The Australian Journal of Agricultural and Resource Economics, 51, pp. 175–194

Investigating distance effects on environmental values: a choice modelling approach*

Giovanni B. Concu†

Analysis of the relationship between distance and willingness to pay (WTP) is important for estimation and transfer of environmental benefits. Several contingent valuation (CV) studies have investigated this topic, but results are mixed. This paper describes a choice modelling (CM) application that estimates distance effects on parameters of three environmental attributes. Combinations of these attributes create different management policies for native vegetation. The CM study is based on a sampling procedure that provides a geographically balanced sample and statistical tests to choose the best specification of the distance–WTP relationship. Welfare analysis shows that disregarding distance causes under-estimation of individual and aggregated benefits and losses, seriously misdirecting resource allocation.

Key words: choice modelling, geographical distance, spatial heterogeneity, stratified sample.

1. Introduction

Investigating distance effects on environmental preferences is important for several reasons. First, distance affects the use of environmental goods, information and substitution possibilities (Sutherland and Walsh 1985). Second, identifying distance effects empirically validates the political and administrative criteria that guide aggregation of individual benefit estimates (Loomis 1996). Third, assessing the effect of distance helps in benefit-transfer applications (Bateman *et al*. 1999; Jiang *et al*. 2005), since they make use of sample or population characteristics to transfer estimates across populations. Fourth, investigating distance effects can provide useful information regarding the appropriate form of funding for environmental projects – for instance, state versus federal funding.

Several contingent valuation (CV) studies have investigated the relationship between values and distance. Some studies found a negative relationship between distance and values (Sutherland and Walsh 1985; Loomis 1996; Hanley *et al*. 2003). Others reported no distance effect for some environmental assets or classes of users (Bateman and Langford 1997; Pate and Loomis 1997).

* The author would like to thank Michael Burton, John Quiggin, the editorial team at *The Australian Journal of Agricultural and Resource Economics*, and two anonymous reviewers for helpful comments and criticism.

† Giovanni B. Concu (email: g.concu@uq.edu.au) is a Postdoctoral Research Fellow at School of Economics, University of Queensland, Brisbane, Queensland, Australia and Associate Researcher at the Centre for North South Economic Research, Italy.

doi: 10.1111/j.1467-8489.2007.00381.x

No attempt has been made, so far, to estimate a distance–value relationship via the choice modelling (CM) technique. Detecting distance effects in CM applications is possibly more important than in CV studies. In open-ended CV, stated willingness to pay (WTP) for a specified change in an environmental good produce a set of individual welfare measures for the respondents in the sample. As long as the sample is representative of the population, the sample mean WTP equals the population mean WTP. Estimating the effect of distance on WTP may be redundant.

In CM, as well as in dichotomous-choice CV, the individual WTP is predicted from the estimated utility parameters. Omission of distance could produce biased parameter estimates even with a representative sample. Further, distance effects depend on the use values/non-use values ratio; in CM applications this ratio varies for each attribute used to describe the policy options. Unbiased distance effects can be estimated only by defining an appropriate distance function for each attribute.

The first step to detect distance effects requires to account for the spatial distribution of the population. In CV and CM applications, survey response rates tend to decrease as distance from the asset under valuation increases (Bateman and Langford 1997; Hanley *et al*. 2003). Random sampling is then unlikely to provide a geographically representative sample, and corrective measures are necessary. The second step is to select a metric for the distance variable. Subjective and objective distance measures are possible candidates. Selection of a functional form that best represents the distance–WTP relationship is the third step. Little theoretical guidance is available for choosing among possible functional forms so tests for different functional forms are required.

This article presents results from a CM study that estimates distance effects on the benefits of an urban park in Perth (Western Australia). The study also determines the direction of the bias when distance is omitted from estimation. Important topics in this application include the use of a sampling procedure to obtain a geographically balanced sample, the assessment of the correlation between subjective and objective distance metrics, the selection of functional forms, and the choice of the econometric model. The article is organised as follows. Section 2 outlines the methodological challenges associated with the detection of distance effects in CM applications. Section 3 describes the CM survey. Section 4 outlines the sampling procedure, the choice of the distance metrics and the survey administration. Section 5 shows the results of the tests for functional form specifications and the econometric models. Section 6 discusses the results, and section 7 summarises and concludes the article.

2. Distance, spatial heterogeneity and environmental valuation

Distance is an important source of preference heterogeneity. Distance works as a substitute for the price mechanism; it regulates the demand for environmental goods through the purchase of private goods necessary to travel (Scotchmer and Thisse 1999). Distance also affects the availability of information, and preferences are, to a certain degree, dependent on the available information (Beckmann 1999). In addition, the number of substitution opportunities increases as distance increases (Stouffer 1940). Finally, a sense of 'ownership' and past experience may be related to distance and may affect preferences. In summary, preferences are not likely to be stable over space. This lack of stability, or *spatial heterogeneity*, implies that functional forms and parameters vary among agents residing at different locations (Anselin 1988). Accounting for spatial heterogeneity requires an assessment of the consequences it has on the sampling procedure, the selection of distance metrics and functional forms, and the selection of an appropriate econometric model.

2.1 Sampling and spatial heterogeneity

Detecting how preferences change over space requires the sampling procedure to provide a sample that represents the spatial distribution of the population. In the context of CV and CM applications, random sampling is bound to provide unbalanced geographical samples for two reasons. First, response rates in surveys decline with distance (Bateman *et al*. 2000, but see Van Bueren and Bennett 2004 for a contrary finding). Second, populations rarely are uniformly distributed over space, and geographical areas with higher population density are likely to be over-represented.

2.2 Distance metrics and utility

The estimated relationship between WTP and distance can be affected by the way the latter is measured. Several alternative metrics are possible.

Perceived travel time is the most relevant factor in determining recreational travelling (McConnell and Strand 1981). Perceived travel time can be measured for sampled individuals, but out-of-sample extrapolation is not possible unless the perceived travel time is available for each individual in the population. Perceived travel time is often approximated by objective travel time. To calculate objective travel time, it is usual to assume some constant road speed that multiplied by geographical distance gives travel duration. However, constant speed means that roads are of the same quality and have the same volume of traffic (Bateman *et al*. 1999) and this hypothesis may not be plausible for large geographical areas.

Alternatively, perceived travel time can be approximated by geographical distance as the crow flies – that is, as a straight line. It is usually possible to compute the geographical distance for each individual in the population. Geographical distance is a very crude measure of spatial variability, and its use should be supported by a demonstrated correlation with perceived travel time, which is the theoretically correct measure.

2.3 Functional forms for the distance–WTP relationship

Little guidance is available on the functional form of the distance–WTP relationships. In the CV literature, distance effects are usually assumed to be linear (Sutherland and Walsh 1985; Loomis 1996), log-linear (Silberman *et al*. 1992; Pate and Loomis 1997) or second order polynomial (Breffle *et al*. 1998). However, Imber *et al*. (1991) and Pearson *et al*. (2002) show that distance effects on WTP can be more complex – in the proximity of the park, WTP increases as distance increases, while moving further away WTP begins to decrease.

In addition, in the field of transportation, regional science and economic geography, distance effects are shown to take several different forms (Beckmann 1999). The relationship between distance and preferences also depends on the role of information, on substitutes, and on the type of natural resource under scrutiny (Hanink 1995). Given that no restriction on the specification of the utility function is anticipated, a search for the best functional form is necessary.

2.4 Spatial heterogeneity and model specification

The econometric model used in CM applications can account for spatial heterogeneity in two ways. Take a relatively general random utility model. The utility function is represented as follows:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \quad \forall j \in C \tag{1}$$

where the utility U_{ij} of alternative j (from the choice set C) for individual i is given by the sum of an observable component V_{ij} and a random component ε_{ij}. The term V_{ij} is assumed to be linear in parameters such that:

$$V_{ij} = \sum_{k=1}^{K} \beta_{ijk} x_{ijk} \tag{2}$$

where $\boldsymbol{x}_{ijk}$ is a vector of K choice characteristics (with $k = 1, \ldots K$) and β_{ijk} a vector of K parameters to be estimated. The βs represent the marginal impact on utility of the choice attributes. Given the random nature of the error term ε_{ij}, the analyst can determine the probability of choosing $j \in C$ once the distribution of εs is specified. For the case $C = \{j,m\}$, the probability that i chooses j over m is given by:

$$\begin{aligned} \Pr_{ij} &= \Pr(U_{ij} > U_{im}) = \Pr(V_{ij} + \varepsilon_{ij} > V_{im} + \varepsilon_{im}) \\ &= \Pr(\varepsilon_{im} - \varepsilon_{ij} < V_{ij} - V_{im}) = \Pr(\varepsilon_{i:j,m} < V_{ij} - V_{im}). \end{aligned} \tag{3}$$

This model shows that the probability of choosing alternative j depends on the relative attractiveness of j over m – that is $(V_{ij} - V_{im})$ – and on the stochastic utility difference $\varepsilon_{i:j,m}$.

One way to introduce spatial heterogeneity in this model is to allow the individual's response to a generic choice characteristic $\mathbf{x}_1$, to vary around some mean response β_1 as a function of individual distance d_i:

$$\beta_{i1} = \beta_1 + f_i(d_i). \tag{4}$$

This leads to a utility function of the form:

$$U_{ij} = (\beta_1 + f_i(d_i))x_{ij1} + \sum_{k=2}^{1} \beta_{jk} x_{ijk} + \varepsilon_{ij}. \tag{5}$$

In this formulation, the observable element of the utility function is specified so as to incorporate explicitly the source of heterogeneity. If the remaining errors are identically and independently distributed (IID) with a (type I) extreme value distribution, the model is the common multinomial logit.

Alternatively, the individual's response to characteristic x_i may be modelled as dependant on a random element ϕ_{ij}:

$$\beta_{i1} = \beta_1 + \phi_{ij}. \tag{6}$$

The coefficient vector β_{i1} varies in the population according to the density function $f(\beta)$. This density is a function of the true distribution parameters of ϕ_{ij} that represent the mean and covariance of βs in the population. It is possible to specify the mean and the variance as a function of distance, so that the individual's response to changes in x_1 becomes:

$$\beta_{i1} = \beta_1 + f_i(d_i) + \phi_{ij}. \tag{7}$$

Assuming the errors are IID extreme value, this formulation corresponds to the mixed logit model (Bhat 2000). In this application, the researcher specifies both the distribution of the βs and the distribution of the εs. This increase in complexity is justified only if distance does not fully explain spatial heterogeneity of preferences.

3. The design of the CM survey

The CM survey was designed in consultation with the management authority of Kings Park in Perth (Western Australia). Kings Park covers around 400 hectares and is located on the fringe of Perth business district. Kings Park is mainly covered by native vegetation or bushland. The management authority indicated three major problems in Kings Park's bushland: weeds, trampling and fires. The CM study aimed to help the management authority to establish the priorities of its conservation efforts.

CM is a stated preference (SP) data-generating technique. Data generation is necessary when: (i) there is not enough variation in market data to develop

Table 1 Attributes and levels of the choice modelling application

Attributes	Levels	Variable in model
Weed-free bushland (%)	30, 40*, 50, 60	*Weed*
Bushland annually destroyed by fire (%)	1, 3, 6*, 9	*Fire*
Bushland accessible to the public (%)	25, 50, 75, 100*	*Acc*
Cost ($)	0.30*, 1, 3, 6	*Cost*

Note: * status quo levels; Acc, Accessibility.

reliable models of how behaviour will change in response to changes in the variables; (ii) a product or service has never been available before; or (iii) a product or service has the characteristics of a public good (Louviere *et al*. 2000).

CM generates data by creating hypothetical markets – usually in the course of an interview or questionnaire. In these markets, individuals are asked to compare products or policies described by attributes, to choose the preferred one, and to repeat the task over several choice sets. The aggregate choice frequencies can be modelled to infer the relative impact of each attribute level on choices. Welfare impacts are computed as the compensating surplus (CS) associated with switching from one product or policy to another (Louviere *et al*. 2000).

Consultations with the Kings Park's management authority and three focus groups helped to identify a set of policy-relevant and demand-relevant attributes (Bennett and Adamowicz 2001). In CM, the attributes describe the outcome of the current management strategy (the status quo) and what would happen if a management alternative were to be introduced (Bennett and Adamowicz 2001). The focus groups also helped to define the attribute levels and the best format for the questionnaire as well as for different management options in Kings Park.

Table 1 shows the final set of attributes and levels. The Weed attribute indicates the percentage of Kings Park's bushland that is free from weeds. The Fire attribute specifies the average percentage of Kings Park's bushland annually destroyed by fires. The Accessibility attribute gives the percentage of the Kings Park's bushland that is accessible to the public. The Cost attribute is the contribution via annual income tax required to support the preferred management strategy.

A management option illustrates how the park authority can allocate its resources – eradicating weeds, preventing fire or closing the bushland to the public to reduce trampling. The systematic variation of the attributes to create management options was designed via a Graeco-Latin procedure. Respondents were presented with eight choice sets, each composed of the status quo and two other management options.

Table 2 Distance zones, population and sample shares

Zone	Distance from Kings Park (km)	Population	Population share	Returned questionnaires	Sample share
1	0–5	170 945	9.4	33	10.2
2	5–10	330 966	18.2	58	17.9
3	10–15	317 817	17.4	55	17.0
4	15–20	223 801	12.3	41	12.7
5	20–30	157 472	8.6	29	9.0
6	30–50	125 513	6.9	22	6.8
7	50–100	78 206	4.3	11	3.4
8	100–150	87 731	4.8	14	4.3
9	150–300	70 587	3.9	13	4.0
10	300–700	97 337	5.3	18	5.6
11	>700	162 289	8.9	30	9.3
Total		1 822 664	100	324	100

4. Sampling and selection of the distance metric

4.1 Drawing a geographically balanced sample

A stratified random sampling procedure (Ben-Akiva and Lerman 1985) coupled with a staggered survey administration gave a geographically balanced sample. In this approach, the geographical area around Kings Park was divided into 11 *distance-zones* (Table 2). Zone 1 included Western Australian residents in an area between 0 and 5 km away from Kings Park, and zone 11 included Western Australian residents living farther than 700 km. Residents from each zone were then randomly drawn and surveyed in successive rounds to progressively adjust the geographical subsamples according to the zones' response rates.

In the first round, in each zone, an equal number of randomly selected residents were contacted by phone. Later they received in the mail the questionnaire with a reply paid envelope. Response rates and sample shares were calculated. For each distance zone, the number of contacts in the second round was determined by the number of responses needed for the sample share to equal the population share, divided by the zone's response rate. The samples were further adjusted in following rounds. The staggered stratified sampling ended when a sufficient number of responses were obtained and when, for each distance zone, the difference between sample share and population share was less than 1 per cent (Table 2).

Sampling started in June and finished in September 2003, and out of 750 questionnaires sent, 324 were returned with the overall response rate around of 42 per cent. Socio-economic characteristics were also collected from survey participants (Tables 3 and 4). There is a self-selection bias in the sample, with an over-representation of female, older, highly educated and wealthy individuals.

Table 3 Population and sample characteristics

	Population	Sample	χ^2	Probability
Gender (%)				
Male	49.8	42.6	2.073	0.1498
Female	50.2	57.4		
Average age (years)	34.3	50.3		
Average weekly income ($)	693.2	989.5		
Level of education (%)				
University	18.5	30.2	19.638	0.0006
Certificate	16.7	14.2		
Up to Y12	13.5	22.2		
Up to Y10	40.3	26.2		
Other	10.9	7.1		
Employment status (%)				
Student	7.6	2.2	79.456	2.27E-16
Employed/Self employed	30.6	65.8		
Unemployed	7.2	1.5		
Retired	52.1	22.2		
Other	2.5	8.3		

Table 4 Other attitudinal and information characteristics of respondents

Variable	Type	Meaning
EnvAtt	Categorical	Environmental attitude = 1 if respondent declares the state government should spend more resources on environmental protection
Rank	Categorical	Ranking of environmental issues = 1 if environment less important, 5 if most important
Info	Continuous	Respondent's knowledge of Kings Park is calculated as the percentage of correct answers to questions on Kings Park
Subst	Categorical	Number of substitutes for Kings Park
Org	Categorical	Membership in environmental organisations

The staggered stratified sampling is a cost-efficient way to obtain a geographically unbiased sample, since random sampling would have required a larger number of contacts. On the other hand, staggered stratified sampling is a lengthy procedure that continues until the sampled zones are satisfactorily represented. Collecting data in different periods can expose the data to influences that vary through time. Therefore, it is necessary to assess the effect of time of response in the data analysis.

4.2 Comparing perceived travel time and geographical distance

The choice of the appropriate distance measure corresponds to selecting the metrics for the d_i variable in Equation (4). Perceived travel time and geographical distance are the two metrics available for this study. Information on

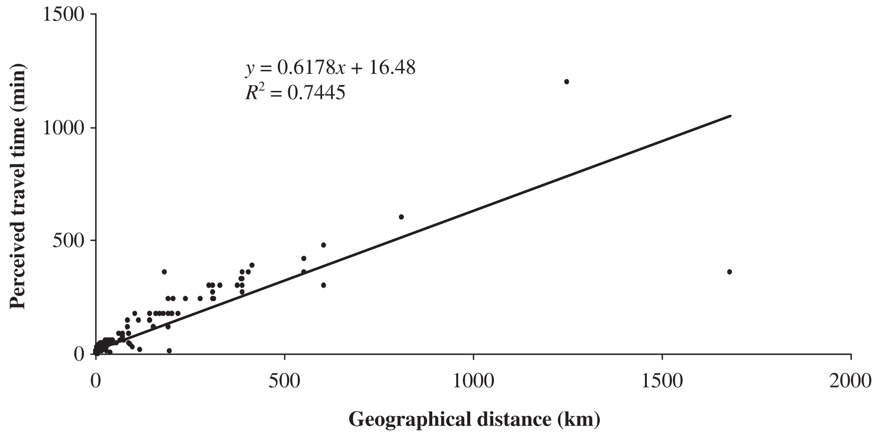

Figure 1 Relationship between perceived travel time and geographical distance.

the perceived travel time is not available for out-of-sample individuals. This limits the possibility of extrapolating results and aggregating benefits over the sampled population. On the other hand, geographical distance can be easily calculated for each individual in the sample and the population, using the spatial coordinates of his or her residential address.

Geographical distance is an inferior measure of spatial variability. However, given the objective of measuring aggregate benefits, it is important to determine whether geographical distance is a good proxy for perceived travel time. Figure 1 plots the two distance measures for sampled individuals. The correlation coefficient is 0.88. Geographical distance is a good proxy of perceived travel time.

5. Results

Two models were estimated. The first was a multinomial logit model that accounted for spatial heterogeneity so that responses to attribute changes depend on geographical distance from Kings Park. The choice of the best functional form for the distance–WTP relationship was based on a series of tests on the specification of the $f_i(d_i)$ function in Equation (4).

The likelihood ratio (LR) criterion (Louviere *et al.* 2000) is a test on a particular set of variables for nested models. The Vuong test (Vuong 1989) and Clarke's distribution-free test (Clarke and Signorino 2003) are tests for non-nested models. Because the Weed, Fire and Accessibility attributes in the CM questionnaire entailed different use value/non-use value ratios, the search for the best functional form was carried out for each one of them.

The tests compared several functional forms (Table 5). The gamma transformation is a flexible specification that can take complex shapes without forcing any particular form to the relationship under study. Its parameters a_1 and a_2 were estimated via a grid search procedure. The Beckmann's

Table 5 Possible functional forms of the distance variable

Function	Formula
Linear	$\text{DIST2} = a_0\text{DIST1}$
Logarithmic	$\text{DIST2} = a_0\ln(\text{DIST1})$
2nd Polynomial	$\text{DIST2} = a_0\text{DIST1} + a_1\text{DIST1}^2$
3rd Polynomial	$\text{DIST2} = a_0\text{DIST1} + a_1\text{DIST1}^2 + a_2\text{DIST1}^3$
Gamma	$\text{DIST2} = a_0(\text{DIST1})^{a_1}e^{(a_2\text{DIST1})}$
Exponential Law	$\text{DIST2} = a_0\exp(-\text{DIST1})$
Beckmann Law	$\text{DIST2} = a_0/(1 + \text{DIST1}^2)$

specification is a simplified gravitational model (Beckmann 1999). The results of the LR tests and distribution-free tests are given in the Appendix. The Vuong test was not powerful enough to discriminate between the different specifications, hence the need to use the distribution-free tests.

The preferred function of the distance–WTP relationship varied among the attributes. For the Weed attribute, no distance effects were recorded. A gamma transformation, with parameters $a_1 = -3$ and $a_2 = 6$, described the distance effects on the Fire attribute. A Beckmann's specification captured the effects of distance on the Accessibility attribute.

For the Fire attribute, Equation (4) was specified as follows:

$$\beta_{i\text{Fire}} = \beta_{\text{Fire}} + a_0(GD_i)^{-3}e^{(6*GD_i)}. \tag{8}$$

For the Accessibility attribute, Equation (4) took the form:

$$\beta_{i\text{Acc}} = \beta_{\text{Acc}} + a_0(1 + GD_i^2)^{-1} \tag{9}$$

where GD_i is the geographical distance of individual i from Kings Park and β_{Fire}, β_{Acc} and a_0 are parameters to be estimated.

The second was a multinomial logit model that did not incorporate the source of spatial heterogeneity. The individual's responses to attribute changes – β_{Weed}, β_{Fire} and β_{Acc} – did not depend on geographical distance. Disregarding distance thus produced differences in the individual and aggregate benefit estimates.

5.1 Individual benefit estimates

Table 6 reports the individual parameter estimates for the two multinomial logit models. For both models, LR tests suggested the set of independent variables to be included in the estimation. Because some of these variables do not vary across choices, they interacted with the choice attributes. Dummies identifying the round of the survey administration were never significant and were dropped from the models.

Table 6 Results of the multinomial logit models

	Distance omitted			Distance included		
Observations	4968			4968		
Log likelihood	–1569.1			–1559.93		
Pseudo R^2	0.1375			0.1426		
Variable	Coef.	S.E.	$P > \|z\|$	Coef.	S.E.	$P > \|z\|$
ASC	–0.217**	0.091	0.017	–0.221**	0.091	0.015
Weed	–0.081**	0.041	0.045	–0.082**	0.041	0.044
weed*log(inc)	0.012**	0.006	0.033	0.013**	0.006	0.032
weed*att(= 1)	0.035***	0.009	0.000	0.035***	0.009	0.000
weed*subst(= 1)	–0.010	0.017	0.542	–0.011	0.017	0.524
weed*subst(= 2)	–0.016	0.013	0.212	–0.016	0.013	0.210
weed*subst(= 3 or more)	0.012	0.012	0.326	0.012	0.012	0.331
weed*subst(na)	0.014	0.012	0.220	0.014	0.012	0.223
Fire	0.185	0.141	0.191	0.152	0.142	0.286
fire*distance(Gamma)	–	–	–	34.202***	8.539	0.000
fire*log(inc)	–0.032	0.020	0.111	–0.034*	0.020	0.091
fire*att(= 1)	–0.072**	0.032	0.024	–0.071**	0.032	0.027
fire*subst(= 1)	0.030	0.060	0.618	–0.006	0.062	0.924
fire*subst(= 2)	–0.022	0.046	0.632	0.006	0.047	0.893
fire*subst(= 3 or more)	–0.090**	0.044	0.042	–0.072	0.045	0.107
fire*subst(na)	0.018	0.042	0.667	0.057	0.043	0.193
Accessibility	–0.002	0.002	0.276	–0.030	0.019	0.115
acc*distance(Beckmann's)	–	–	–	0.024**	0.011	0.032
acc*log(inc)	–0.004	0.015	0.782	–0.001	0.002	0.419
acc*att(= 1)	–0.003	0.003	0.227	–0.004	0.003	0.192
acc*rank(= 4)	0.022***	0.007	0.002	0.022***	0.007	0.001
acc*rank(= 3)	0.013**	0.007	0.047	0.014**	0.007	0.035
acc*rank(= 2)	0.008	0.007	0.261	0.008	0.007	0.242
acc*rank(= 1:less important)	0.013*	0.007	0.082	0.013*	0.007	0.072
acc*subst(= 1)	–0.002	0.005	0.772	–0.002	0.005	0.705
acc*subst(= 2)	–0.009**	0.004	0.029	–0.010**	0.004	0.014
acc*subst(= 3 or more)	–0.010**	0.004	0.012	–0.011***	0.004	0.004
acc*subst(na)	–0.008**	0.004	0.023	–0.010***	0.004	0.007
acc*country(overseas)	–0.012***	0.002	0.000	–0.012***	0.002	0.000
acc*educ(= Y12)	0.008**	0.003	0.024	0.009**	0.003	0.013
acc*educ(= cert)	0.008***	0.003	0.007	0.008***	0.003	0.005
acc*educ(uni)	0.006*	0.003	0.059	0.006*	0.003	0.053
acc*org(= 1)	–0.006**	0.003	0.041	–0.006*	0.003	0.051
acc*Information index	0.000**	0.000	0.011	0.000**	0.000	0.013
acc*# of children	0.002**	0.001	0.046	0.002**	0.001	0.043
Cost	–0.089**	0.042	0.033	–0.086**	0.042	0.039
cost*income	0.00001***	0.000	0.000	0.00001***	0.000	0.000

*** significant at 1%; ** significant at 5%; * significant at 10%.
Subst(na), groups non-users and respondents that did not provide an answer to the number of substitutes.

In the multinomial logit model that disregarded spatial heterogeneity, the parameter of the ASC variable is significant and negative. It indicates that the utility associated with moving away from the status quo is negative. For the Weed attribute, both income and environmental attitude have

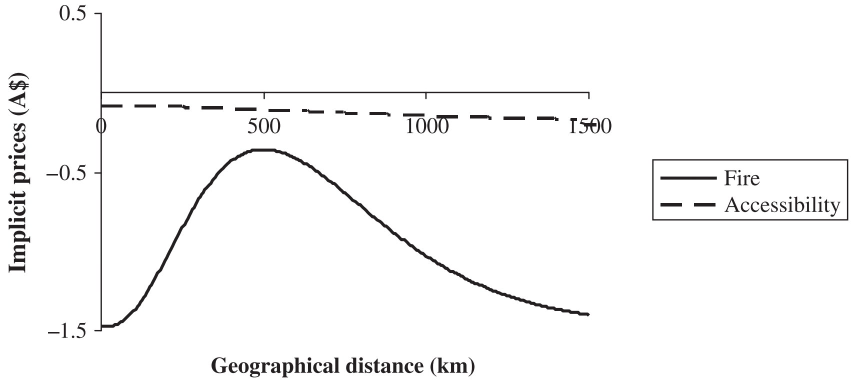

Figure 2 Effects of distance on implicit prices.

positive parameters that are statistically significantly different from zero. The environmental attitude also negatively affects the individual's responses to the Fire attribute. The negative coefficients indicate a WTP to prevent fire damages.

For the Accessibility attributes, the individual ranking of environmental policies and the number of substitutes for Kings Park have, respectively, positive and negative signs that are statistically different from zero. Further, individuals with a higher level of education, more knowledge of Kings Park and more children are more likely to prefer that Kings Park is accessible to the public. Other variables that affect the individual's response to the accessibility attribute are the country of origin and holding a membership to an environmental organisation.

The Cost attribute has the expected sign. The individual valuation of this attribute depends on income. Wealthier respondents are less concerned about paying for the park.

The multinomial logit model with spatial heterogeneity provided similar results for the ASC and Weed attribute parameters. For the Fire attribute, both income and environmental attitude have statistically significant and negative signs. Distance affects the utility associated with the Fire attribute according to the gamma transformation specification with parameters $a_1 = -3$ and $a_2 = 6$. For the Accessibility attribute, the results are similar to those of the model that omits distance but a Beckmann's specification represents distance effects on the utility of this attribute.

Figure 2 shows the effects of distance on the implicit prices of the Fire and Accessibility attributes. An implicit price is the relative effect on utility of a given attribute, quantified in monetary terms (Bennett and Adamowicz 2001). Distance effects on the implicit price of the Fire attribute have an intricate form. The utility for fire prevention in Kings Park decreases with distance and then increases again. People living in rural areas seem to be more concerned about fires, possibly because they are more familiar with fire

Table 7 Individual benefits for alternative management strategies

			Individual benefits (A$)			
			With distance		Without distance	
			Mean	95% CI	Mean	95% CI
Management Alternative						
Status Quo						
Fire	*Weed*	*Acc*				
6	40	100				
Scenario 1						
Fire	*Weed*	*Acc*				
6	60	100	–$2.57	–$2.36~–$2.78	–$2.56	–$2.36~–$2.76
Scenario 2						
Fire	*Weed*	*Acc*				
1	40	100	–$6.15	–$5.31~–$6.99	–$0.75	–$0.54~–$0.95
Scenario 3						
Fire	*Weed*	*Acc*				
6	40	75	$4.36	$4.01~$4.70	$1.15	$1.03~$1.27
Scenario 4						
Fire	*Weed*	*Acc*				
9	30	100	$7.44	$6.89~$7.98	$4.14	$3.89~–$4.38
Scenario 5						
Fire	*Weed*	*Acc*				
3	60	75	–$3.78	–$3.16~–$4.40	–$3.69	–$3.46~–$3.92

Note: Acc, Accessibility.

events. For the Accessibility attribute, the preferred distance specification indicates that the utility associated with the attribute decreases as distance increases – that is, reducing accessibility to Kings Park's bushland is of less concern to residents living far away from the park.

The *t*-tests reject the hypothesis that the parameters of two models are equal. For most of the significant coefficients, omission of distance results in underestimation of the parameter and larger standard errors. The consequence of differences on individual benefit estimates can be observed in Table 7.

Table 7 reports individual gains or losses associated with implementing five different management strategies. Individual benefit estimates are calculated for an individual with an average income, living at the sample average distance from Kings Park, and with a preference for more public money spent on the environment ($EnvAtt = 1$). Benefit estimates are computed using a CS (Boxall *et al*. 1996):

$$\mathrm{CS}_i = -\frac{1}{\beta_{\mathrm{Cost}}}\left\{V_i^0 - V_i^1\right\}. \tag{10}$$

$-\beta_{\mathrm{Cost}}$ is assumed to be the constant marginal utility of income; multiplying it by the difference of the observable utilities Vs converts the expected utility change into a monetary measure. The compensating measure calculates the welfare change produced by leaving the status quo (V^0) and implementing a new management scenario (V^1).

In scenario 1, Kings Park's management authority reduces weed encroachment in the bushland and increases the weed-free bushland by 20 per cent. In scenario 2, park managers increase efforts to prevent fire and bring the average area of bushland annually damaged to 1 per cent. In scenario 3, Kings Park's authority improves the conditions of the native vegetation by fencing off 25 per cent of the bushland. In scenario 4, the worst case scenario, the weed-free area decreases to 30 per cent and fires destroy around 9 per cent of the bush each year. In scenario 5, park authorities target both weed and fire damage while closing 25 per cent of bushland to the public.

Positive figures in Table 7 indicate a welfare gain relative to the status quo. Confidence intervals are calculated as suggested in Krinsky and Robb (1986). For scenarios 2–4, *t*-tests indicate that implicit prices are statistically different. Individual gains and losses are underestimated when distance is omitted from the model.

5.2 Aggregate benefit estimates

Aggregate welfare measures are calculated using Equation (10) and taking into account the spatial distribution of the Western Australian population.[1] The consequences of omitting distance and the spatial distribution of the population are illustrated in Table 8. Distance omission causes gross underestimation of benefits and losses. Such an outcome can easily lead to an inefficient allocation of resources.

6. Discussion of the results

Distance effects take different, sometimes complex forms across the attributes. This result raises questions regarding the possibility of correctly estimating distance effects when attributes are bundled together as is the case in CV applications. The complexity of the estimated relationship for the Fire attribute may be due to the emotive nature of fire events, especially as experienced by rural respondents. This result casts some doubts on the ability of respondents to focus on a particular issue and asset in a CM context.

[1] For aggregation purposes, the Western Australian population is divided into two groups: a 'pro-environment' group and a 'conservative' group. It is assumed that the population has the same share of each group as the sample. The 'pro-environment' group contains individuals that declared the government should spend more on the environment ($EnvAtt = 1$). The conservative group are all other individuals. All the other socio-economic variables are kept at their most conservative values. Income is assumed to take the average value for the Western Australian population (A$693.34).

Table 8 Aggregate benefits for alternative management strategies

			Aggregate benefits (millions A$)	
			With distance	Without distance
Management Alternative				
Status Quo				
Fire	*Weed*	*Acc*		
6	40	100		
Scenario 1				
Fire	*Weed*	*Acc*		
6	60	100	–$3.335	–$1.647
Scenario 2				
Fire	*Weed*	*Acc*		
1	40	100	–$9.010	–$0.221
Scenario 3				
Fire	*Weed*	*Acc*		
6	40	75	$6.621	$1.803
Scenario 4				
Fire	*Weed*	*Acc*		
9	30	100	$10.955	$4.741
Scenario 5				
Fire	*Weed*	*Acc*		
3	60	75	–$5.077	–$2.861

Note: Acc, Accessiblity.

Disregarding spatial heterogeneity has major consequences on both individual and aggregate benefit estimates. The main result is that distance omission produces underestimation of benefits and losses. The magnitude of this bias varies across scenarios or policy options.

For policy purposes, the results show that benefits and losses are distributed over the sampled population of Western Australians. That is, Western Australian residents gain some benefits from Kings Park and would suffer a loss if Kings Park is mismanaged. It is appropriate then, that Western Australian residents contribute to fund the park management via taxes. In other words, funding from the state government to support Kings Park management is warranted.

7. Summary and conclusion

This article has illustrated how distance effects on utility can be accounted for in a CM application, and how distance omission can bias individual and aggregate estimates. The CM application is based on the comparison of a multinomial logit model that accounted for the spatial heterogeneity of preferences, with a multinomial logit model that omitted spatial heterogeneity.

Accounting for spatial heterogeneity in the ML model required the preliminary selection of a geographically balanced sample, the choice of a distance metric and the identification of the best functional form for the distance–WTP relationship. A stratified random sampling procedure coupled with staggered survey administration provided a sample that satisfactorily mirrors the spatial distribution of the population. Geographical distance was used to represent spatial variability. This metric was strongly correlated with the theoretically correct measure. It also had the major advantage of allowing extrapolation from the sample to the population. For each attribute a series of likelihood ratio tests, Vuong tests and distribution-free tests identified the preferred specification for the distance–utility relationship.

Overall, the empirical results emphasise the need to accommodate spatial heterogeneity in environmental benefit estimation. Comparing the parameter estimates of the two multinomial logit models shows that distance omission causes parameter underestimation and larger standard errors. Consequently, both individual and aggregate benefits and losses are grossly underestimated. Not accounting for spatial heterogeneity is likely to lead to erroneous policy advice and hence misallocation of resources.

In this application, the multinomial logit model with spatial heterogeneity is more general in specification than other models used in the current literature that examine distance effects. However, its results are driven by the chosen population, the specific nature of the policy options and the set of choice attributes. Further research is therefore necessary in at least three directions: use of the mixed logit model; accounting for another important source of spatial heterogeneity such as the crossing of administrative boundaries; and definition of different sets of attributes and policies. Notwithstanding the limitation associated with the sampled population and the policy options, this application provides useful insight into the relationship between distance and utility.

References

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Kluwer Academic, Dordrecht, The Netherlands.

Bateman, I.J. and Langford, I.H. (1997). Non-users' willingness to pay for a national park: an application and critique of the contingent valuation method, *Regional Studies* 31, 571–582.

Bateman, I.J., Lovett, A.A. and Brainard, J.S. (1999). Developing a methodology for benefit transfers using geographical information systems: modelling demand for woodland recreation, *Regional Studies* 33, 191–205.

Bateman, I.J., Langford, I.H., Nishikawa, N. and Lake, I. (2000). The Axford Debate revisited: a case study illustrating different approaches to the aggregation of benefits data, *Journal of Environmental Planning and Management* 43, 291–302.

Beckmann, M.J. (1999). *Lectures on Location Theory*. Springer-Verlag, Berlin.

Ben-Akiva, M. and Lerman, S. (1985). *Discrete Choice Analysis*. MIT Press, Cambridge, MA.

Bennett, J. and Adamowicz, W. (2001). Some fundamentals of environmental choice modelling, in Bennett, J. and Blamey, R. (eds), *The Choice Modelling Approach to Environmental Valuation*. Edward Elgar, Cheltenham, 37–69.

Bhat, C.R. (2000). Incorporating observed and unobserved heterogeneity in urban work travel mode choice modelling, *Transportation Science* 34, 228–238.

Boxall, P.C., Adamowicz, W.L., Swait, J., Williams, M. and Louviere, J. (1996). A comparison of stated preference methods for environmental valuation, *Ecological Economics* 18, 243–253.

Breffle, W.S., Morey, E.R. and Lodder, T.S. (1998). Using Contingent Valuation to estimate a neighbourhood's Willingness to Pay to preserve undeveloped urban land, *Urban Studies* 35, 715–727.

Clarke, K.A. and Signorino, C.S. (2003). Discriminating methods: tests for non nested discrete choice models, University of Rochester. Department of Political Science, Political Methodology Working paper, http://polmeth.wustl.edu/working03.chron.html.

Hanink, D.M. (1995). The economic geography in environmental issues: a spatial analytic approach, *Progress in Human Geography* 19, 372–387.

Hanley, N., Schlapfer, F. and Spurgeon, J. (2003). Aggregating benefits of environmental improvements: distance-decay functions for use and non-use values, *Journal of Environmental Management* 68, 297–304.

Imber, D., Stevenson, G. and Wilks, L. (1991). A contingent valuation survey of the Kakadu Conservation Zone, Resource. Assessment Commission, research paper no.3, February 1991.

Jiang, Y., Swallow, S.K. and McGonagle, M.P. (2005). Contest-sensitive benefit transfer using stated choice models: specification and convergent validity for policy analysis, *Environmental and Resource Economics* 31, 477–499.

Krinsky, I. and Robb, A.L. (1986). On approximating the statistical properties of elasticities, *Review of Economics and Statistics* 68, 715–719.

Loomis, J.B. (1996). How large is the extent of the market for public goods: evidence from a nationwide Contingent Valuation survey, *Applied Economics* 28, 779–782.

Louviere, J.J., Hensher, D.A. and Swait, J.D. (2000). *Stated Choice Methods. Analysis and Applications*. Cambridge University Press, Cambridge.

McConnell, K.E. and Strand, I.E. (1981). Measuring the cost of time in recreation demand analysis: an application to sport fishing, *American Journal of Agricultural Economics* 63, 153–156.

Pate, J. and Loomis, J. (1997). The effect of distance on willingness to pay values: a case study of wetlands and salmon in California, *Ecological Economics* 20, 199–207.

Pearson, L.J., Tisdell, C. and Lisle, A.T. (2002). The impact of Noosa National Park on surrounding property values: an application of the Hedonic Price method, *Economic Analysis and Policy* 32, 155–171.

Scotchmer, S. and Thisse, J.F. (1999). Space and value: an outlook and new perspectives, in Kirman, A. and Gerard-Varet, L.A. (eds), *Economics Beyond the Millennium*. Oxford University Press, Oxford, UK, pp. 152–168.

Silberman, J., Gerlowski, D.A. and Williams, N.A. (1992). Estimating existence value for users and nonusers of New Jersey beaches, *Land Economics* 68, 225–236.

Stouffer, S.A. (1940). Intervening opportunities: a theory relating mobility and distance, *American Sociological Review* 5, 845–867.

Sutherland, R.J. and Walsh, R.G. (1985). Effect of distance on the preservation value of water quality, *Land Economics* 61, 281–291.

Van Bueren, M. and Bennett, J. (2004). Toward the development of a transferable set of value estimates for environmental attributes, *Australian Journal of Environmental and Resource Economics* 48, 1–32.

Vuong, Q.H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses, *Econometrica* 57, 307–333.

Appendix

Table A1 Likelihood ratio tests for nested models

Attribute		Linear: a_0DIST	Quadratic: a_0DIST^2	Exponential law: $a_0/(\exp(a_1\text{DIST}))$	Beckmann's law: $a_0/(1 + \text{DIST}^2)$	Natural logarithmic ln(DIST)	Gamma $a_0\text{DIST}^{a1}$ $\exp(a_2\text{DIST})$	Polynomial $a_0\text{DIST} + a_1\text{DIST}^2 + a_2\text{DIST}^3$
Weed	No distance	H_0: $a_0 = 0$ 0.514	H_0: $a_0 = 0$ 0.159	H_0: $a_0 = 0$ 0.701	H_0: $a_0 = 0$ 0.273	H_0: $a_0 = 0$ 1.780	H_0: $a_0 = 0$ 1.974	H_0: $a_0 = a_1 = a_2 = 0$ 1.776
	Gamma	H_0: $a_1 = 1$, $a_2 = 0$ 1.460	H_0: $a_1 = 2$, $a_2 = 0$ 1.815	H_0: $a_1 = 0$, $a_2 < 0$ 1.272				
	3rd order Polynomial	H_0: $a_1 = a_2 = 0$ 1.262	H_0: $a_0 = a_2 = 0$ 1.617					
Fire	No distance	H_0: $a_0 = 0$ 2.117	H_0: $a_0 = 0$ 0.001	H_0: $a_0 = 0$ 4.338	H_0: $a_0 = 0$ 0.732	H_0: $a_0 = 0$ 10.848	H_0: $a_0 = 0$ 14.833	H_0: $a_0 = a_1 = a_2 = 0$ 16.116
	Gamma	H_0: $a_1 = 1$, $a_2 = 0$ 12.717	H_0: $a_1 = 2$, $a_2 = 0$ 14.832	H_0: $a_1 = 0$, $a_2 < 0$ 10.495				
	3rd order Polynomial	H_0: $a_1 = a_2 = 0$ 14.000	H_0: $a_0 = a_2 = 0$ 16.115					
Accessibility	No distance	H_0: $a_0 = 0$ 3.054	H_0: $a_0 = 0$ 5.052	H_0: $a_0 = 0$ 1.910	H_0: $a_0 = 0$ 4.393	H_0: $a_0 = 0$ 0.005	H_0: $a_0 = 0$ 11.326	H_0: $a_0 = a_1 = a_2 = 0$ 8.685
	Gamma	H_0: $a_1 = 1$, $a_2 = 0$ 8.272	H_0: $a_1 = 2$, $a_2 = 0$ 6.275	H_0: $a_1 = 0$, $a_2 < 0$ 9.416				
	3rd order Polynomial	H_0: $a_1 = a_2 = 0$ 5.631	H_0: $a_0 = a_2 = 0$ 3.634					

Figures are calculated χ^2; χ^2 critical value with 1 d.f. at 5% = 3.84; χ^2 critical value with 2 d.f. at 5% = 5.99; χ^2 critical value with 3 d.f. at 5% = 7.81.

Table A2 Distribution-free tests for non-nested models

Attribute	Gamma vs. polynomial			Gamma vs. natural logarithmic			Gamma vs. Beckman's law		
Weed	Sign	*Observed*	*Expected*	Sign	*Observed*	*Expected*	Sign	*Observed*	*Expected*
	Positive	1624	828	*Positive*	885	828	*Positive*	851	828
	Negative	32	828	*Negative*	771	828	*Negative*	805	828
	Zero	0	0	*Zero*	0	0	*Zero*	0	0
	All	1656	1656	*All*	1656	1656	*All*	1656	1656
	One-sided tests: H_o: median of gamma – poly = 0 vs. H_a: median of gamma – poly > 0 Pr(#positive ≥ 1624) = Binomial (n = 1656, x ≥ 1624, P = 0.5) = 0.0000 H_o: median of gamma – poly = 0 vs. H_a: median of gamma – poly < 0 Pr(#negative ≥ 32) = Binomial (n = 1656, x ≥ 32, P = 0.5) = 1.0000			One-sided tests: H_o: median of gamma – log = 0 vs. H_a: median of gamma – log > 0 Pr(#positive ≥ 885) = Binomial (n = 1656, x ≥ 885, P = 0.5) = 0.0027 H_o: median of gamma – log = 0 vs. H_a: median of gamma – log < 0 Pr(#negative ≥ 771) = Binomial (n = 1656, x ≥ 778, P = 0.5) = 0.9977			One-sided tests: H_o: median of gamma – beck = 0 vs. H_a: median of gamma – beck > 0 Pr(#positive ≥ 851) = Binomial (n = 1656, x ≥ 851, P = 0.5) = 0.1344 H_o: median of gamma – beck = 0 vs. H_a: median of gamma – beck < 0 Pr(#negative ≥ 805) = Binomial (n = 1656, x ≥ 805, P = 0.5) = 0.8760		
Fire	Sign	*Observed*	*Expected*	Sign	*Observed*	*Expected*	Sign	*Observed*	*Expected*
	Positive	1485	828	*Positive*	840	828	*Positive*	906	828
	Negative	171	828	*Negative*	816	828	*Negative*	750	828
	Zero	0	0	*Zero*	0	0	*Zero*	0	0
	All	1656	1656	*All*	1656	1656	*All*	1656	1656
	One-sided tests: H_o: median of gamma – poly = 0 vs. H_a: median of gamma – poly > 0 Pr(#positive ≥ 1485) = Binomial (n = 1656, x ≥ 1485, P = 0.5) = 0.0000 H_o: median of gamma – poly = 0 vs. H_a: median of gamma – poly < 0 Pr(#negative ≥ 171) = Binomial (n = 1656, x ≥ 171, P = 0.5) = 1.0000			One-sided tests: H_o: median of gamma – log = 0 vs. H_a: median of gamma – log > 0 Pr(#positive ≥ 840) = Binomial (n = 1656, x ≥ 840, P = 0.5) = 0.2860 H_o: median of gamma – log = 0 vs. H_a: median of gamma – log < 0 Pr(#negative ≥ 816) = Binomial (n = 1656, x ≥ 816, P = 0.5) = 0.7305			One-sided tests: H_o: median of gamma – beck = 0 vs. H_a: median of gamma – beck > 0 Pr(#positive ≥ 906) = Binomial (n = 1656, x ≥ 906, P = 0.5) = 0.0001 H_o: median of gamma – beck = 0 vs. H_a: median of gamma – beck < 0 Pr(#negative ≥ 750) = Binomial (n = 1656, x ≥ 750, P = 0.5) = 0.9999		

Table A2 *Continued*

Attribute	Gamma vs. polynomial			Gamma vs. natural logarithmic			Gamma vs. Beckman's law		
Accessibility	Sign	*Observed*	*Expected*	Sign	*Observed*	*Expected*	Sign	*Observed*	*Expected*
	Positive	1372	828	*Positive*	902	828	*Positive*	806	828
	Negative	284	828	*Negative*	754	828	*Negative*	850	828
	Zero	0	0	*Zero*	0	0	*Zero*	0	0
	All	1656	1656	*All*	1656	1656	*All*	1656	1656
	One-sided tests:			One-sided tests:			One-sided tests:		
	H_o: median of gamma – poly = 0 vs.			H_o: median of gamma – log = 0 vs.			H_o: median of gamma – beck = 0 vs.		
	H_a: median of gamma – poly > 0			H_a: median of gamma – log > 0			H_a: median of gamma – beck > 0		
	Pr(#positive ≥ 1372) = Binomial			Pr(#positive ≥ 902) = Binomial			Pr(#positive ≥ 806) = Binomial		
	(n = 1656, $x \geq 1372$, P = 0.5) = 0.0000			(n = 1656, $x \geq 902$, P = 0.5) = 0.0002			(n = 1656, $x \geq 806$, P = 0.5) = 0.8656		
	H_o: median of gamma – poly = 0 vs.			H_o: median of gamma – log = 0 vs.			H_o: median of gamma – beck = 0 vs.		
	H_a: median of gamma – poly < 0			H_a: median of gamma – log < 0			H_a: median of gamma – beck < 0		
	Pr(#negative ≥ 284) = Binomial			Pr(#negative ≥ 754) = Binomial			Pr(#negative ≥ 850) = Binomial		
	(n = 1656, $x \geq 284$, P = 0.5) = 1.0000			(n = 1656, $x \geq 754$, P = 0.5) = 0.9999			(n = 1656, $x \geq 850$, P = 0.5) = 0.1453		