Tourism Management 32 (2011) 511–519

Contents lists available at ScienceDirect

Tourism Management

journal homepage: www.elsevier.com/locate/tourman

Implicit prices for longer temporary exhibitions in a heritage site and a test of preference heterogeneity: A segmentation-based approach

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ARTICLE INFO

Article history:
Received 21 October 2009
Accepted 3 April 2010

JEL classification:
Q51
C51

Keywords:
Choice modelling
Preference heterogeneity
Test of difference
Confidence intervals
Convolutions approach
Segmentation

ABSTRACT

This paper examines whether or not people with different characteristics have significantly different nonmarket preferences for longer temporary exhibitions in a cultural heritage site, using a choice modelling study. In order to perform the examination, several methods to calculate confidence intervals (the bootstrap, jackknife, Krinsky and Robb, and Delta methods), and a convolutions approach are adapted. A sample is segmented into relatively homogeneous subgroups according to their sociodemographic or attitudinal characteristics. The results from a case study show that (1) the implicit price for longer exhibitions by one month is AU$5.01 per household; (2) sociodemographic and attitudinal characteristics as segmentation criteria do not cause significantly different implicit prices; and (3) different methods of testing the relationship between mean WTP estimates did not lead to different conclusions.

1. Introduction

The incorporation of preference heterogeneity into utility models of survey respondents is one of the key issues of nonmarket valuation studies (Boxall & Adamowicz, 2002; Walker & Ben-Akiva, 2002). Behavioural heterogeneity, if not incorporated, might cause inaccurate, biased estimates in the utility model (Jones & Hensher, 2004, p. 1013; Louviere, 2001, p. 141). The role of heterogeneous characteristics of tourists in the analysis of destination choice (using a mixed logit model) and the need for clustering based on the characteristics were well documented by Correia, Santos, and Barros (2007). Correia et al. also described that unobserved heterogeneity might lead to different preference levels estimated using discrete choice models. Preferences are normally expressed as willingness to pay (WTP) in nonmarket valuation studies.

Although more and more nonmarket valuation results are accumulated in the literature, one question remains unclearly answered: Whether or not different people with different characteristics have significantly different preferences for the improved quality of nonmarket goods and services? If their preferences are significantly different, researchers are able to explain the sources of the difference—heterogeneity sources—and to use this information for the prediction of preferences. On the other hand, if their preferences are not significantly different, researchers face a serious puzzle in which the heterogeneity sources cannot be relied upon to infer different nonmarket preferences. This might be still true even when the sources are found to be significant explanatory variables in choice models.

Preference differences are normally examined by observing confidence intervals (CIs) of WTP estimates, and there are several studies on this subject. Park, Loomis, and Creel (1991) argued that although different functional forms of choice models tend to provide different mean estimates of implicit prices, their CIs are not always statistically different. In addition, Cooper (1994) and Hole (2007) compared several commonly used approaches to calculating CIs of implicit prices. Cooper compared the bootstrap, Krinsky and Robb, Cameron, and jackknife methods, using a logit regression model applied to a simulated dichotomous contingent valuation method (CVM). Hole included the delta, Fieller, Krinsky and Robb, and bootstrap methods and tested these on both simulated data sets and an empirical data set. They found that the predicted CIs from these approaches are reasonably accurate and similar. In particular, they concluded that the bootstrap and the jackknife methods outperform other methods when a sample size is relatively small, or when unobserved heterogeneity is present in the data. This conclusion can be explained by the fact that the

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doi:10.1016/j.tourman.2010.04.002

bootstrap and the jackknife methods do not depend on the assumption of the jointly and asymptotically normal distribution of estimates (Cooper, 1994, p. 121; Hole, 2007). Hole (2007, p. 838) concluded (based on the results of empirical data analysis) that selection of different methods will not cause any difference in the resulting policy implication. Furthermore, Poe, Severance-Lossin, and Welsh (1994) introduced a convolutions approach to evaluating the difference between two simulated distributions and showed that simulated distributions of point estimates (used in CVM) are substantially and positively skewed, and skewness varies substantially across different studies.

The main objective of this paper is to investigate whether or not groups of people, who are significantly different in their sociodemographic or attitudinal characteristics, have significantly different implicit prices for longer temporary exhibitions in a heritage site. Valuation studies on specific heritage sites are quite limited (Choi, Ritchie, Papandrea, & Bennett, 2010; Noonan, 2003). In this paper, a significant difference is hypothesised—H_0: Respondents with different characteristics have significantly different mean WTP estimates—and empirically tested through a choice modelling case study. Respondents are segmented using cluster analysis pursuant to their sociodemographic or attitudinal similarities. The secondary objective of this paper is to examine several methods available for testing the relationship between segment-specific implicit prices, including the bootstrap method, the jackknife method, the Krinsky and Robb method, the delta method, and a convolutions approach. These methods are adapted and their estimation results are compared in this research. This paper demonstrates that some heterogeneity sources that are commonly used in the literature may not work as criteria for classifying people with different nonmarket preferences.

This paper is organised as follows. Choice modelling is introduced and heterogeneity sources are briefly described. The testing methods for the hypothesis are then described in detail, followed by descriptions of the survey instrument. The final two sections report the results and end with the conclusion.

2. Choice modelling and heterogeneity sources

2.1. Choice modelling

Choice modelling (CM), also known as choice experiment (Bennett & Adamowicz, 2001), is one of the stated preference nonmarket valuation techniques. This technique has been used in a wide range of areas including marketing and transportation, and applied to environmental management (Adamowicz, Boxall, Williams, & Louviere, 1998; Rolfe & Bennett, 1996), tourism (Correia et al., 2007; Morley, 1994), and cultural resources (Mazzanti, 2002; Morey, Rossmann, Chestnut, & Ragland, 1997).

CM studies involve a series of questions called ‘choice sets’ given to survey respondents. For each choice question, respondents select their most preferred option from several options. One of the options is usually given as a ‘status quo’ or ‘no action’ policy, whilst other ‘change’ options are designed using variations in the levels taken by constituent ‘characteristics’ or ‘attributes’. The overall choice process of answering these questions—respondents making ‘trade-offs’ according to the relative values of the given options—is described by the random utility model (RUM) (Louviere, 2001).

According to the RUM, the latent utility of the ith alternative for individual q (U_{iq}) can be described with two components, systematic (observable) component and random (unobservable) component: $U_{iq} = V_{iq} + \varepsilon_{iq}$. Furthermore, V_{iq} can be expressed as $\beta_{i1}X_{i1q} + \beta_{i2}X_{i2q} + \cdots \beta_{ik}X_{ikq}$. When the model is estimated and parameter estimates become available, compensating surplus (CS) for a proposed change in a project or policy (V^0 is the initial condition and V^1 a new condition) can be described as:

$$CS = \frac{-1}{\lambda\beta_\mu^*}\left[V^0 - V^1\right] \tag{1}$$

where $\lambda\beta_\mu^*$ is the monetary coefficient (β_μ) including the scale parameter (λ). CS needs to be estimated in order to provide information on the public benefit of the proposed project or policy, especially when public goods are concerned.

In order to understand the functional impact of unobserved factors on the estimates, it is useful to consider the meaning of λ. The distributional assumption of the error term requires researchers to modify each estimated model to have a particular variance, as the variance of the independently and identically distributed extreme value type 1 (EV1) is $\pi^2/6$ (Hensher, Rose, & Greene, 2005, p. 488; Train, 2003, p. 38). Thus, the variances of multinomial logit (MNL) models are normalised to be $\pi^2/6$, that is 1.65, by dividing the original coefficients (β_k^*) by $6^{1/2}/\pi$ and σ (the standard deviation of the error component) (Train, 2003, p. 28). As a result, $\lambda = (\pi/6^{1/2}) \times 1/\sigma$ (Hensher et al., 2005, p. 488; Louviere, 2001, p. 30). In other words, λ scales each coefficient “to reflect the variance of the unobserved portion of utility”, thus “a larger variance in unobserved factors leads to smaller coefficients, even if the observed factors have the same effect on utility (Train, 2003, p. 45).”

In many choice models, researchers are interested in the value of a marginal change in a single attribute. For this reason, the utility difference in the brackets in Equation (1) becomes the marginal utility of a unit change of the kth attribute ($\lambda\beta_k^*$). As a result, willingness to pay (WTP) for the marginal change in any single attribute can be described as Equation (2):

$$WTP = -\frac{\lambda\beta_k^*}{\lambda\beta_\mu^*} = -\frac{\beta_k}{\beta_\mu} \tag{2}$$

Therefore, the reliability of WTP estimates is determined by the significance levels of the component parameters (β_k and β_μ). The significance levels are expressed as the Wald-statistic ($Wald = \beta_k/$(standard error of β_k)), and the statistic is expressed as a p-value. However, it should be noted that WTP estimates are likely to be biased, unreliable, or invalid if the population heterogeneity has not been properly incorporated into the models (Hensher et al., 2005, p. 481; Louviere, Hensher, & Swait, 2000, p. 141).

2.2. Heterogeneity sources

Two types of heterogeneity sources are normally considered: sociodemographic and economic variables (SDs) and ‘latent’ attitudinal variables (LVs). Differences in population characteristics occur not only in commonly available and observed SDs such as income, gender, age, and education (Barton, 2002; Boxall & Adamowicz, 2002; Scarpa et al., 2003), but also in unobserved LVs such as attitudes, beliefs, perceptions, experience, motivations, and institutional trust (Ashok, Dillon, & Yuan, 2002; Barton, 2002; Ben-Akiva et al., 1999; Berenguer, Corraliza, & Martin, 2005; Boxall & Adamowicz, 2002; Johansson, Heldta, & Johansson, 2006; McFadden, 2001, p. 355; Ready et al., 2004; Train, McFadden, & Goett, 1987; Walker & Ben-Akiva, 2002). There have been some efforts to include psychological understanding of human behaviour into standard models of nonmarket valuation, such as Hanley and Craig (1991), Kahneman, Ritov, Jacowitz, and Grant (1993), Stern, Dietz, and Guagnano (1995), and Widegren (1998), Brown, Champ, Bishop, and McCollum (1996), Bateman et al. (2002), McFadden (2001), Barton (2002), and Boxall and Adamowicz (2002). In particular, some of the nonmarket valuation literature argues that