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Investigating distance effects on environmental values: A choice modelling approach

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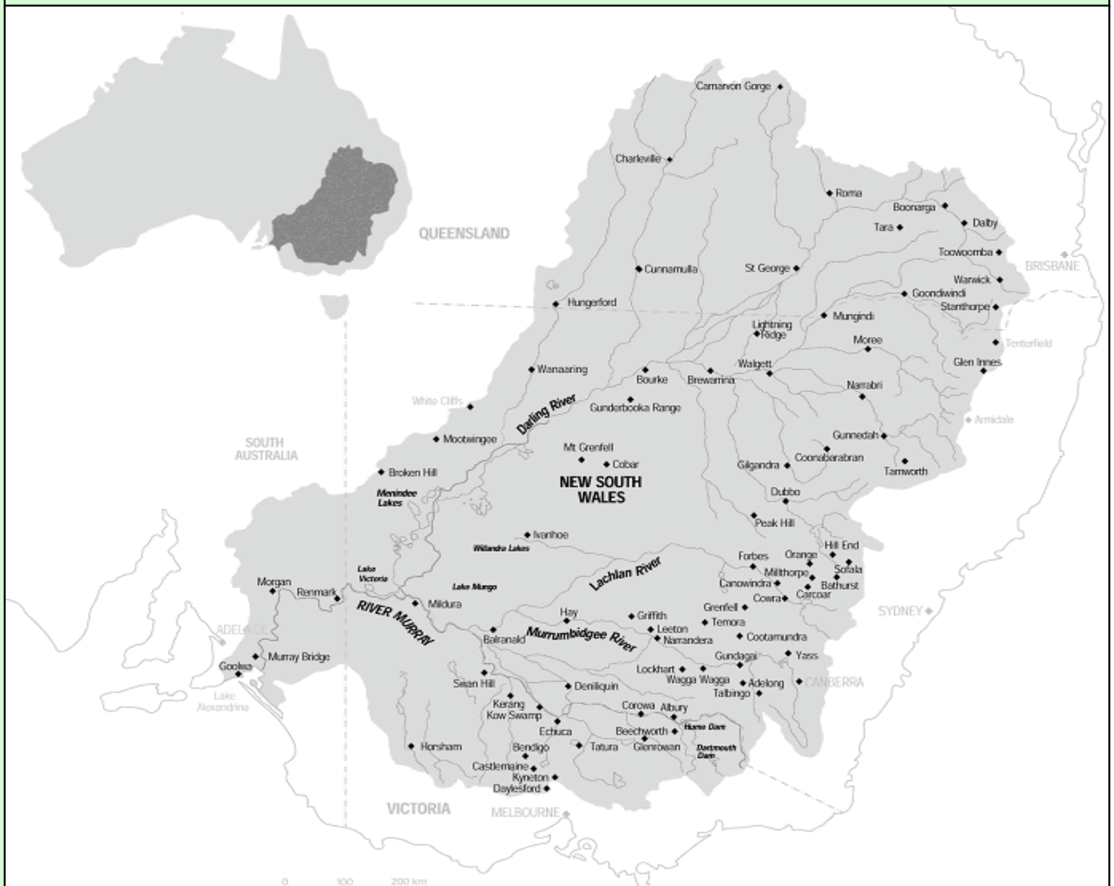

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INVESTIGATING DISTANCE EFFECTS ON ENVIRONMENTAL VALUES.
A CHOICE MODELLING APPROACH

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Abstract:

This paper describes a Choice Modelling experiment set up to investigate the relationship between distance and willingness to pay for environmental quality changes. The issue is important for the estimation and transfer of benefits. So far the problem has been analysed through the use of Contingent Valuation-type of experiments, producing mixed results. The Choice Modelling experiment allows testing distance effects on parameters of environmental attributes that imply different trade-offs between use and non-use values. The sampling procedure is designed to provide a "geographically balanced" sample. Several specifications of the distance covariate are compared and distance effects are shown to take complex shapes. Welfare analysis also shows that disregarding distance produces under-estimation of individual and aggregated benefits and losses, seriously hindering the reliability of cost-benefit analyses.

Keyword: Choice Modelling techniques, distance, aggregation, sampling, functional forms.

1. Introduction

There are several empirical and policy-related justifications to investigate distance effects on environmental preferences. First, distance affects use of environmental goods, information and substitution possibilities that in turns affect preferences (Sutherland and Walsh 1985). Omitting distance in individual benefit estimation would produce biased results. Second, identification of the relevant population for aggregation purposes is generally guided by a political/administrative criterion. That is, benefits are assumed to differ from zero within given political boundaries and to be nil outside. Detecting distance effects could provide an empirical validation to this criterion by eventually identifying the point in space at which benefits go to zero (Loomis 1996). Furthermore, aggregating unbiased individual estimates over the correct number of (spatially distributed) beneficiaries would provide unbiased aggregate benefits. Third, since benefit transfer uses sample (or population) characteristics to adapt original estimates from sampled population A to population B (or from asset i to asset j), assessing the effect of distance would help in benefit transfer applications (Bateman et al. 1999, Jiang et. al. 2005). On a policy ground, investigating distance effects can also provide useful information regarding the appropriate form of taxation (local, state or federal) necessary to fund environmental projects.

The possibility to correctly detect distance effects depends primarily on two factors: the divergence between the spatial distributions of the sample and the population, and the functional form chosen to represent the distance-value relationship. In Stated Preference (SP) 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 in SP studies is then unlikely to provide a geographically representative sample, and corrective measures are necessary. Given the interplay of use values, non-use values, information and substitution opportunities in shaping environmental benefits, one finds little guidance for choosing among possible functional forms for the distance-values relationship. Location theory, for instance, indicates that human interactions over space can be captured by different specifications some of which, such as the gravitational model, have little theoretical foundations but strong explanatory power (Beckmann 1999). Tests for different functional forms are required.

Several Contingent Valuation (CV) applications have investigated the relation between values and distance (Sutherland and Walsh 1985, Loomis 1996, Pate and Loomis 1997, Bateman and Langford 1997, Hanley et al. 2003) Their results are mixed and vary according to the features of the assets under valuation, the sample's geographical distribution, the specified functional form of the distance/WTP relationship and the format of the CV questions. No attempt has been made so far to estimate a distance-value relationship via the Choice Modelling (CM) technique. In CM studies, environmental policies are defined in terms of "attributes" and respondents are asked to choose among alternative policies constructed by systematically varying the attribute "levels". Choices reveal how individuals trade-off the attributes and from these trade-offs it is possible to estimate utility parameters. Detecting distance effects in CM applications is possibly more important than in CV studies. In open-ended CV, for instance, the population's distribution of WTP is fitted and it doesn't matter what causes its variation as long as the sample is representative of the population. In CM, WTP is predicted from the estimated utility parameters. Omission of distance would produce biased estimates even with a geographically representative sample. Further, since in CM preferences are elicited through attributes variations, distance effects are expected to depend on the use/non-use ratio entailed by each attribute. Hence unbiased distance effects can be estimated only by defining appropriate distance function for each attribute.

This article illustrates how distance effects can be estimated in a CM study of environmental protection programs. The sampling procedure is designed to provide a "geographically balanced" sample, i.e. a sample that mirrors the spatial distribution of the population around the asset under valuation. Several functional forms are compared via tests for nested and non-nested models. Finally, benefit estimates are presented for two choice models, one without distance and another with the preferred specifications of the distance covariates. The goal is to identify the magnitude and the direction of the bias due to the omission of distance.

2. The Choice Modelling approach.

The Choice Modelling (CM) approach (also known as Choice Experiment) is basically "a structured method of data generation" (Hanley *et al.*, 1998). It has been used in a large number of marketing, transportation and health care applications and it is increasingly applied in environmental valuation (Adamowicz 2004). CM is based on Lancaster's characteristic approach (Lancaster, 1966) and random utility theory. According to these approaches, choice behaviour can be described by a function which relates the utility U_{ij} of each alternative *j* for an individual *i* to the set of the alternative's attributes (Q_j) and individual characteristics (S_i):

$$U_{ij}=V_{ij}(Q_j, S_i) + \varepsilon_{ij} \tag{1}$$

It is assumed that each utility value can be partitioned into two components: an observable or systematic component V_{ij} and an unobservable, random component, ε_{ij}. Because of the random component, the choice problem is inherently stochastic from the point of view of the researcher and it can be formulated in probabilistic terms. Individuals are assumed to choose the alternative that yields the highest utility. That is, the alternative *j* is chosen if $U_{ij}>U_{ik}$ for each $j\neq k$. The function linking the probability of an outcome to the utility associated with each alternative can be written as:

$$Pr_{ij}[j \mid Q_j, S_i]=Pr[(U_{ijj})> (U_{ik})] \qquad \forall\, j\neq k \tag{2}$$

or

$$Pr_{ij}[j \mid Q_j, S_i]=Pr[(V_{ij}+\varepsilon_{ij})> (V_{ik}+\varepsilon_{ik})] \qquad \forall\, j\neq k \tag{3}$$

and then

$$\Pr_{ij}[j \mid Q_j, S_i] = \Pr[(\varepsilon_{ik}-\varepsilon_{ij}) < (V_{ij}-V_{ik})] \qquad \forall\, j \neq k \tag{4}$$

Depending on the distributional properties of the error terms and the design of the experiment, parameters of the deterministic element V_{ij} can be estimated. In the most general form, V_{ij} can be parameterized as follow:

$$V_{ij} = \alpha_j + \Sigma_q \beta_q Q_{jq} + \Sigma_{qs} \theta_{qs} Q_{jq} S_{is} + \Sigma_{js} \varphi_{js} \alpha_j S_{is} + \Sigma_{js} \psi_{js} Q_q Q_p \tag{5}$$

where α_j, β_q, γ_s, θ_{qs}, φ_{js}, ψ_{js} are parameters to be estimated conditional on a vector of intercept terms for J-1 of the J choice options, the matrixes of choice attributes Q, interaction terms of attributes Q_qQ_p, attributes and individual characteristics $Q_{jq}S_{is}$ and intercept terms and individual characteristics. Note that the choice probabilities in equations (2) and (3) depend only on the difference in utility and only parameters that capture differences across alternatives can be estimated. That is why only J-1 intercept terms are specified and the individual characteristics enter only as interaction terms.

Distance effects can be computed as interactions effects on the intercept terms or on the attributes. Intercept terms are alternative specific constants (ASC) that capture the average effect on utility of all factors not included in the model. As only differences in utility matter, researchers set the absolute level of the constant for, say, alternative i to zero and the parameters α_j is to be interpreted as the average effect of unincluded factors on utility of alternative j relative to alternative i. In CM applications, researchers set the attributes and their levels and submit to the assessment of survey participants several environmental goods (or policies) constructed by systematically combining attribute levels usually according to an orthogonal experimental design. It is also customary to set the current status or policy as the alternative for which the alternative specific constant is zero. The α's can be easily interpreted as the utility gains of losses associated with moving away from the status quo. For policy reasons it may be useful to know how individuals living at different distances from the asset under valuation gain or lose when abandoning the status quo. However, distance is expected to primarily affect the parameter estimates for the attributes. Indeed, attribute variations imply changes in the use and non-use benefits, and these benefits are likely to change for individuals according to their location (and other socio-economic characteristics). Unbiased parameter estimates require these distance effects to be computed for each attribute. The parameter θ_{qs} in (5) depicts these effects and measure the change in the attribute parameter β_q caused by, say, the distance variable. Implicit prices, i.e. the individual WTP for a 1% change of an attribute, can be computed as a function of distance. Implicit prices are the ratio of the parameter of q attribute and the parameter of a monetary attribute, β_q / β_{cost}. Distance interactions change the implicit prices to:

$$(\beta_q + \theta_{qs}\mathrm{DIST}) / \beta_{cost} \tag{6}$$

It is also possible to determine how individual i's compensating surplus CS_i for a change from policy A to policy B is affected when distance interacts with attributes. The compensating surplus CS_i would be itself a function of distance:

$$\mathrm{CS}_j = -(1/\beta_{cost})*[(\Sigma_q\beta_q \mathrm{Q}_{Aq} + \Sigma_{qs}\theta_{qs}\,\mathrm{Q}_{Aq}\mathrm{DIST}_i) - (\alpha_B + \Sigma_q\beta_q \mathrm{Q}_{Bq} + \Sigma_{qs}\theta_{qs}\,\mathrm{Q}_{Bq}\mathrm{DIST}_i)] \tag{6}$$

where Q_{Aq} and Q_{Bq} are the attribute levels for the two policy options A and B. Since the empirical structure of the utility function - i.e. the model mapping the attributes of the alternatives and the individual's socio-economic characteristics into utility - influences the choice probabilities and hence the predictive capacity of the model, the functional form of the distance variable for each attribute must be selected through a search of the statistically best specification.

3. Survey implementation, sampling and model specification.

The CM survey was designed in consultation with the management authority of Kings Park in Perth (Western Australia). Kings Park is located in the heart of the Perth metropolitan area, just 1 km away from the Central Business District. It is used by daily visitors for a range of activities from bird and fauna watching to family activities in the park's playground. The management authority indicated three major problems in the conservation of the park's bushland: weeds that replace native species, degradation caused by human treading, and fires. These problems are also common in other protected area in Western Australia. The CM study was designed to understand how people perceive these issues, help the management authority to prioritise its conservation efforts and investigate the possibility of raising funds to further improve the conditions of the bushland. This last topic was particularly important, given that state funds for the park are controversial, and some members of the public argue for funding via council taxes, others for federal funding. Three focus groups were organised to identify attributes, levels, the proper format for different management options and test the whole questionnaire. Table 1 shows the final set of attributes and levels [insert table 1]. The *Weed* attribute indicates the percentage of bushland that is free from weed. The *Fire* attribute specifies the average percentage of bushland annually destroyed by fires. The *Accessibility* attribute gives the percentage of the bushland that is accessible to the public. The *Cost* attribute is the contribution via annual income tax required to each West Australian resident to support the management strategy made up by these attribute. A management option illustrates how the park authority can allocate its resource – eradicating weeds, preventing fire or restoring degraded bushland. The systematic variation of the attribute was designed by a Graeco-Latin fractional factorial orthogonal procedure. It identified 16 management options. Respondents were presented with 8 choice sets each composed by the status quo and two other management options. Several socio-economic characteristics and attitudinal variable were also collected from survey participants (table 2) [insert table 2].

The sampling procedure was designed to produce a geographically balanced sample by using a stratified random sampling (Ben-Akiva and Lerman, 1985) coupled with the administration of the survey “in waves”. The sample is stratified according to 11 distance-zones or concentric bands around the park (table 3) [insert table 3]. The population of each zone is determined using data from the 2001 Census of Australian Bureau of Statistics (ABS 2001). It gives the proportion of the sample that needs to be drawn from each zone. Care is also taken for the sub-sample to be distributed in the zone as the population and it is not clustered in a particular direction unless the population is. In the first waves, an equal number of randomly selected West Australian residents was first contacted by phone and invited to take part in the survey. Questionnaires were sent by mail with a reply-paid envelope. Once the questionnaires were returned, response rates and shares of each zone in the sample were calculated and compared to the zones’ population share. Difference between the population and the sample shares suggested the need to adjust the sample and gave the number of contacts in the second wave to be sought in each zone. Following waves further adjusted the sample so as to replicate the spatial differences in population distribution. The sampling started in June and finished in September 2003. A total of 750 questionnaires were sent, 324 returned and 207 were used for the estimation exercise. The overall response rate is 28%.

The model in (5) is estimated using several different specifications of the distance variable for each attribute. Table 4 lists the different functional forms used in this study [insert table 4]. The parameter a_1 and a_2 of the Gamma Transformation are estimated via a grid search procedure. This functional form is chosen because it can replicate the shape of simpler specifications (linear, log-linear, polynomial, logarithmic) and it also can represent more complex relationships. Indeed, as shown by Imber et al. (1991) and Espey and Owusu-Edusei (2001), the impact of proximity to an environmental amenity on benefits could be positive in the short distance and turn negative as distance increase. The Gamma Transformation model can replicate this spatial trend and collapses into simpler models such as linear or exponential if the one of its parameters is zero. The Beckmann’s specification is a simplified gravitational model (Beckmann 1999). In order to choose the best specification, a series of tests is required. Nested models are compared using the likelihood ratio criterion (Louviere *et al*., 2000) that is a test on a particular set of variables. A model is said to be nested to another if it constrains one or more parameters to be equal to zero. The likelihood ratio test takes the form:

$$-2\ln L^* = -2\ln\left(\frac{\max L(\omega)}{\max L(\Omega)}\right) \tag{8}$$

where max $L(\omega)$ and max$L(\Omega)$ are the maximum likelihood values of respectively the constrained and the general model. This statistics is approximately distributed as a chi-squared with degrees of freedom equal to the number of constraints. Non-nested models are compared using Clarke's distribution-free test (Clarke and Signorino, 2003). The distribution-free test is a modified paired sign test that determines if the median log-likelihood ratio is statistically different from zero. If the two non-nested models are equally close to the true specification, individual log-likelihood ratios should be equally divided between greater than and less than zero. For instance, comparing the Gamma Transformation and a 2nd order polynomial specification, the first is "better" than the second if more than half of the individual log-likelihood ratios are greater than zero and vice versa. The number of positive difference is distributed binomial(*# of obs*, 0.5).

4. Model results.

Results of the specification tests for selected nested and non-nested models are reported in appendix A. For the *Fire* attribute, the preferred specification is the Gamma Transformation. For the *Accessibility* attribute, the best functional form of the distance variable is a Beckmann's specification, while the *Cost* attribute interacts with distance in logarithmic form. No distance effects are recorded for the *Weed* attribute. The model in (5) is estimated assuming the error terms are i.i.d. extreme value. This hypothesis is at the core of MacFadden's Conditional Logit (Greene 2003). Results are reported in table 5 for a model that omits distance interactions for all attributes and a model in which distance interacts with the attributes according to the preferred specifications [insert table 5]. For both models, likelihood Ratio tests suggest that the same set of independent variables (distance omitted) is to be included in the estimation model.

In both models, the significant negative sign of the ASC indicates that the utility associated with moving away from the status quo is negative. This is known as a status quo bias or endowment effect (Adamowicz et al. 1998). For the *Weed* attribute, individuals' income (in logarithmic form) and environmental attitude (*EnvAtt=1*) have both significant and positive parameters. No distance effects are recorded. This is not surprising given that the *Weed* attribute entails only changes in non-use values (see Concu 2005). Substitution variables, even if retained on the basis of the Likelihood Ratio test, are not significant. Income and environmental attitude are significant also for the *Fire* attribute. Note their negative signs. Higher levels of the *Fire* attribute represent increased fire damages in the park. Hence, the negative coefficients indicate a willingness to pay to prevent these damages. Distance effects on the *Fire* attribute are captured by a Gamma Transformation with parameters $a_1=-3$ and $a_2=6$ obtained by a grid search procedure. Figure I depicts the behaviour in space of the implicit price of *Fire* attribute, calculated using equation (6). It shows the complexity of the relation between distance and values when the attribute involves *both* use *and* non-use value changes. WTP for fire prevention in Kings Park decreases with distance and then increases again. It appear that country people are more concerned about fires, maybe because more familiar with fire events. Effects of distance on the third attribute are decreasing (fig.1). Reducing accessibility to Kings Park bushland does not seem to concern residents living far away from the park. Other variables affect the magnitude of the values for the *Accessibility* attribute (substitute availability, country of origin, education level and knowledge of Kings Park, number of children). More educated, more informed and more numerous family members have a preference toward having the bushland accessible. The *Cost* attribute has a negative and significant parameter, as expected. Income effects are also negative, showing that higher income earners are less eager to pay for Kings Park. As distance from the park increases, respondents are also more concern about a tax increase to fund the management alternatives. The magnitude of the implicit prices for the three environmental attributes depends on socio-economic characteristics that affect the intercepts of the distance functions in Figure I. These functions tend to an asymptote and the gains or losses associated with each attribute change become distance-independent. A properly designed management strategy for would provide benefits to all Western Australian residents. In the light of these distance effects, it can be stated that state funds for Kings Park are justified. The market area for Kings Park is at least as large as Western Australia. It is not possible to say, however, if federal resources would be also appropriated. The sampling frame is indeed constrained to the Western Australian residents. Crossing a state border it expected to be a cause for spatial discontinuity, preventing to extrapolate these results to the population of another state.

The consequences of omitting distance on individual parameters can be assessed comparing the models in table 5. *t*-tests on the hypothesis that the parameters of the models with and without distance are equal is strongly rejected for all parameters except the alternative specific constant, the base coefficient for the weed attribute and the interaction between environmental attitude and the *Weed* attribute. For most of the 22 significant coefficients, the omission of distance determines underestimation of the parameter and larger standard errors. Aggregated welfare measures for Kings Park's bushland management strategies are computed using equation (7). Information on income and distance distribution of Western Australian residents is taken from the 2001 Australian Bureau of Statistics Census. Sample shares are used for the attitudinal variable. For the other variables, aggregation is carried out using the most conservative estimates. The benefits from the status quo (V_0) are compared with the benefits from five other management scenarios (V_1), as reported in table 6 [insert table 6]. Scenario 1 hypnotizes that the Kings Park's management authority sets up a project to further reduce weed encroachment, bringing the weed-free area up to 60% of the bushland. In scenario 2 the park managers increase the efforts to prevent fires and reduce the average area of bushland annually damaged to 1%. Scenario 3 supposes that the park authority reduces damages by closing access in 25% of the bushland area. A fourth scenario, named the "worst case" determines a deterioration of the conditions of the bushland. Scenario 5 embodies a change in all the three attributes. The consequences of ignoring distance and assuming a uniformly distributed population are illustrated in table 6. Gains from implementing a scenario are indicated by negative figures. Distance omission determines gross underestimation of benefits (scenario 5) and losses (scenario 4). More importantly, for scenarios 1 to 3, the consequences of omitting distance are so severe that it turns benefits into losses and vice versa. Such an outcome can easily lead to an inefficient allocation of resources. Table 7 tells also that the public gains from scenario 1 that, by construction, implies only a change in the *Weed* attribute, i.e. a change in non-use values. Non-use values of native species in Kings Park bushland are worth around Au$3.6 million. Further, the values that the public assigns to the actual services of the bushland are substantial. Losing part of the bushland because of fires and weed encroachment produces a loss of $10.2 million (scenario 4). Contrasting this figure with the amount of money the park authority actually spend on the bushland (Au$330.000), it shows that there is huge scope for increasing public funding of the park.

5. Conclusion.

Using spatial information in environmental valuation could help to avoid under and over estimation of individual parameters and to identify the relevant population of a natural asset.

Failing to take into account distance would determine underestimation of aggregate benefits and losses, depending on the distance effects on individual parameters and the geographical distribution of the sampled population. Furthermore, omission of distance not only creates underestimation of benefits and losses, but may indicate welfare gains when the public would lose from a policy change. The risk of serious misallocation of resource is considerable.

This article investigates how distance effects can be accounted for in a Choice Modelling application. The issue is relevant when using such an approach because of its multi-attribute nature. It is necessary not only a sample that represents the geographical distribution of the population, but also accurate specification tests for the distance variable. The study illustrates the gross underestimation of benefits and losses determined by distance omission. It also shows that it is possible to determine how large the smallest area for aggregation purposes is. For fiscal policy, including distance in benefit estimation can provides rationale for a local, state or federal taxation. This article demonstrates that for the park under valuation, state funding is appropriate. The study also shows that this approach is limited by the sampling frame adopted. While it is possible to identify the smallest area for aggregation, the sampling frame limits the possibility to make out-of-sample predictions, especially when there factors, such as the crossing of administrative boundaries, which may induce spatial discontinuity of benefits.

This article also finds that distance effects can take quite complex shapes and that simple specifications of the distance variables may not be able to capture. This result is due to the nature of the environmental attributes in the CM experiments, and their implied use/non-use values trade-offs. Replications of this study with other environmental goods, attributes and model specifications are clearly necessary.

APPENDIX

Table A1. Specification tests for nested models.

		Nested Models: LR tests					
	Models	Linear	2nd Ord Poly	3rd Ord Poly	Beckmann's	Gamma	Logarithmic
Weed	No Distance	H_0:β_{dist}=0 0.514	H_0:β_{dist}=0 0.940	H_0:β_{dist}=0 1.776	H_0:β_{dist}=0 0.273	H_0:β_{dist}=0 1.974	H_0:β_{dist}=0 1.780
	Linear	-	H_0:β_{dist2}=0 0.427	H_0:β_{dist2}=0; β_{dist3}=0 1.262	-	H_0: a_1=1; a_2=0 1.460	-
	2nd Ord Poly	-	-	H_0: β_{dist3}=0 0.8352051	-	-	-
Fire	No Distance	H_0:β_{dist}=0 2.117	H_0:β_{dist}=0 **14.268**	H_0:β_{dist}=0 **16.116**	H_0:β_{dist}=0 0.732	H_0:β_{dist}=0 **14.833**	H_0:β_{dist}=0 **10.848**
	Linear	-	H_0:β_{dist2}=0 **12.151**	H_0:β_{dist2}=0; β_{dist3}=0 **14.000**	-	H_0: a_1=1; a_2=0 **12.717**	-
	2nd Ord Poly	-	-	H_0: β_{dist3}=0 1.849	-	-	-
Accessibility	No Distance	H_0:β_{dist}=0 3.054	H_0:β_{dist}=0 **5.785**	H_0:β_{dist}=0 **8.685**	H_0:β_{dist}=0 **4.393**	H_0:β_{dist}=0 **11.326**	H_0:β_{dist}=0 0.005
	Linear	-	H_0:β_{dist2}=0 2.731	H_0:β_{dist2}=0; β_{dist3}=0 **5.631**	-	H_0: a_1=1; a_2=0 **8.272**	-
	2nd Ord Poly	-	-	H0: βdist3=0 2.900	-	-	-
Cost	No Distance	H_0:β_{dist}=0 **3.879**	H_0:β_{dist}=0 **4.969**	H_0:β_{dist}=0 **6.803**	H_0:β_{dist}=0 2.511	H_0:β_{dist}=0 NA	H_0:β_{dist}=0 **7.189**
	Linear	-	H_0:β_{dist2}=0 1.090	H_0:β_{dist2}=0; β_{dist3}=0 2.924	-	H_0: a_1=1; a_2=0 -	-
	2nd Ord Poly	-	-	H_0: β_{dist3}=0 1.834	-	-	-

H_O indicates the restriction imposed on the general model. β_{dist2} and β_{dist3} are the parameters of $DIST^2$ and $DIST^3$ respectively. a_1 and a_2 are parameters of the Gamma transformation. Figures are the calculated chi2 value (-2lnL*). Chi^2 critical value with 1 d.f. at 5%= 3.84. Chi^2 critical value with 2 d.f. at 5%= 5.99. Figures in **BOLD** indicate H_0 is rejected.

Table A2. Specification tests for non-nested models.

Att: **Fire**

Gamma vs 3_{rd} Ord Polynomial

Sign	***observed***	***expected***
Positive	1485	828
negative	171	828
Zero	0	0
All	1656	1656

One-sided tests:

Ho: median of gamma - poly = 0 vs. Ha: median of gamma - poly > 0

Pr(#positive >= 1485) = Binomial(n = 1656, x >= 1485, p = 0.5) = 0.000

Ho: median of gamma - poly = 0 vs. Ha: median of gamma - poly < 0

Pr(#negative >= 171) = Binomial(n = 1656, x >= 171, p = 0.5) = 1.0000

Gamma vs Logarithmic

Sign	***observed***	***expected***
positive	840	828
negative	816	828
zero	0	0
all	1656	1656

One-sided tests:

Ho: median of gamma - log = 0 vs. Ha: median of gamma - log > 0

Pr(#positive >= 840) = Binomial(n = 1656, x >= 840, p = 0.5) = 0.286

Ho: median of gamma – log = 0 vs. Ha: median of gamma - log < 0

Pr(#negative >= 816) = Binomial(n = 1656, x >= 816, p = 0.5) = 0.730

Logarithmic vs 3_{rd} Ord Polynomial

sign	***observed***	***expected***
positive	1463	828
negative	193	828
Zero	0	0
All	1656	1656

One-sided tests:

Ho: median of log - poly = 0 vs. Ha: median of log – poly > 0

Pr(#positive >= 1463) = Binomial(n = 1656, x >= 1463, p = 0.5) = 0.00

Ho: median of log – poly = 0 vs. Ha: median of log - poly < 0

Pr(#negative >= 193)= Binomial(n = 1656, x >= 193, p = 0.5) = 1.00

Att: **Accessibility**

Gamma vs 3_{rd} Ord Polynomial

Sign	***observed***	***expected***
Positive	1372	828
negative	284	828
Zero	0	0
All	1656	1656

One-sided tests:

Ho: median of gamma - poly = 0 vs. Ha: median of gamma - poly > 0

Pr(#positive >= 1372) = Binomial(n = 1656, x >= 1372, p = 0.5) = 0.000

Ho: median of gamma - poly = 0 vs. Ha: median of gamma - poly < 0

Pr(#negative >= 284) = Binomial(n = 1656, x >= 284, p = 0.5) = 1.0000

Gamma vs Beckmann

Sign	***observed***	***expected***
positive	806	828
Negative	850	828
Zero	0	0
All	1656	1656

One-sided tests:

Ho: median of gamma - beck = 0 vs. Ha: median of gamma – beck > 0

Pr(#positive >= 806) = Binomial(n = 1656, x >= 806, p = 0.5) = 0.865

Ho: median of gamma - beck = 0 vs. Ha: median of gamma - beck < 0

Pr(#negative >= 850) = Binomial(n = 1656, x >= 850, p = 0.5) = 0.145

Beckmann vs 3_{rd} Ord Polynomial

sign	***observed***	***expected***
positive	1470	828
negative	186	828
zero	0	0
all	1656	1656

One-sided tests:

Ho: median of gamma - log = 0 vs. Ha: median of gamma - log > 0

Pr(#positive >= 1470) = Binomial(n = 1656, x >= 902, p = 0.5) = 0.000

Ho: median of gamma - log = 0 vs. Ha: median of gamma - log < 0

Pr(#negative >= 186) = Binomial(n = 1656, x >= 754, p = 0.5) = 1

Att: **Cost**

Logarithmic vs Linear

Sign	***observed***	***expected***
Positive	844	828
negative	812	828
Zero	0	0
All	1656	1656

One-sided tests:

Ho: median of gamma - poly = 0 vs. Ha: median of gamma - poly > 0

Pr(#positive >= 844) = Binomial(n = 1656, x >= 1372, p = 0.5) = 0.223

Ho: median of gamma - poly = 0 vs. Ha: median of gamma - poly < 0

Pr(#negative >= 812) = Binomial(n = 1656, x >= 284, p = 0.5) = 0.7913

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Table 1. Attributes, levels and corresponding variables.

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

*(sq) = status quo levels

Table 2. Socio-economic characteristics of respondents.

Variable	Type	Meaning
EnvAtt	Categorical	*Environmental attitude*
Rank	Categorical	*Ranking of environmental issues*
Info	Continuous	*Respondents' knowledge of KP*
Subst	Categorical	*# of substituted for Kings Park*
Distance	Continuous	*Geographical distance from Kings Park*
Gender	Categorical	
Age	Continuous	*Age of the respondent*
Child	Continuous	*Number of children in the household*
Country	Categorical	*Country of origin:*
Educ	Categorical	*Attained level of education:*
Empl	Categorical	*Employment status*
Income	Continuous	*Weekly individual income*
Org	Categorical	*Membership in environmental organizations*

Table 3. Definition of distance zones, population and sample share.

	Distance from Kings Park	**Population share**	**Sample share**	**Differences (in %)**
ZONE 1	0-5 Km	9.4	10.1	-0.7
ZONE 2	5-10Km	18.2	17.4	0.8
ZONE 3	10-15 Km	17.4	17.9	-0.5
ZONE 4	15-20 Km	12.3	14.0	-1.7
ZONE 5	20-30 Km	8.6	9.7	-1.1
ZONE 6	30-50 Km	6.9	6.8	0.1
ZONE 7	50-100 Km	4.3	2.9	1.4
ZONE 8	100-150 Km	4.8	4.8	0.0
ZONE 9	150-300 Km	3.9	3.9	0.0
ZONE	300-700 Km	5.3	6.3	-1.0
ZONE	Over 700 Km	8.9	6.3	2.6
		100.0	100.0	

Table 4. Functional forms of the distance variable.

Function	Formula
Linear	$DIST2=a_oDIST1$
Logarithmic	$DIST2=a_0ln(DIST1)$
2nd Polynomial	$DIST2=a_oDIST1+a_1DIST1^2$
3rd Polynomial	$DIST2 = a_0DIST1 + a_1DIST1^2 + a_2DIST1^3$
Gamma	$DIST2 = a_0(DIST1)^{a_1} e^{(a_2DIST1)}$
Exponential Law	$DIST2 = a_0 exp(-DIST1)$
Beckmann Law	$DIST2 = \frac{a_0}{1 + DIST1^2}$

Table 5. Results of the Conditional Logit Models.

	Distance included			Distance omitted		
Observations	4968			4968		
Log Likelihood	-1556.330			-1569.118		
Pseudo R2	0.1445			0.1375		
Variable	*Coef.*	*St.Err.*	*P>|z|*	*Coef.*	*St.Err.*	*P>|z|*
ASC	-0.218*	0.091	0.016	-0.217*	0.091	0.017
Weed	-0.082**	0.041	0.043	-0.081**	0.041	0.045
weed*ln(income)	0.013**	0.006	0.030	0.012**	0.006	0.033
weed*att(=1)	0.035***	0.009	0.000	0.035***	0.009	0.000
weed*subst(=1)	-0.017	0.013	0.197	-0.016	0.013	0.212
weed*subst(=2)	0.011	0.012	0.357	0.012	0.012	0.326
weed*subst(=3 or more)	0.013	0.012	0.279	0.014	0.012	0.220
weed*subst(na)	-0.009	0.017	0.592	-0.010	0.017	0.542
Fire	0.152	0.142	0.285	0.185	0.141	0.191
fire*ln(income)	-0.034*	0.020	0.096	-0.032	0.020	0.111
fire*distance(GAMMA)	32.097***	8.597	0.000	-	-	-
fire*att(=1)	-0.072**	0.032	0.025	-0.022***	0.032	0.024
fire*subst(=1)	0.005	0.047	0.916	-0.090	0.046	0.632
fire*subst(=2)	-0.074	0.045	0.100	0.018**	0.044	0.042
fire*subst(=3 or more)	0.055	0.044	0.209	0.030	0.042	0.667
fire*subst(na)	-0.007	0.062	0.907	-0.004	0.060	0.618
Accessibility	-0.038*	0.019	0.052	-0.002	0.015	0.782
acc*ln(income)	-0.001	0.002	0.431	-0.003	0.002	0.276
acc*distance(beckmanns')	0.031***	0.012	0.007	-	-	-
acc*att(=1)	-0.004	0.003	0.196	0.022	0.003	0.227
acc*rank(=4)	0.023***	0.007	0.001	0.013***	0.007	0.002
acc*rank(=3)	0.014**	0.007	0.033	0.008**	0.007	0.047
acc*rank(=2)	0.008	0.007	0.244	0.013	0.007	0.261
acc*rank(=1: less important)	0.014*	0.007	0.067	-0.009*	0.007	0.082
acc*subst(=1)	-0.010**	0.004	0.014	-0.010**	0.004	0.029
acc*subst(=2)	-0.011***	0.004	0.004	-0.008**	0.004	0.012
acc*subst(=3 or more)	-0.010***	0.004	0.008	-0.002**	0.004	0.023
acc*subst(not applicable)	-0.003	0.005	0.619	-0.012	0.005	0.772
acc*country(overseas)	-0.012***	0.002	0.000	0.008***	0.002	0.000
acc*educ(=Y12)	0.006**	0.003	0.050	0.008**	0.003	0.024
acc*educ(=cert)	0.009**	0.003	0.012	0.006***	0.003	0.007
acc*educ(uni)	0.008***	0.003	0.004	-0.006*	0.003	0.059
acc*org(=1)	-0.006**	0.003	0.048	0.000**	0.003	0.041
acc*# of children	0.002**	0.001	0.047	0.002**	0.000	0.011
acc*Information Index	0.000**	0.000	0.012	-0.089**	0.001	0.046
Cost	-0.216***	0.065	0.001	-0.089**	0.042	0.033
cost*income	0.000***	0.000	0.000	0.000***	0.000	0.000
cost*ln(distance)	-0.038***	0.014	0.009	-	-	-

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

Table 6. Aggregate benefits for alternative management strategies (in Aus $).

Management Alternative			Models	
			Distance included	**Distance omitted**
Status Quo				
Fire	*Weed*	*Acc*		
6	40	100		
Scenario 1				
Fire	*Weed*	*Acc*	-3,668,910	2,291,707
6	60	100		
Scenario 2				
Fire	*Weed*	*Acc*	-8,343,830	1,033,502
1	40	100		
Scenario 3				
Fire	*Weed*	*Acc*	82,617	-1,607,847
6	40	75		
Scenario 4				
Fire	*Weed*	*Acc*	10,225,618	2,019,388
9	30	100		
Scenario 5				
Fire	*Weed*	*Acc*	-11,171,536	-1,580,110
3	60	75		

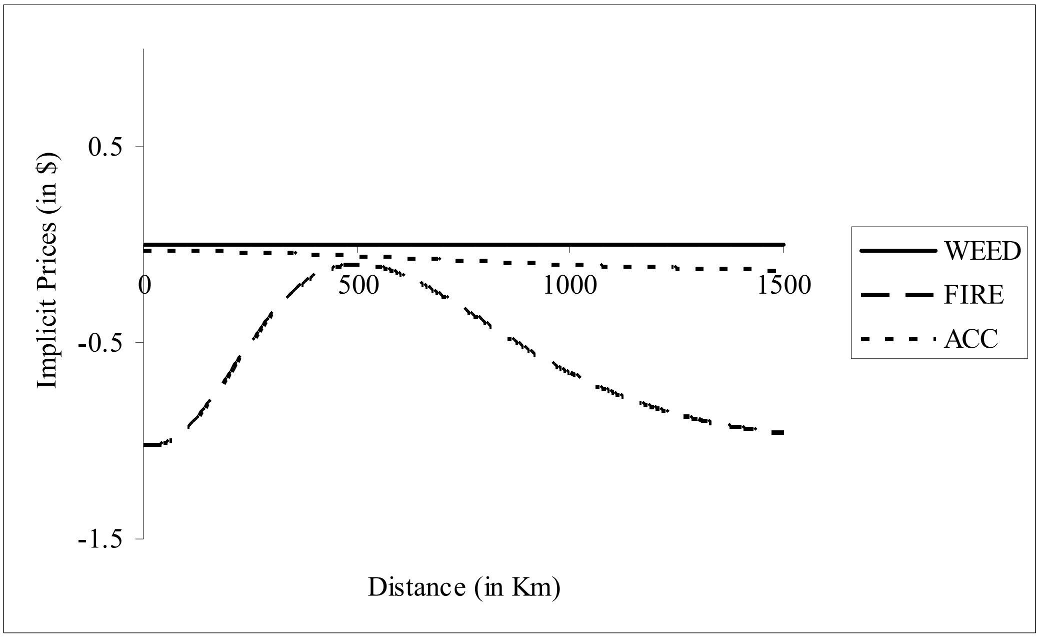

Figure I. Effects of distance on implicit prices.