However, as pointed out earlier, the dataset has both advantages and disadvantages. The major advantage is the size of the dataset, capturing a wide range of different museums, locations, competitive situations and travel distances. The major disadvantage is the lack of information on nature of the trip. Although the latent class application addresses the issue of multi-purpose visits at least in part, much more research is required to determine how the context of a visit influences willingness to travel and how the context may be derived from travel distance. Advances in this area would contribute significantly to resolving an important shortcoming of many travel distance applications. Mixture modeling as used in our application may be an interesting route to pursue this further. Furthermore, as mentioned earlier, 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. Blockbuster exhibitions in particular 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, Museum Cardholders are likely to be museum visitors who anticipate going more often and for whom the card is a financially attractive option. Other segments, such as non-cardholders or tourists 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.

Although a survey would be limited in covering the number and range of museums, it might be an attractive next step to address some of the shortcomings of our dataset. The factors in our model have been inferred from the limited user variables in the database. The survey would allow further investigation of audience 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 combining 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.

Acknowledgements

The authors would like to thank two anonymous reviewers for their helpful comments and are very grateful to the Dutch Museum Association for supplying the dataset.

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 does not change if we add an arbitrary constant to all v_{ji}s.
4. We refer the interested reader to Cramer (2003) for a recent (non-econometric) introduction to logit models. Further details on the model developed here are available from the authors.
5. For the development of the mixture model, too, further details are available from the authors.
6. The parameters in one segment 'exploded'; their absolute values became vary large.
7. The latter parameter is not estimated when all respondents are considered as a single segment. When two or more segments 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 segments. For these museums the attractiveness parameters have been set equal to -20. The implied choice probability is virtually equal to 0.

References

Alberini, A., Riganti, P. and Longo, A. (2003) "Can People Value the Aesthetic and Use Services of Urban Sites? Evidence from a Survey of Belfast Residents." *Journal of Cultural Economics* 27: 193–213.

Bille, H. T. (1997) "The Willingness-to-Pay for the Royal Theatre in Copenhagen as a Public Good." *Journal of Cultural Economics* 21: 1–28.

Bozdogan, H. (1987) "Model Selection and Akaike's Information Criterion (AIC): The General Theory and its Analytical Extensions." *Psychometrika* 52: 345–370.

Corning, J. and Levy, A. (2002) "Demand for Live Theater with Market Segmentation and Seasonality." *Journal of Cultural Economics* 26: 217–235.

Cramer, J.S. (2003) *Logit Models from Economics and Other Fields.* Cambridge University Press, Cambridge.

Cuadrado, M. and Frasquet, M. (1999) "Segmentation of Cinema Audiences: An Exploratory Study Applied to Young Consumers." *Journal of Cultural Economics* 23: 257–267.

Epstein, R.A. (2003) "The Regrettable Necessity of Contingent Valuation." *Journal of Cultural Economics* 27: 259–274.

Finn, A., McFadyen, S. and Hoskins, C. (2003) "Valuing the Canadian Broadcast Corporation." *Journal of Cultural Economics* 27: 177–192.

Forrest, D., Grime, K. and Woods, R. (2000) "Is it Worth Subsidizing Regional Repertory Theatre?" *Oxford Economic Papers* 52: 381–397.

Frey, B.S. (1998) "Superstar Museums: An Economic Analysis." *Journal of Cultural Economics* 22: 113–125.

Green, D.P., Kahneman, D. and Kunreuther, H. (1994) "How the Scope and Method of Public Funding Affect Willingness to Pay for Public Goods." *Public Opinion Quarterly* 58: 49–67.

Heckman, J. and Singer, B. (1984) "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data." *Econometrica* 52(2): 271–320.

Hutter, M. (1998) "Communication Productivity: A Major Cause for the Changing Output of Art Museums." *Journal of Cultural Economics* 22: 99–112.

Martin, F. (1994) "Determining the Size of Museum Subsidies." *Journal of Cultural Economics* 18: 255–270.

McFadden, D. (1974) "Conditional Logit Analysis of Qualitative Choice Behavior", in P. Zarembka (ed.), *Frontiers in Econometrics*, Academic Press, New York.

McFadden, D. (1981) "Econometric Models of Probabilistic Choice", in C. Manski and D. McFadden (eds.), *Structural Analysis of Discrete Data with Econometric Applications*, MIT Press, Cambridge, MA.

Morey, E. and Rossmann, K.G. (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: 215–229.

Navrud, S. and Ready, R.C. (2002) *Valuing Cultural Heritage; Applying Environmental Techniques to Historic Buildings, Monuments and Artifacts.* Edward Elgar, Cheltenham.

Noonan, D.S. (2003) "Contingent Valuation and Cultural Resources: A Meta-Analytic Review of the Literature." *Journal of Cultural Economics* 27: 159–176.

Papandrea, F. (1999) "Willingness to Pay for Domestic Television Programming." *Journal of Cultural Economics* 23: 149–166.

Pollicino, M. and Maddison, D. (2001) "Valuing the Benefits of Cleaning Lincoln Cathedral." *Journal of Cultural Economics* 25: 131–148.

Poor, P.J. and Smith, J.M. (2004) "Travel Cost Analysis of a Cultural Heritage Site: The Case of Historic St. Mary's City of Maryland." *Journal of Cultural Economics* 28: 217–229.

Prietro-Rodríguez, J. and Fernández-Blanco, V. (2000) "Are Popular and Classical Music Listeners the Same People?" *Journal of Cultural Economics* 24: 147–164.

Santagata, W. and Signorello, G. (2000) "Contingent Valuation of a Cultural Public Good and Policy Design: The Case of "Napoli Musei Aperti." *Journal of Cultural Economics* 24: 181–204.

Schwartz, S. (1978) "Estimating the Dimensions of a Model." *Annals of Statistics* 6: 461–464.

Thompson, E., Berger, M., Blomquist, G. and Allen, S. (2002) "Valuing the Arts: A Contingent Valuation Approach." *Journal of Cultural Economics* 26: 87–113.

Throsby, D. (2003) "Determining the Value of Cultural Goods: How Much (or How Little) Does Contingent Valuation Tell Us?" *Journal of Cultural Economics* 27: 275–285.

Wedel, M., DeSarbo, W.S., Bult, J.R. and Ramaswamy, V. (1993) "A Latent Class Poisson Regression Model for Heterogeneous Count Data with an Application to Direct Mail." *Journal of Applied Econometrics* 8: 397–411.

Wedel, M. and DeSarbo, W.S. (1995) "A Mixture Likelihood Approach for Generalised Linear Models." *Journal of Classification* 12(1): 21–56.

Wedel, M. and Kamakura, W. (2000) *Market Segmentation. Conceptual and Methodological Foundations*, 2nd edn. Kluwer Academic Publishers, Boston/Dordrecht/London.

Willis, K.G. (2002) "Iterative Bid Design in Contingent Valuation and the Estimation of the Revenue Maximizing Price for a Cultural Good." *Journal of Cultural Economics* 26: 307–324.

Whitehead, J.C. and Finney, S.S. (2003) "Willingness to Pay for Submerged Maritime Cultural Resources." Journal of Cultural Economics 27: 231–240.