TASK COMPLEXITY IN MULTI-ATTRIBUTE STATED CHOICE ENVIRONMENTAL VALUATION

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Abstract: This study aims to investigate task complexity problems in attribute-based stated choice valuation of non-monetary costs of automobile use. Two factors leading to task complexity problems were considered: (1) non-linearity in the utility function indicating uncertainty in preferences, and (2) parameterization of the scale of the stochastic error of the utility indicating decision complexity. Empirical investigations on the complexity of non-market attributes valuation were made based on a web-based stated route choice survey of work trips in Metro Manila. The results show strong suggestions that degree of complexity of the choice problem is affected by not only the number of alternatives but also by the range and the description of attributes.

Key Words: *State choice, Preference uncertainty, Decision complexity*

1. INTRODUCTION

Stated preference has been an important indicator in predicting values of traffic externalities in the absence of markets. In addition, the valuation of non-market external costs of automobile use is a critical input in many of institutional evaluation and pricing policies particularly in this age where the impacts of the transport sector, not only on the local but also on the regional and global level, are becoming major environmental sustainability concerns. Various issues surround the contextualization of these external costs for valuation. One of these issues is defining the external costs or benefits in terms of its quantitative dimensions such as its quality level or in terms of its functional dimensions such as its role in environmental systems. Aside from that, dimensions of these externalities also vary according to context. These add complexity in the process of valuation of the non-market environmental goods associated with automobile use from stated choices.

Most applied stated choice survey has dealt with single dimension goods. These surveys usually aim to get willingness-to-pay (WTP) for an environmental resource or amenity, say value of clean air. However, most often, environmental systems cannot be simply aggregated into a single good as most of them come naturally in bundles. Clean roadside air quality, for instance, as a resource, may be broken down into attributes like visibility, impact on roadside buildings, impact to soil and streams, and impact to human health. There are two approaches in dealing with set of attributes, (1) Attribute-based Stated Choice Method (SCM), and (2) Contingent Valuation Method (CVM). Attribute-based SCM is an approach where respondents are asked to choose from a set of alternatives with an array of attributes (Louviere *et al*., 2000). It is commonly analyzed using multinomial disaggregate model such as the multinomial logit (MNL). In contrast, CVM elicits WTP value in open or closed form on the context of made-believe circumstances that improve or damage to existing environmental amenity. Environmental valuation studies using attribute-based SCM are limited compared to CVM and other environmental valuation methods such as hedonic pricing and travel cost. If price is the only attribute, the SCM simply reverts back to CVM. There are some advantages in using attribute-based SCM over CVM: (1) the ability to deduce behavioral tendencies of respondents over variation of goods or goods' attributes; (2) policy implications are less suggestive, thus less susceptible to context biases or behavioral heuristics (Herriges and Kling, 1999); and (3) avoid zero protest votes present in CVM (Wardman and Bristow, 2004).

This paper aimed to investigate the task complexity in situations where environmental goods have varying goods dimension using empirical data. Though task complexity may be caused by many factors within or outside the control of the decision-maker, we only focused on factors affecting utility of the decision maker, i.e. preference uncertainty and decision complexity. Section 2 describe the how the models were specified while section 3 describe an empirical investigation using internet survey data on the valuation of the social costs of motor-vehicle use in Metro Manila. The result of the empirical test aims to contribute to the design of multi-attribute stated choice internet survey.

2. CHOICES IN MULTI-ATTRIBUTES ALTERNATIVES

The intricacy of non-market goods can often be captured by the broad array of the resource attributes. The valuation of the external costs of automobile use can be likened to the valuation of other environmental goods like, for example, preferences over an environmental good such as forestland uses can be categorized into old-growth forest conservation, hardwood native timber production, and recreation (Ananda and Herath, 2006). Another example is policy involving economic and environmental systems which often consists of multiple objectives. Policies involving agricultural non-point source pollution may require trade-off between contradicting objectives on soil erosion and water pollution (Lakshminarayan et al., 1995). The impacts of motorization on the environment likewise comes in many dimensions such as air and noise pollutions, accidents, and environmental decay (e.g. Sælensminde, 2001, Iraguen and de Dios Ortuzar, 2004). To address multi-dimensionality of valuation problems, researchers have used multiple contingent valuation (CV) (Protiere *et al.*, 2004, Gonzalez and Leon, 2003, Feitelson *et al.*, 1996, Parumog *et al.*, 2003) and choice experiments. While it has been argued that attribute valuation methods such as conjoint analysis provides a powerful alternative to CV, challenges arises as to the complexity of decision-making.

This section presents two frameworks on how get inference on the preferences uncertainty of the respondents and the decision complexity of the choice questions. Both these factors influence the task complexity of the choice problems.

2.1. Multi-attribute utility

Ecosystem valuation consists of a variety of environmental services or goods broken down into attributes or objectives. Here, we introduce the multi-attribute utility (MAU) theory that considers preferences over a range of attribute. Let us assume an environmental good q with M attributes or services $Q(q^1, q^2, \ldots q^M)$. This assumes that the subject has a well-behaved utility function that follows $U(x, Q, s, p)$. The utility is quasi-concave with respect to market goods X, environmental good Q, and socioeconomic variables s. Debreu (1960) initially articulated utility specifications with multi-attribute preferences in his discussion of goods partitioning in stochastic choice models utilities while Fishburn (1964) did the same in terms of expected utility. Keeney (1993) extended the utility theory to describe decisions involving preferential and utility independence, which decompose the multi-attribute utility function to more practical form for elicitation.

The very flexible additive multi-attribute utility model based on the environmental good Q is defined as in equation 1.

$$u(q^1, q^2, \ldots q^M) = \sum_{i=1}^{M} k_i u_i q^i \tag{1}$$

Additive utility assume that individual has strong preference independence. In cases, however, where individual experiences uncertainty in preferences, multiplicative utility structure persist. The k_is are the scale parameters, $u(q^M)$ are the single-attribute utility associated with q^M. We follow Keeney and Raffia (1976) in showing that the condition of preference independence among attributes that presents the multiplicative multi-attribute utility structure shown in equation 2.

$$Ku(q^1, q^2, \ldots q^M) + 1 = \prod_{i=1}^{M} \left(Kk_i u_i \left(q^i \right) + 1 \right) \tag{2}$$

In this notation, K is the scaling constant that is a function of k_i. The multiplicative utility function can represent powerful preference structure as it can represent nonlinearities in utility and interaction between attributes. Note that if K=0, then the utility goes back to equation 1.

The specification of the multi-attribute utility has great implications on environmental valuation. Additive utility assumes preference independence and assume that values are simply the marginal utility of attribute divided by the marginal utility of cost, which is simply the utility parameter of attribute over costs. In case of multiplicative utility, the marginal utility becomes a function of the assumed function (e.g., quadratic) and interactions. Uncertainty in preferences may be inferred from the functional form of the value functions.

2.2. Decision complexity

Simon (1957) presents the idea that consumer approach simplification of its cognitive burden by making a decision based only on a part or selected attributes of an alternative. Most choice-modeling framework assumes that respondents have perfect information-processing capacity. Econometric models usually fail to acknowledge the common knowledge in behavioral decision theory that choice environment, the inability of individual to make complex decision, and choice context affects decision-making.

A conventional random utility maximization (RUM) model relies on the random utility to interpret preferences. The utility disturbances are the basis of the probabilistic inference on utilities. However, they are given very little consideration in the interpretation of the model. Deterministic variables observable to the researchers are main concerns and the underlying nature of the errors are critical to the explanation of the choice behavior are often overlooked. Psychological models or behavioral decision theory touched on task complexity and the environment. Furthermore, more and more research incorporating decision-makers' limitation in processing information about alternatives in choice problems and in econometric modeling are done.

In the following discussions, we follow Swait and Adamowics (2001) in presenting complex decision and apply it to a multi-attribute discrete choice valuation framework. Their proposed framework assumes a heteroscedastic discrete choice model where the variance or scale of the stochastic error is parameterized. The model presents a relaxation on the neoclassical perfect decision-maker by incorporating assumption based on information theory. With an individual maximizing his or her utility according to discrete commodities x with attributes q, prices p, and numeraire z, the following formulation based on Hanemann (1982) shows the utility maximization subject to: (1) budget constraint; (2) mutually exclusive alternative constraint; and (3) optimal quantity control.

$$\begin{aligned}
&Max U(x_i \ldots x_j, q_i \ldots q_j, z) \ \ subject \ \ to \\
&\sum_{i=1}^{J} p_i x_i + z = M \\
&y_i \cdot y_j = 0 \forall i \neq j \\
&y_i = y_i^* \forall i
\end{aligned} \tag{3}$$

This framework reflects a perfect, utility maximizing, decision-maker and can be directly implemented through conditional indirect utility function readily estimated through MNL. In this framework, the respondent, in its task of making choices, exert an amount of effort to understand the context in terms of attribute levels of the alternative, and that when effort is not applied, all attributes appear the same to the respondents. As effort directly depends on the individuals, it represents the complexity of the choice environment. Swait and Adamowicz (2001) presented a way how integrate the complexity of the thinking process in the equation. They assume an E_k representing the effort, where the k indexes the choice problem that the respondents faces within the planning horizon identified as k=1 … K. The effort budget of an individual is B. The quantities of B and E are unobservable latent variables. H_k represents the complexity of the task of choosing from k alternatives. The following notations represent the consumer's decision problem:

$$\begin{aligned}
&Max \ \ U(y_{11} \ldots y_{j1}, q_{11} \ldots q_{J1}, E_1 H_1; \ldots; y_{1K} \ldots y_{Jk}, q_{1K}, q_{JK}, E_K H_K; z, E_{K+1}, H_{K+1}) \ \ subject \ \ to \\
&\sum_{i=1}^{J} p_i y_i + z \leq M \\
&\sum_{k=1}^{K+1} E_k \leq B \\
&y_{ik} \cdot y_{jk} = 0 \forall i \neq j \\
&y_{ik} = y_{ik}^* \forall i
\end{aligned} \tag{4}$$

By employing the random utility theory, with certain assumption of error distribution the probability of choosing an alternative becomes:

$$\Pr(j=1)=\frac{\exp\left[\mu_i(E_iH_i)\cdot V_{i1}\right]}{\sum_{j\in C}\exp\left[\mu_i(E_iH_i)\cdot V_{ij}\right]} \tag{5}$$

where μ_i is the scale factor related to scale factor that is inversely proportional to the error variance in the RUM.

Complexity may be formally represented though the concept of entropy which is formalized using the information theory by Shannon (1948). This theory was applied initially in the processing language or information in communications. The theory assumes that a probability distribution $\Pi = (\pi_1, \pi_2, \pi_3, \ldots \pi_J)$ has an associated entropy (or lack of predictability):

$$H(X)=H(\pi_x)=-k\sum_{j=1}^{J}\pi(x_j)\log\pi(x_j) \tag{6}$$

which is at maximum when all the probabilities, $H_{max}=ln(J)$, when all the probabilities have the same values $P_i=1/J$ and a minimum of 0 when the probability has a value of 1. The complexity of the situation is assumed to affect the stochastic utility the term specifically its variance a function of entropy of the decision. To capture nonlinearities in entropy, a quadratic function is assumed for the entropy. The complexity function is formulated as:

$$\mu_i(E_iH_i)=\mu_n(C_n)=\exp(\theta_1 H_n+\theta_2 H_n^2) \tag{7}$$

$$\text{where } H_n = -\sum_{j\in D} Q_{jn}\ln Q_{jn} \tag{8}$$

$$\text{and } Q_{in}=\frac{\exp(\beta X_{in})}{\sum_{j\in D}\exp(\beta X_{in})} \quad for\ \ all\ \ i\in D \tag{9}$$

Swait and Adamowicz (2001) infer that the these equations (4-9) allows the scale variance to capture how a consumer make an effort up to a degree of certain complexity after which they resort to simplifying decision heuristics which generate greater preference inconsistencies across decision makers. If this assumptions were correct, $\theta_1 \leq 0$ and $\theta_2 \geq 0$, or opposite in case of the variance.

3. EMPIRICAL APPLICATION: MULTI-ATTRIBUTE ROUTE CHOICE

To investigate task complexity using empirical data, a stated preference route choice survey of private work trips in Metro Manila is analyzed. A route choice experiment where, apart from the current route taken, two alternative routes with varying environmental improvements in air and noise quality, greenery and streetscape, road safety. Attributes were assigned to vary randomly and stated choice problem is repeated six times. The choice is complicated as aside from deterministic attributes travel time and travel cost, subjective attributes such as the mentioned environmental quality improvements were incorporated. We focused on subjective variables corresponding to environmental qualities we wanted to investigate (i.e. air pollution, noise, accident risk). As air quality is a complex concept to grasp when done in pollutant-specific manner, we present it in percentages of improvement. This readily translate into unit reductions or scaling of regional air quality index which is an aggregate scale describing concentrations of major pollutants such as carbon monoxide (CO), sulphur dioxide (SO2), nitrogen dioxide (NO2), ozone (O3) and fine particular matter in policy context. Noise is likewise offered in percentages of reduction. Greenery and streetscape are with or without scenario. In the current route, the number of fatalities a year is pegged at 150.

Table 1 shows how the attributes are determined for the hypothetical route alternatives. Random noise is added to actual inputted travel time TT and actual travel cost TC. The noise is deemed as a random draw from normal distribution with standard deviation that is one-third the value of TT. On the other hand, noise for TC entails addition of the absolute value of a random draw from normal distribution with standard deviation that is one-third the value of TC. In the other attributes, embedded scripts performed random drawing of the attributes levels.

Table 1 Attributes levels

Attributes	Current	Attribute levels
Travel time:	*TT*	*TT* + R ~N(0,TT/3)
Travel cost:	*TC*	*TC* + | R ~N(0,TC/3) |
Air Quality Improvement:	Base	20% improvement, 30% improvement, 80% improvement
Reduction in Noise Pollution:	Base	20% reduction, 30% reduction, 80% reduction
Greenery and streetscape:	Base	greenery and streetscape improvements, greenery improvement, streetscape improvement, and no improvements
Road fatalities/year:	150	20, 50, 75 and 100

In the six repetitions of the choice experiment, the dimensions of the attributes were varied to investigate changes in respondent preferences as the complexity of alternatives deepens. Table 2 shows the dimensions of the choice problem.

Table 2 Dimensions of the choice problems

Choice dim. type	No. of Attributes	Obs.	Attributes	Repetitions
SC 1	7	190	Price, Time, Air quality, Noise, Greenery, Streetscape, Fatalities	3
SC 2	4	64	Price, Time, Air quality, Noise	1
SC 3	5	61	Price, Time, Greenery, Streetscape, Fatalities	1
SC 4	8	65	Price, Additional cost for environmental amenity, Time, Air quality, Noise, Greenery, Streetscape, Fatalities	1
Total				6

Web survey of private work trips in Metro Manila was conducted for about three weeks, from June 5 to July 1, 2005. Samples were drawn by sending e-mails to human resource department heads of different private offices, government offices, non-government offices, and institutions listed in various online directories. They were informed of the purpose and timeframe of the study and were asked to forward the website to the personnel of their offices. One follow-up email was sent for each request.

The questionnaire has five parts: work trip characteristics; environmental quality perception in commonly used route; environmental attitudes; the experimental choice problems; and the socioeconomic characteristics of respondents. Characteristics of the work trip asked include home and work location, motor vehicle characteristics, travel time and cost to work. A 5-level scale of commonly used route's environmental quality perception, which consists of air pollution, noise pollution, greenery and streetscape, and road safety, as well as a 10-level perception scale of the general environmental quality rating composed the second part of questionnaire. Ordinal rating questions on government spending on environment, stance about the environment, and subsidies made up the attitude questions. We received 83 filled questionnaires, from which we have gathered 380 stated route choices of different dimensions after eliminating lexicographic and unreasonable responses. The choice experiment format SC 1 to SC 4 has 190, 64, 61, and 65 usable observations, respectively.

4. RESULTS OF ANALYSIS AND FINDINGS

This section shows the results of the estimation of the models incorporating task complexity. We estimated the basic MNL model with additive and multiplicative utility, and the MNL considering task complexity. At first, we define a linear in-utility specification in the form:

$$V_j = \alpha_j + \beta_M X_M + \beta_{TC} X_{TC} + \varepsilon_j \tag{10}$$

Where the β_M corresponds to the attribute parameter matrix and β_{TC} is the price vector parameter. The parameter estimates are presented in Table 3. The models show that estimates are greatly affected by the number of samples since among the repetitions only SCM1 is found to be robust. SCM3 follows with marginal significance mainly carried by the variables related to traffic safety.

Table 3 MNL Estimates of attribute-based SCM with additive utility

Variable	SCM 1		SCM 2		SCM 3		SCM 4	
1. Alternative 1 constant	1.497	(1.94)	0.447	(0.44)	-0.600	(-0.30)	0.060	(0.04)
2. Alternative 2 constant	1.277	(1.62)	0.598	(0.54)	-0.706	(-0.36)	0.019	(0.01)
3. Price (PhP)	-0.010	(-3.14)	-0.024	(-2.90)	-0.003	(-0.61)	-0.003	(-0.63)
4. Time (Minutes)	-0.043	(-4.36)	-0.059	(-4.01)	-0.019	(-1.14)	-0.040	(-3.98)
5. Air quality (1-% of improvement)	-0.544	(-1.10)	-0.490	(-0.43)			0.378	(0.47)
6. Noise (1-% of reduction)	-0.095	(-0.22)	-0.640	(-0.76)			-0.642	(-0.84)
7. Greenery (with or without)	0.040	(0.15)			-0.054	(-0.09)	0.103	(0.16)
8. Streetscape (with or without)	-0.287	(-0.86)			-1.548	(-1.64)	-0.723	(-1.25)
9. Number of fatalities a year	-0.011	(-3.25)			-0.020	(-3.60)	-0.010	(-1.68)
10. General rating of quality of road and roadside (1 worst -10 best)	0.340	(3.34)	0.150	(0.94)	0.280	(1.20)	0.210	(0.85)
11. Income (1=>20,000, 0-otherwise)	-0.410	(-1.07)	0.070	(-0.12)	0.250	(0.35)	-0.710	(-0.93)
No. of observations	190		64		61		65	
$\ell(\beta)$	-170		-52		-54		-59	
χ^2 (p-level)	125	(0.000)	7	(0.546)	28	(0.001)	13	(0.323)
ρ^2	0.27		0.06		0.21		0.1	
Estimated WTP								
Travel time savings (in mins)	4.41	(2.87)	2.47	(3.55)	5.6	(0.57)	13.53	(0.66)
100% air pollution reduction	55.24	(1.13)	20.68	(0.43)			-128.04	(-0.42)
100% noise reduction	9.67	(0.22)	27.01	(0.75)			217.66	(0.51)
Greenery	-4.07	(-0.15)			15.88	(0.09)	-34.8	(-0.16)
Landscape	29.2	(0.86)			455.1	(0.59)	245.21	(0.66)
Traffic fatality reduction a year	1.11	(2.14)			5.76	(0.60)	3.29	(0.60)

Using the main effects variables [with subscripts TC (travel time), TC (travel cost), AI (air quality, NS (Noise), and AC (traffic fatalities)], we likewise estimated the multiplicative utility function in the form to see interaction and nonlinear effects in the utility. In this analysis, we eliminated the variables landscape and greenery due to the low significant of estimate and high correlation of the variables.

$$V_j = \alpha_j + \beta_1 X_{TT} + \beta_2 X_{TT}^2 + \beta_3 X_{TC} + \beta_4 X_{TC}^2 + \beta_5 X_{AI} + \beta_6 X_{NS} + \beta_7 X_{AI} \cdot X_{NS} + \beta_8 X_{AC} \cdot + \beta_9 X_{AC} + \beta_{10} X_{AC}^2 \quad (11)$$

The estimates of the nonlinear in utility equation are shown in Table 4. Using the nonlinear utility specifications, and the elimination of some variables, the fit of the models, except for SCM 2, improved significantly (based on adjusted ρ^2). It can be seen that while nonlinear effects and interaction effects are insignificant in most models, it can be deduced that its effect in the general fit of the model is significant.

Table 4 MNL Estimates of SCM with multiplicative utility

Variable	SCM 1		SCM 2		SCM 3		SCM 4	
1. Alternative 1 constant	1.935	(2.29)	0.609	(0.56)	1.931	(1.30)	0.364	(0.20)
2. Alternative 2 constant	1.724	(2.02)	0.719	(0.58)	1.844	(1.26)	0.346	(0.19)
3. Price (PhP)	-0.015	(-2.34)	-0.032	(-1.97)	-0.012	(-0.83)	-0.020	(-1.61)
4. Price (PhP)^2	0.000	(0.88)	0.000	(0.51)	0.000	(0.36)	0.000	(0.99)
5. Time (Minutes)	-0.060	(-2.55)	-0.102	(-1.81)	-0.005	(-0.12)	-0.120	(-2.74)
6. Time (Minutes)^2	0.000	(0.85)	0.000	(0.83)	0.000	(-0.44)	0.001	(2.38)
7. Air quality (1-% of improvement)	-1.434	(-1.33)	-0.573	(-0.26)			2.179	(0.92)
8. Noise (1-% of reduction)	-0.995	(-1.03)	-0.720	(-0.31)			0.849	(0.35)
9. Air quality · Noise	1.532	(0.95)	0.066	(0.02)			-2.337	(-0.64)
10. Number of fatalities a year	-0.008	(-7.53)			-0.037	(-1.55)	0.018	(0.81)
11. Number of fatalities a year^2	0.000	(-0.27)			0.000	(0.79)	0.000	(-1.29)
12. General rating of quality of road and roadside (1 worst -10 best)	0.321	(3.20)	0.138	(0.86)	0.357	(1.60)	0.245	(0.20)
13. Income (1=>20,000, 0-otherwise)	-0.379	(-0.99)	0.163	(0.27)	0.239	(0.33)	-0.797	(-0.93)
N	190		64		61		65	
$\ell(\beta)$	-169		-51		-55		-57	
χ^2 (p-level)	127	(0.000)	14	(0.208)	71	(0.000)	48	(0.000)
ρ^2	0.27		0.12		0.39		0.29	
Travel time savings	3.98	(2.00)	2.77	(1.23)	0.83	(0.24)	5.59	(1.28)
100% air pollution reduction	24.69	(0.26)	16.88	(0.24)			-42.79	(-0.42)
100% noise reduction	-6.27	(-0.08)	21.69	(0.29)			39.68	(0.37)
Traffic fatality reduction a year	0.71	(2.15)			2.48	(0.52)	-0.14	(-0.13)

To investigate the decision complexity, we estimated the models incorporating choice complexity in the equations (3-9). A quadratic form for the complexity function was used in the estimation. Using the additive utility specifications, the results of models considering choice complexity is shown in Table 5. In all models, the entropy parameters both at linear and quadratic terms follows right signs for complex decision and are significant. SCM3, with variables greenery and landscape, shows the highest scale of complexity followed by SCM4 and SCM1 with eight and seven attributes, respectively. The value estimates tends to become less significant as the scale of the entropy parameters become bigger.

Table 5 Estimates of MNL of SCM with complexity parameters

Variable		SCM1		SCM2		SCM3		SCM 4	
1.	Alternative 1 constant	5.135	(3.92)	0.752	(1.39)	4.773	(1.36)	4.217	(1.26)
2.	Alternative 2 constant	4.902	(3.82)	0.683	(1.27)	4.290	(1.30)	3.605	(1.10)
3.	Price (PhP)	-0.023	(-6.50)	-0.009	(-1.79)	-0.016	(-1.29)	-0.019	(-2.36)
4.	Time (Minutes¥)	-0.084	(-8.90)	-0.044	(-2.39)	-0.071	(-1.87)	-0.062	(-3.06)
5.	Air quality (1-% of improvement)	-0.032	(-0.05)	0.254	(0.52)			0.465	(0.32)
6.	Noise (1-% of reduction)	-0.772	(-2.04)	-0.243	(-0.84)			-0.186	(-0.14)
7.	Greenery (with or without)	-0.111	(-0.44)			1.695	(1.50)	0.979	(0.98)
8.	Streetscape (with or without)	-0.913	(-2.03)			-8.786	(-2.20)	-2.280	(-2.19)
9.	Number of fatalities a year	-0.028	(-7.53)			-0.049	(-6.17)	-0.040	(-3.92)
10.	General rating of quality of road and roadside (1 worst -10 best)	0.93	(6.34)	0.11	(1.39)	0.69	(1.45)	0.72	(1.40)
11.	Income (1=>20,000, 0-otherwise)	-0.35	(-0.98)	0.28	(1.13)	3.63	(2.38)	0.34	(0.28)
θ^1		-6.47	(-6.51)	-3.56	(-1.67)	-11.39	(-2.23)	-9.07	(-1.62)
θ^2		7.64	(6.45)	4.64	(2.13)	12.75	(1.80)	10.26	(1.24)
No. of observations		190		64		61		65	
$\ell(\beta)$		-163		-48		-50		-57	
χ^2 (p-level)		125	(0.000)	40	(0.000)	42	(0.001)	48	(0.000)
ρ^2		0.28		0.29		0.30		0.29	
Estimated WTP									
Travel time savings		3.67	(.78)	4.85	(2.03)	4.34	(1.17)	3.26	(1.87)
100% air pollution reduction		1.40	(0.05)	-27.69	(-0.55)			-24.64	(-0.32)
100% noise reduction		33.80	(1.94)	26.53	(0.88)			9.83	(0.14)
Greenery		4.85	(0.44)			-103.52	(-1.10)	-51.90	(-0.97)
Landscape		39.96	(2.07)			536.65	(1.23)	120.83	(2.01)
Traffic fatality reduction a year		1.21	(4.99)			2.99	(1.27)	2.09	(2.09)

The Figure 1 below shows the entropy functions (equation 7) with respect to the probability of choosing the first alternative, or choosing current route and not the new alternatives with improved environmental attributes. The trend is that, as complexity of the question increases, i.e. less level of attributes, the respondent tends not to choose the improved alternatives and choose the default alternative. The results also shows that choice problem involving mainly non-use, dummy attributes such as greenery and landscape (i.e. SCM3) appear to be more complex for respondents than attributes posing direct effects.

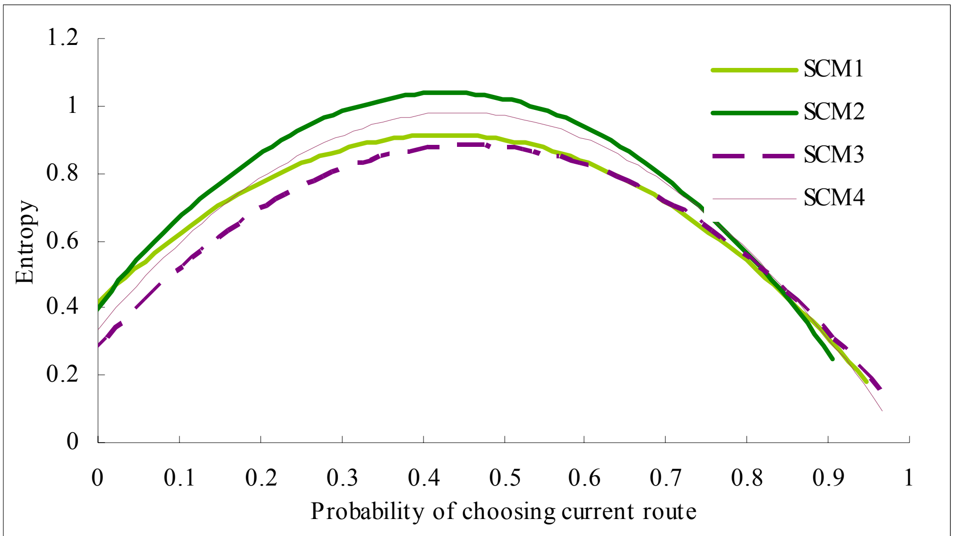

Figure 1 Entropy as a function of probability remaining in current route

5. SUMMARY AND CONCLUSIONS

In this paper, we considered two factors leading to task complexity problems: (1) non-linearity in the utility function indicating uncertainty in preferences, and (2) parameterization of the scale of stochastic error of utility indicating decision complexity. The results of estimations show presence of preference uncertainty and decision complexity in the empirical application, which leads to inferior WTP estimates. Empirical application also shows a strong suggestion that degree of complexity is affected not only by the number of alternatives but also by the range and the description of the attribute.

Based on the results of this study, we identified some factors that should be considered in preparing multi-attribute stated questions. First is the length or the number of attributes in the design of choice alternatives. While results for up to four attributes are found acceptable in the empirical examples in this study, the number of attributes may vary according to the complexity of the good in question but attention should be taken in the specification of attributes so as not to complicate tasks of choice-makers. Second is the range and description of attributes. From the experiment here, it is shown that attributes presented in crisp numbers, percentage or quantities, are better understood by the respondents than qualitative descriptions. The dimension of the attribute levels is likewise a critical factor to take into account. The experiment has likewise shown that using random draws from continuously distributed, time and cost attributes has produced robust parameter estimates. A small sample pre-testing should be able to reveal the points in avoiding complexity in stated choice valuation problems.

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