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The Impact of Latent Attitudinal Variables on Stated Preferences :

What Attitudinal Variables Can Do for Choice Modelling*

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〈Contents〉

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Ⅰ. Introduction

A key issue in the development of stated preference nonmarket valuation is the incorporation of preference heterogeneity (Boxall and Adamowicz, 2002; Train, 2003; Walker and Ben-Akiva, 2002). Louviere *et al.* (2000, p. 141) argue that preference heterogeneity is a part of the random component, and that if the feature of different error variances across choices is ignored, they will show up as parts of parameters and the intercept of the utility model. Failure to incorporate 'behavioural heterogeneity (individual variations in tastes and preferences)' can lead researchers to 'inferior model specification, spurious test results and invalid conclusions' (Jones and Hensher, 2004, pp. 1013~1014; Louviere *et al.*, 2000; Train, 2003).

Boxall and Adamowicz (2002, pp. 421~422) point out two sets of approaches that have dominated efforts to incorporate heterogeneity. The first is to include individual-specific characteristics into estimated indirect utility functions. These characteristics are mostly exogenous socioeconomic or demographic variables (SDs). The second employs generalized models such as random parameter logit or probit models to allow model parameters to vary across individuals. These models are limited because the sources of heterogeneity are not identified (Boxall and Adamowicz, 2002, p. 422). The question arises if 'latent' attitudinal variables (LVs) such as environmental attitudes, beliefs, and motivations can be used to account for heterogeneity.

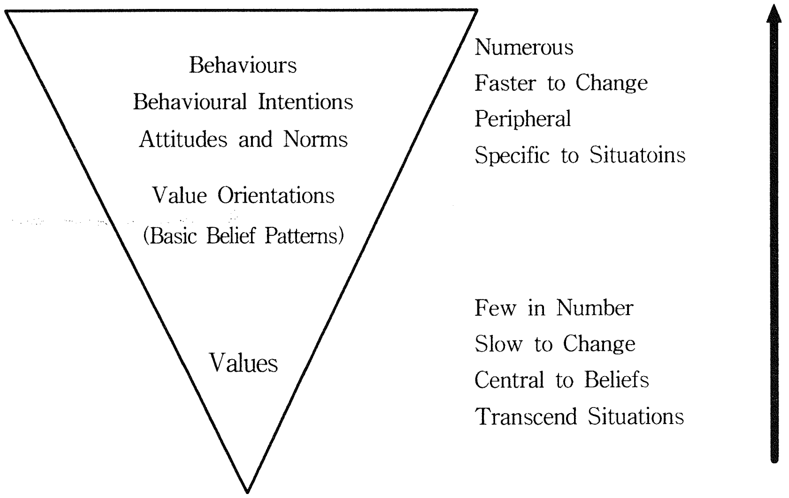
This paper examines the potential role of LVs in choice modelling studies and demonstrates that both model significance and parameter estimates are influenced by their inclusion, and that they are significant explanatory factors for WTP. There are five major sections. After reviewing the theoretical background, the research methodology is described. In sections three and four, characteristics of a case study sample and the results generated are reported and discussed, followed by a brief conclusion.

Ⅱ. Choice Modelling and the Psychology of Choice Behaviour

The CM technique is based on the 'characteristic theory of value' of Lancaster (1966), in which any good can be described as a bundle of component attributes and their levels (Bateman *et al.*, 2002, p. 278). For instance, an international rain forest conservation policy can be comprised of location (country), area (size), rarity, potential to visit, effect on local populations, special features of the area, and price of the proposal (Rolfe and Bennett, 2001). Respondents in CM exercises are provided with a series of questions called choice sets. For each question, they are expected to choose one preferred option from several alternatives.

In most choice models, we are interested in the welfare effects of marginal changes in attribute levels. For example, the marginal willingness to pay (WTP) for kth attribute (β_k)—also known as a 'part-worth' or

〈Figure 1〉 The Cognitive Hierarchy Model of Human Behaviour



Source: Fulton, D. C., M. J. Manfredo and J. Lipscomb, "Wildlife Value Orientations: A Conceptual and Measurement Approach," *Human Dimensions of Wildlife* 1(2), 1996, pp. 24~47.

'implicit price'[1]—is described by the following equation, where $\lambda\beta_m$ is the monetary coefficient, incorporating the scale parameter (λ) (Rolfe *et al.*, 2002, p. 5; van Bueren and Bennett, 2004): WTP $= -\lambda\beta_k / \lambda\beta_m$.

SP techniques, including CM, seek a behavioural intention (or willingness), not an actual behaviour (Ajzen and Driver, 1992; Barro *et al.*, 1996; Bateman *et al.*, 2002, p. 113; Heberlein and Bishop, 1986; Mitchell and Carson, 1989, p. 186). It is useful, therefore, to examine briefly the causal linkages between attitudes, behavioural intentions, and actual behaviours.

Fulton *et al.* (1996) use an inverse pyramid to illustrate the relationship

1) For detailed descriptions of related issues such as compensation variance and part-worth, see Hanemann (1984), Louviere *et al.* (2000), and Rolfe *et al.* (2002).

between basic values (what individuals consider to be important) and behaviour (See <Figure 1>). Value orientations are expressed as basic belief patterns and reflect the values of individuals. In turn, value orientations provide the foundations for attitudes and norms that guide behavioural intentions and actual behaviour. Values are limited in number, take time to change, are fundamental to beliefs, and are not directly related to specific situations. Moving upward in the inverse pyramid, attitudes and norms are numerous and rapidly evolving and are situation-and behaviour-specific. Behavioural intentions are known as the immediate precedents to actual behaviours (Ajzen, 1991) and as their 'most direct predictor' (Vaske and Donnelly, 1999, p. 527).

The hierarchical model of Fulton *et al.* (1996) is common in more detailed psychological constructs of choice behaviour. Some examples are the attitude-behaviour model developed by Eagly and Chaiken (1993), the psychological construct developed for the value-belief-norm (VBN) theory of Stern (2000) and Ajzen *et al.* (1991) theory of planned behaviour (TPB). Based on this hierarchical structure, we can justify the usage of LVs as explanatory variables for choice bahaviours or intentions (WTP).

Ⅲ. Methodology

1. Questionnaire Design

In a CM application, eight attributes were used to describe Old Parliament House (OPH), Australia, and its potential management changes. Attribute

〈Table 1〉 Attributes and Their Levels for the OPH Case

Attributes	Current Situation	Levels	Variable Names
Acces Policy	0% replica (100% original)	0%, 30%, 50%, replica	REP
Exhibitions	National Portrait Gallery	Dummy(0, 1)	NPG
	Temporary exhibitions (every 8 months)	Every 6, 4, 2 month	TEM
Programs	Interactive display	Dummy(0, 1)	INT
	Traveling exhibitions	Dummy (One traveling, all traveling)	EXH
	Events	Dummy(0, 1)	EVE
Facilities	Shop, café, fine dining restaurant, and conference rooms	None Previous level+shop and café Previous level+fine dining Previous level+conference rooms	FAC
Funding	$2 annual tax	$1, $4, $6, $8, $10	TAX

levels for current and changed management are shown in <Table 1>. These attributes and their levels were used to prepare 40 choice scenarios, using the efficient (D-optimal) design method (Rose and Bliemer, 2005). These scenarios were blocked to create four questionnaire versions. Each version included five choice sets. Each set had four alternatives: one for the status quo, two for the alternative 'change' options, and 'Not Sure'.

2. Latent Attitudinal Variables

To create attitudinal variables, a cultural worldview (CW) scale[2] was developed (Choi *et al.*, 2006). The CW scale measures (using five-point Likert scales) people's 'general' cultural attitudes using four factors: cultural linkages (F1), recognition of cultural values (F2), preservation of traditions and customs (F3), and cultural loss (F4). The scale is similar to the new ecological paradigm of Dunlap *et al.* (2000).

In addition, the theory of planned behaviour (TPB) of Ajzen (1991) was adapted to measure (using seven-point scales) behaviour-specific attitudes. It is 'the most widely researched' model of the attitude-behaviour relationship (Armitage and Conner, 2001, p. 471). It involves three variables that measure 'behaviour-specific' attitudes of respondents: attitude toward the behaviour (ATT), subjective norms (SN), and perceived behavioural control (PBC).

Ⅳ. Sample Population and Segmentation

Questionnaires were sent to 4,000 randomly selected people (nationwide) between March and May 2006. There were 785 useful responses collected, and their sociodemographic characteristics are shown in <Table 2> Compared with census data from the Australian Bureau of Statistics (ABS) (2006), female, older (over 55 years), and married Australians were over-represented.

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2) Scales are measurement instruments based on collections of items or statements. These items represent 'theoretical variables' (also known as 'latent constructs', 'latent variables', or 'factors') that are 'not readily observable by direct means' (DeVellis, 1991, p. 8). The underlying assumption is that people's attitudes influence their cultural preferences (Ajzen, 1991; Boxall and Adamowicz, 2002; Dunlap and Van Liere, 1978).

〈Table 2〉 Compositions of the OPH Sample on the Selected SDs

SDs		Number	%	ABS	SDs		Number	%	ABS
GEN	Male	310	39.7	49.5	UNI	No	350	44.8	48.5
	Female	471	60.3	50.5		Yes	431	55.2	51.5
OLD	17-14	18	2.3	9.8	INC	Under 10,399	35	5.0	2.7
	25-34	89	11.4	19.6		$10,400~20,799	115	16.3	16.8
	35-44	141	18.0	20.5		$20,800~31,199	102	14.4	13.8
	45-54	148	18.9	19.1		$31,200~41,599	92	13.0	10.4
	55-64	166	21.2	15.0		$41,600~51,999	75	10.6	10.3
	65-74	144	18.4	9.6		$52,000~103,999	211	29.9	33.0
	75+	76	9.7	6.5		> 104,000	76	10.8	13.0

Using the CW factors and the TPB variables, the sample was segmented into relatively homogeneous subgroups, using a combined hierarchical-nonhierarchical cluster analysis. The squared Euclidean distance method for a similarity measure and the within-groups linkage method (the average linkage method) for a clustering algorithm were used to determine the number of clusters and their memberships.[3)]

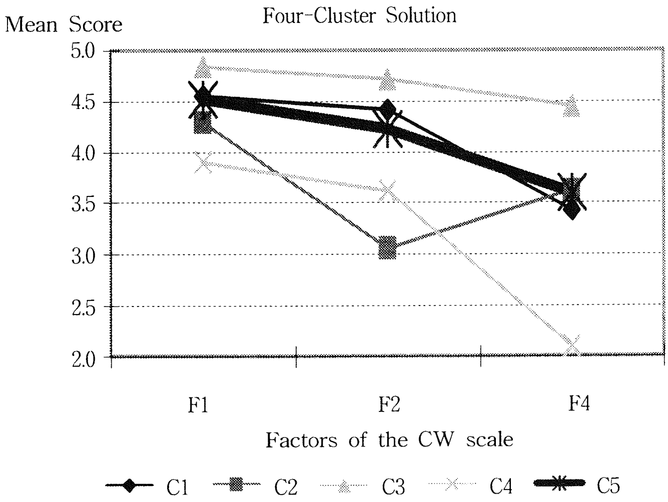
A four-cluster solution[4)] resulted based on three CW factors,[5)] and a three-cluster based on the TPB variables. Firstly, <Figure 2> shows the

3) Summated mean values were used. This approach is advantageous when researchers want to compare results between different populations and to use centroids in cluster analysis (Hair *et al.*, 2005).

4) Nonhierarchical cluster analysis produced four-and seven-cluster solutions, and both of them are highly significant in a criterion validity test using Statement *B* and *F* tests (Hair *et al.*, 2005). However, the four-cluster solution was chosen because of a practical comparability issue between clusters.

5) F4 (cultural loss) was excluded from the cluster analyses because it did not perform well in validity tests in its development process (Choi *et al.*, 2006).

〈Figure 2〉 Results from Cluster Analysis Based on Three CW Factors

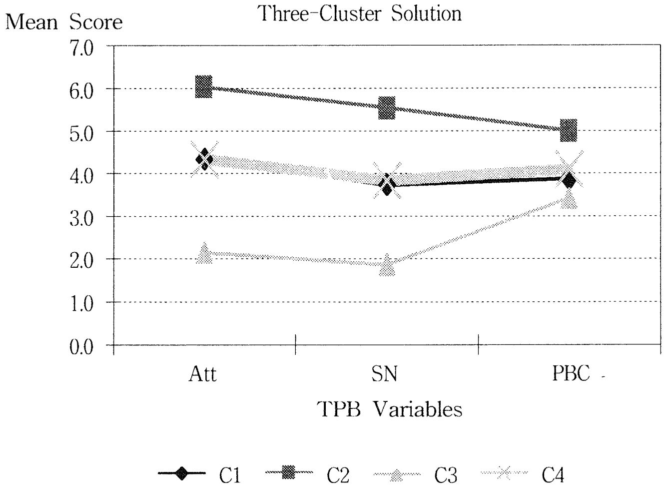


Cluster*	Count		F1	F2	F4
C1	327	(42%)	4.55	4.42	3.42
C2	101	(13%)	4.29	3.06	3.62
C3	251	(32%)	4.84	4.71	4.45
C4	106	(14%)	3.90	3.62	2.09
Total	785		4.52	4.23	3.60

Note : * *F*-tests showed that mean values of all factors are significantly different between clusters.

subgroup profiles in the CW factors. As the biggest subgroup (42%), the first subgroup (C1) closely follows the average scores of the total sample and as the second most culture-friendly group. The second subgroup (C2) has the lowest scores in 'recognition of diverse cultural values' (F2). The third subgroup (C3) includes those respondents with the highest scores in all the factors, while. the fourth subgroup (C4) has the lowest score in

〈Figure 3〉 Results from Cluster Analysis Based on the TPB Variables



Cluster*	Count		ATT	SN	PBC
C1	379	(50%)	4.34	3.74	3.87
C2	215	(28%)	6.03	5.54	5.00
C3	163	(22%)	2.13	1.85	3.42
Total	757		4.34	3.84	4.09

Note : * *F*-tests showed that mean values of all factors are significantly different between clusters.

'preservation of traditions and customs' (F4).

Secondly, <Figure 3> illustrates the subgroup profiles in the TPB variables. The first cluster (C1) is the biggest subgroup (50%), and its scores are very similar to the average sample scores. The second cluster (C2) has 28 percent of the total respondents who show the highest scores in all of the variables. C3 is the smallest subgroup with the lowest scores all the variables.

Ⅴ. Results and Discussion

1. Approach One : Interactions

Discrete choice models include a series of explanatory variables, which are either attribute variables or interaction terms. A basic model (Model Basic) was set to have attribute variables only. Different models were constructed by interacting constant (1 for 'Not Sure' option and 0 for other options) either with SDs (Model S), CW (Model F), TPB (Model T), both SDs and CW (Model SF), or both SDs and TPB (Model ST).

The first hypothesis is $H_1 : C = 0$, where C is a vector of the coefficients for the newly added interaction variables. This can be tested comparing log likelihood (LL) values−the likelihood ratio (LR) test :[6] $LR = -2(LL_{old} - LL_{new})$, where LL_{old} and LL_{new} are the LL values for a base model and a new model with more variables added. LR follows the χ^2 distribution, whose degree of freedom equals the number variables newly added to the new model (Hensher *et al.*, 2005; Louviere *et al.*, 2000). If the value is bigger than that of the critical value of χ^2 (at the 0.05 level, for instance), the new model is significantly better than the old model. This signifies that C is different from zero.

Two points can be made out of the results from these models, shown

6) Log likelihood values that are closer to zero are better for a model. For example, a model with a LL=-200.00 is better than another model with a LL=-400.00.

〈Table 3〉 LL Values and LR Test Results of Various MNL Models with Interaction Terms

	Model Basic	Model S	Model F	Model T	Model SF	Model ST	Model STS	Model STF	Model STT	Model STSF
LL	-4749.79	-4389.74	-4721.38	-4366.56	-4358.89	-4062.62	-4053.02	-4036.24	-4049.82	-4034.96
*LR**		720.10*	56.82*	766.45*	781.80*	1374.34*	19.21**	52.76**	25.59**	55.32**
$\chi^2(\alpha=0.05)$		14.07	9.49	7.81	19.68	18.31	5.99	11.07	7.81	9.49

Note : * The base model is Model Basic.
** The base model is Model ST.

in <Table 3>. First, estimates for the monetary attribute (TAX) are negatively significant in all models, which were expected. Second, the LR tests showed that other models are all significantly better than the basic model (Model Basic), and Model ST was the best form among these models.

Model ST was thus used to test the impact of interactions between attribute variables and other individual-specific variables : SDs (Model STS), the CW factors (Model STF), and the TPB variables (Model STT), and the mixture (Model STSF). The LR tests showed that all of these are significantly better than Model ST. Based on these results, we can confidently reject the null hypothesis ($H_1 : C = 0$) at the 0.05 level. These kinds of interaction significantly improve the goodness-of-fit of the model.

2. Approach Two : Population Segmentation

The second approach was based on the segmentation results. We can investigate any potential influence of LVs on the modelling of subgroups and their WTP estimates. There are two formal null hypotheses to be

〈Table 4〉 TAX Coefficients from Models Basic and STSF

Cluster Variables	Model Basic				
	All	C1	C2	C3	C4
CW	-0.0224**	-0.0049	0.0982***	-0.0093	-0.0484
TPB	-0.0224**	-0.0084	-0.0214	-0.0556**	
Cluster Variables	Model STSF				
	All	C1	C2	C3	C4
CW	-0.0819***	-0.0473*	-0.1816***	-0.0865***	-0.1123**
TPB	-0.0819***	-0.1305	-0.0912	-0.0384***	

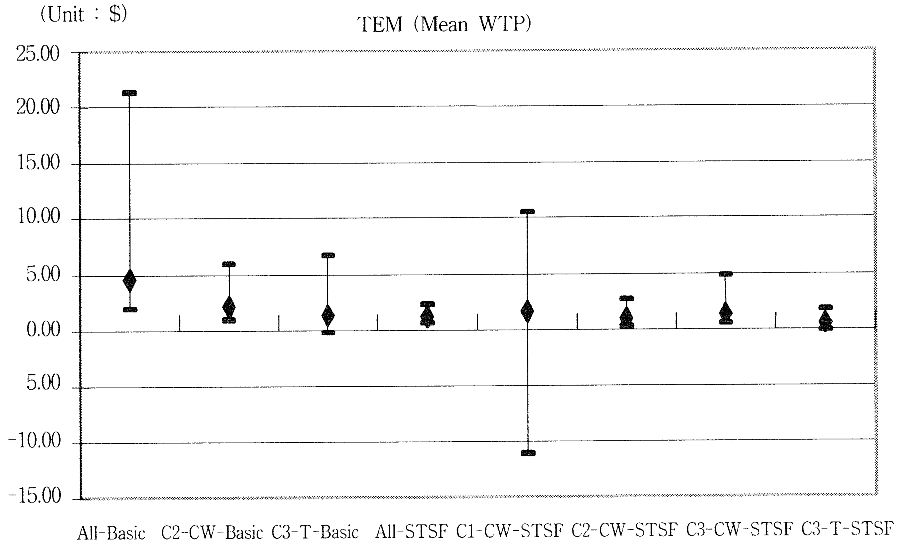
Noet : * Significant at the 0.10 level, ** Significant at the 0.05 level, *** Significant at the 0.01 level.

tested. This second null hypothesis is $H_2: f \neq 0$ for a particular attribute that is significantly different from zero for the original sample, where f is a vector of coefficients of the attribute (for example, TAX) for subgroups. If the segmentation influences on the significance of the coefficients, we should reject this hypothesis. The third null hypothesis is $H_3: WTP_1 = WTP_2$, where WTP_1 and WTP_2 are the implicit prices for a marginal change in a particular attribute (for example, TEM), measured on two different samples (1 and 2). This can be tested using a parametric bootstrapping method[7] and the nonoverlapping criteria. If significance

7) There are two general bootstrapping methods. One is nonparametric bootstrapping, developed by Efron (1979). Observations or respondents are randomly selected with replacement from the original sample to create a new artificial sample with the same size. This process is repeated by a large number of times (n) to create n sets (or rows) of simulated coefficients and their standard errors, from which mean WTP estimates are calculated. The other one is parametric bootstrapping, suggested by Krinsky and Robb (1986). Using a coefficient vector and its variance-covariance matrix from a data analysis, a new set (usually 1,000) of coefficient vectors are

〈Figure 4〉 Confidence Intervals of WTP Estimates, TEM

(Unit : $)



intervals of two *WTP* estimates overlap, WTP_1 is not different from WTP_2.

The significance of TAX coefficients was considered for the clusters segmented based on the CW and TPB variables. Comparing the results shown in <Table 4>, it is significant for the original sample (ALL), while insignificant for some clusters. Therefore, we can conclude that these segmentations significantly influence the elasticity of the TAX attribute: the rejection of $H_2(f \neq 0)$. Although the TAX coefficient of the original sample is significant, those of its subgroups can be insignificant.

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drawn from associated distributions, and the same number of WTP estimates can be calculated. As a result, a confidence interval of expected WTPs can be calculated. Percentile type confidence intervals are normally used for this purpose (Efron, 1979; Krinsky and Robb, 1986). If two intervals overlap each other, they are said to be 'statistically not different from each other'.

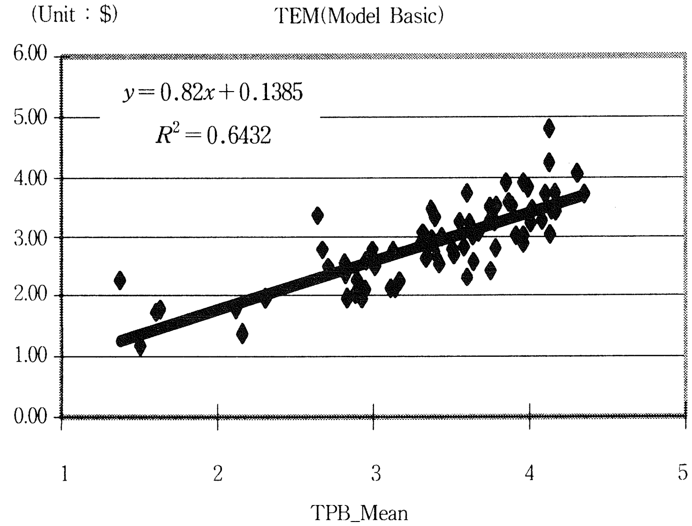
Testing H_3, bootstrapping results for one attribute (TEM), as an example, are shown in <Figure 4>. Percentile type significance intervals (95%) for mean WTP estimates are displayed, with median values in the middle. These intervals all overlap–we cannot reject that these WTP estimates are not different (H_3). This conclusion applies to both issues of difference in the expected WTP. In terms of the width of the intervals, those of all respondent analysed by Model Basic and C1-CW analysed by Model STSF were wider than the rest. The latter result might be due to a low significance of TAX parameter (p-value=0.081).

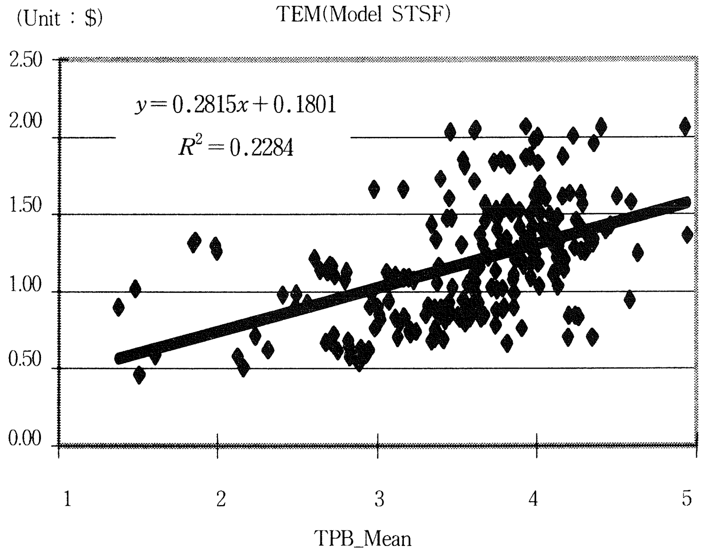
3. Approach Three : Benefit Transfer Potential of Attitudinal Variables

The third approach is to examine the potential of considering these LVs for benefit transfer (BT) techniques. It is not well known how we should interpret heterogeneous characteristics of populations, and calibrate a particular level of preference to reliably predict another level of preference for a specific population and location (Barton, 2002; Ready *et al.*, 2004). When there are a large number of samples, we examine the relationship between implicit prices (WTP) for a particular attribute (j) from individual samples (s) and their characteristics in attitudinal variables (A). For simplicity, we can assume that this relationship can be described as a linear function: $WTP_{js} = a + bA_{js}$.

If the regression coefficient (b) equals zero, there is no relationship. The formal null hypothesis to be tested is $H_4: b = 0$. To test this, we can create a large number of hypothetical samples by manipulating a segmentation result with many clusters (for example, eight), and WTP

〈Figure 5〉 The Relationship (WTP vs. TPB)





estimates and average scores of attitudinal variables can be calculated for individual samples.

A large number of hypothetical samples were created by combining eight clusters (a 8-cluster solution) based on the TPB variables. The manipulation of these clusters resulted in 254 samples with different average TPB scores. When these samples were tested for the significance of TAX and TEM to calculate WTP estimates, 71 and 217 samples were screened to be useful using Models Basic and STSF. <Figure 5> shows scatter plots and trend lines. When linear regression analyses were carried out, significant regression coefficients[8] were observed for TEM at the 0.01 level. Based on these results, we can confidently reject H_4– attitudinal variables have a significant explanatory power for the variance in WTP estimates.[9] In the case of Model Basic, average TPB scores explain 64 percent of the variance in WTP.[10] These significant relationships provide a benefit transfer potential of these latent variables to be incorporated as a part of utility models.

8) The regression coefficient for TEM had the t-ratio of 11.15 (Model Basic) and 7.98 (Model STSF), and the adjusted R^2 were 0.6380 and 0.2248, respectively.

9) However, these results might be not universally applicable or generalisable because the manipulated samples are not independent. Although a significance test was carried out, the intention was to examine a potential relationship between WTP measures and average TPB scores.

10) A quadratic regression form ($y = a + bx + cx^2$), where a and b are coefficients showed a better adjusted R^2 (0.6699). A linear regression model for FAC showed a smaller adjusted R^2 (0.4320).

Ⅵ. Conclusion

The conventional nonmarket valuation studies have predominantly focused on socio-demographic variables to address heterogeneous characteristics of respondents, while ignoring 'latent' attitudinal variables without any sound reason. This paper investigated the influence of attitudinal variables when they are incorporated into a choice modelling context, and found that they are not only significant determinants of stated preferences, but also useful tools to distinguish heterogeneous subgroups. If this impact is generalisable, ignorance or failure to incorporate attitudinal variables can lead to a serious bias in welfare estimations. In particular, the reliability of benefit transfer techniques can be improved by taking these into account.

For the benefit of future studies, replications of the same methodology will be critical to generalise the results, and to standardise the seed points for a nonhierarchical cluster analysis. A relatively large sample can be segmented into a standardized set of subgroups. Then, intergroup comparisons and transfers of WTP estimates could be possible in a more reliable way.

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요 약

진술선호에 미치는 잠재 심리변수의 영향:
초이스모델링에서 심리변수의 역할

최 성 록

진술선호법(stated preference methods)을 이용하는 비시장가치 연구의 핵심과제는 응답자 이질성(heterogeneity)에 대한 대응이라 해도 과언이 아니다. 기존 연구에서 이를 위해 사용되는 두 가지 접근법은 ① 사회경제변수와 같은 응답자 특성변수를 간접효용함수에 포함시키는 것과 ② 변수 추정치의 분산을 허용하는 mixed logit이나 probit과 같은 일반화된 모델을 적용하는 것이다. 본 연구에서는 심리태도변수(attitudinal variables)를 특성변수로서 사용하는 세 번째 접근법을 제시하고 검증하였다. 심리태도변수는 초이스 모델링 연구에서 설명변수와 분할 지표변수(segmentation criteria)로 적용되었다. 연구결과에 의하면 심리태도변수는 모델의 신뢰성과 속성 변수 추정치뿐만이 아니라 지불의사액에도 영향을 주는 것으로 나타났다.

주제어 : 비시장가치평가, 문화세계관 스케일, 계획된 행동이론, 잠재변수, 심리-행동, 초이스모델링

The Impact of Latent Attitudinal Variables on Stated Preferences: What Attitudinal Variables Can Do for Choice Modelling

Andy S. Choi

A key issue in the development and application of stated preference nonmarket valuation is the incorporation of unobserved heterogeneity in utility models. Two approaches to this task have dominated. The first is to include individual-specific characteristics into the estimated indirect utility functions. These characteristics are usually socioeconomic or demographic variables. The second employs generalized models such as random parameter logit or probit models to allow model parameters to vary across individuals. This paper examines a third approach: the inclusion of psychological or 'latent' variables such as general attitudes and behaviour-specific attitudes to account for heterogeneity in models of stated preferences. Attitudinal indicators are used as explanatory variables and as segmentation criteria in a choice modelling application. Results show that both the model significance and parameter estimates are influenced by the inclusion of the latent variables, and that attitudinal variables are significant factors for WTP estimates.

Keywords: nonmarket valuation, cultural worldview scale,
theory of planned behaviour, latent variables,
attitude-behaviour, choice modelling