RR 90-02

CONSTRAINED PART-WORTH ESTIMATION IN CONJOINT ANALYSIS USING THE SELF-EXPLICATED UTILITY MODEL

Ivo A. van der Lans

Willem J. Heiser

Department of Data Theory

University of Leiden

CONSTRAINED PART-WORTH ESTIMATION IN CONJOINT ANALYSIS USING THE SELF-EXPLICATED UTILITY MODEL[1].

Abstract

Across-attribute constraints upon part-worths in the individual-level main-effects-only conjoint analysis model are derived from Huber's self-explicated utility model. Part-worths obeying these constraints compare favourably, on cross-validated Pearson correlations and percentages of first choice hits, with unconstrained part-worths, self-explicated part-worths, and Srinivasan, Jain, and Malhotra's method constraining part-worths within attributes.

INTRODUCTION

Since its introduction in marketing research (Green and Rao 1971) conjoint analysis has turned out to be an important tool for predicting consumer's preferences for multiattribute alternatives. Nowadays the role of conjoint analysis in marketing research seems all but decreasing. In an update of their 1982 survey on the commercial use of conjoint analysis Wittink and Cattin (1989) notice that "the annual commercial use in the early 1980s appears to have exceeded the annual use during the 1970s." They estimate the number of commercial conjoint studies in the US to be about 400 a year in the early 1980s. Moreover conjoint analysis has been and still is the subject of a large number of academic studies as one can conclude from Green and Srinivasan's (1989) bibliography on conjoint analysis and related methodology in marketing research.

Improving Reliability and Predictive Validity of Conjoint Analysis

The major goal of conjoint analysis is to predict consumer's preferences for multiattribute alternatives and because of that several methods to improve the reliability and predictive

1 This work was supported in part by a grant of the Netherlands Organization for Scientific Research (NWO) to the first author. The authors are grateful to Paul Green for providing the data used in this paper.

validity of conjoint analysis have been proposed. We can distinguish between four methods for improving the reliability and predictive validity of conjoint analysis (Hagerty 1985). The first method focusses upon improving the reliability and predictive power of conjoint analysis by estimation of utility functions that use less degrees of freedom than the part-worth function (Cattin 1981; Krishnamurthi and Wittink 1989; Pekelman and Sen 1979). It can be used only if there are continuous attributes. Part-worths are constrained to be a function (e.g. a linear or quadratic function) of the physical continuum underlying the attribute levels. The second method aggregates responses across (sub)groups of respondents (e.g., Green, Carroll, and Carmone 1976; Moore 1980). Recent developments in this area are Hagerty's (1985) derivation of an optimal weighting scheme to compute transformed individual responses, where the optimal weighting scheme is obtained by a form of Q-type factor analysis, and Kamakura's (1988) clustering procedure. Both procedures aggregate data across respondents in such a way as to improve the predictive validity, whereas Kamakura's (1988) method balances this objective with the identification of meaningful and manageable segments. The third method improves predictive validity by imposing order constraints on part-worth estimates "based on *a priori* knowledge of the ordering of part-worths for different levels of an attribute" (Srinivasan, Jain, and Malhotra 1983). Besides the use of *a priori* knowledge to impose order constraints on part-worth estimates Srinivasan, Jain, and Malhotra (1983) suggest that one can impose idiosyncratic order constraints derived from additional self-explicated attribute level desirability data. The fourth method utilizes self-explicated attribute level desirability and attribute importance data in addition to full-profile evaluations for estimating part-worths in a Bayesian procedure combining the self-explicated utility model and the individual-level main-effects-only conjoint analysis model (Cattin, Gelfand, and Danes 1983).

Closely related to the previous methods is hybrid conjoint analysis (Green 1984; Green, Goldberg, and Montemayor 1981). Hybrid conjoint analysis models were developed to cope with the need to incorporate ever-larger numbers of attributes and attribute levels in conjoint analysis. They aim at (sub)group estimation of part worths while at the same time retaining individual differences by inclusion of individual self-explicated utilities. In the data collection phase each respondent has to generate self-explicated attribute level desirability scores and self-explicated attribute importance weights and, in addition, to evaluate a subset of stimuli from a fractional factorial orthogonal design only.

In this paper we propose an alternative method to improve the reliability and predictive validity of conjoint analysis. This method uses self-explicated data in tandem with full-profile evaluations and in that respect it is similar to the methods proposed by Cattin, Gelfand, and Danes (1983), Green, Goldberg, and Montemayor (1981), and Srinivasan, Jain, and

Malhotra (1983). We estimate constrained part-worths at the individual level, where the constraints are derived from self-explicated data as suggested by Srinivasan, Jain, and Malhotra (1983). However, whereas they propose the use of *intra*-attribute rankings of attribute levels on desirability, we use complete rankings of attributes levels on desirability *across* attributes. One way to arrive at such complete rankings across attributes is to derive them from self-explicated desirability ratings. In addition to a complete ranking of desirabilities we use rankings of self-explicated importance weights to constrain part-worth estimates. Using a self-explicated utility model, in particular Huber's (1974) two-stage rating procedure, we combine these two pieces of information into constraints upon part-worth estimates. In this way we impose more constraints upon part-worth estimates than Srinivasan, Jain, and Malhotra (1983). This reduces the *variance* due to inaccuracy in estimating the correct part-worths (Hagerty 1985; 1986) and therefore our method can be expected to be less vulnerable to small ratios of the number of stimuli to the total number of attribute levels. However because self-explicated data will generally not be errorless and we can not expect the self-explicated model to be more than an approximation to the actual underlying structure (Mitchell 1982) our method will presumably introduce some *bias* in the part-worth estimates. Therefore its predictive validity will depend upon the trade-off between a reduction in variance due to inaccuracy in estimating the correct part-worths and increase in bias (Hagerty 1985; 1986).

We first describe the self-explicated utility model and address some issues related to it. After that we specify the constraints we impose upon part-worth estimates. These constraints are very lenient in the sense that they are not, or at least hardly, invalidated by a number of modifications and alternatives to the self-explicated utility model. In other words, under the constraints imposed, we can still obtain part-worth estimates that reflect modified and alternative models. Subsequently we report some empirical results on the internal predictive validity of our method in comparison with some other methods. Finally we discuss these empirical results and some possible future applications and extensions of our method. Technical details for constrained part-worth estimation are given in the appendix.

DERIVATION OF CONSTRAINTS FROM THE SELF-EXPLICATED UTILITY MODEL

As stated, we use self-explicated data and the self-explicated utility model (Huber 1974) to derive constraints upon part worths. This self-explicated utility model is a linear compensatory model (Wilkie and Pessemier 1973) and is given by the following algebraic expression (cf. Green 1984)

(1) $$U_{h[i_1 i_2 \cdots i_J],k} = \sum_{j=1}^{J} w_{jk}\, u_{ijk}$$

in which

i_j		denotes level i of attribute j,
$h[i_1,i_2 \ldots i_J]$		denotes the full-profile stimulus h (h= 1,H) characterized by levels $i_1,i_2,\ldots,i_j,\ldots,i_J$ of attributes $1,2,\ldots,j,\ldots,J$,
$U_{h[i_1 i_2 \cdots i_J],k}$	$\equiv$	respondent k's (k = 1,K) self-explicated utility for full-profile stimulus h,
w_{jk}	$\equiv$	respondent k's self-explicated importance weight for attribute j, and
u_{ijk}	$\equiv$	respondent k's self-explicated desirability score for level i of attribute j.

Self-explicated importance weights and self-explicated desirability scores are usually elicited from respondents using some rating procedure. Self-explicated utilities are computed from these self-explicated importance weights and desirability scores using equation 1, where it is necessary to assume that the ratings have interval or ratio scale properties (Orth 1987; Schmidt 1973). In general (see for instance Green 1984) it is assumed that full-profile stimulus evaluations can be predicted, at least to some extend, by a linear transformation of the self-explicated utilities, $U_{h[i_1 i_2 \cdots i_J],k}$, that is

(2) $$Y_{h[i_1 i_2 \cdots i_J],k} \cong a + b \sum_{j=1}^{J} w_{jk}\, u_{ijk}$$

where

$\cong$		denotes the fact that the right-hand side of equation 2 is fitted to the left-hand side of equation 2. We use a least squares fitting criterion though other criteria of fit, like Srinivasan and Shocker's (1973a,b) C^*, deserve equal attention (see also Appendix A),
$Y_{h[i_1 i_2 \cdots i_J],k}$	$\equiv$	respondent k's evaluation of full-profile stimulus h,
a,b	$\equiv$	to be estimated additive constant and slope parameter.

Although the self-explicated approach to obtain interval measures of full-profile evaluations is regarded to be simple, it is troubled by some methodological issues.

Issues Related to the Use of the Self-Explicated Model

Wilkie and Pessemier (1973) and Green (1984), among others, have called attention for several methodological issues related to the self-explicated utility model in equation 2.

One major issue is the appropriateness of cross-sectional versus individual level analyses of the self-explicated utility model. Wilkie and Pessemier (1973) and Mitchell (1982) advocate individual level analyses because in practice these give better predictions than cross-sectional analyses. One reason for the failure of cross-sectional analyses may be that respondents are too heterogeneous to allow using a single additive constant, a, and slope parameter, b (Green 1984). With regard to this issue the choice of normalization of self-explicated desirabilities and self-explicated importance weights is of crucial importance. Should one normalize ratings within individuals? If so, how should one normalize them. Should they be normalized to have constant range within individuals, to have constant sum, or what else? As stressed and illustrated by Nickerson and McClelland (1989), without normalization, individual differences in response tendencies can have a large impact upon the fit of equation 2. To circumvent these problems we can estimate separate additive constants, a_k, and slope parameters, b_k, for each individual which comes down to fitting equation 2 at the individual level. Thus equation 2 turns into

$$(3) \qquad Y_{h[i_1 i_2 \cdots i_J],k} \cong a_k + b_k \sum_{j=1}^{J} w_{jk}\, u_{ijk}$$

A second issue, raised by Green (1984), is the extent to which individuals are able to estimate their u_{ijk}'s and w_{jk}'s on a reliable basis. Clearly, Green's remark concerns the ability of individuals to generate reliable ratio or interval scale self-explicated desirability scores and ratio scale self-explicated importance weights. If we fit the cross-sectional model in equation 2 ratio scale self-explicated desirability scores are required (Schmidt 1973). If we fit the individual level model in equation 3, or if we normalize the self-explicated desirabilities within individuals then we need only interval scale self-explicated desirabilities. It is also possible to modify the self-explicated utility model such that interval scale self-explicated desirabilities and importance weights are sufficient (Arnold and Evans 1979; Orth 1987). It remains questionable, however, to what extend we can obtain self-explicated interval scale measures of desirability and importance. It seems more safe to assume that ratings are ordinal measures of the hypothesized underlying scales at most. For instance, the question has been raised whether the self-explicated model should include (monotonic) power and/or exponential transformations of u_{ijk}'s and w_{jk}'s (Wilkie and Pessemier 1973). Shepard (1964) has noted that self-explicated importance weights are not always accurate in the sense that people overestimate the importance of less important attributes, which we can interpret as a need for a power transformation of the w_{jk}'s. In a study on the self-explicated utility model Green and Schaffer (1989) were not able to confirm Shepard's comments. They found that using various different power transformations of w_{jk}'s, leaving the u_{ijk}'s unaffected, resulted in a decrease of average product moment correlations between self-explicated utilities and full-profile stimulus evaluations. They also report a decrease in incidence of first choice hits. However their conclusions concern aggregated results only. That is, the average product moment correlation and incidence of first choice hits decrease when they applied the same power transformation to each individual's w_{jk}'s. Thus it might still be that different individuals benefit from different power transformations.

A third issue is whether the linear compensatory model in equations 1, 2, and 3 is more appropriate than alternative models like the model in which the w_{jk}'s are excluded (we call it the equal weights model), or conjunctive models, disjunctive models, and lexicographic models (Wilkie and Pessemier 1973, p.437; see Coombs 1964 for a discussion of the models). Clearly the equal weights model is equivalent to the self-explicated utility model after raising w_{jk}'s to the power of zero. It can be appropriate if individuals implicitly include importances into their self-explicated desirability ratings (Wilkie and Pessemier 1973). The lexicographic model can be represented by a monotonic transformation of the w_{jk}'s that makes important attributes relatively more important and unimportant attributes relatively less important (cf. Green and Schaffer 1989). The noncompensatory nature of conjunctive and disjunctive models can not be fully represented by any monotonic transformation of u_{ijk}'s or w_{jk}'s.

A fourth issue relating to the use of the self-explicated model is that "the function that transforms the U's to Y's may not be linear" (Green 1984). One way to deal with this problem is to estimate optimal monotonic transformations of full-profile evaluations like in MONANOVA (Kruskal 1965) and ADDALS/MORALS (De Leeuw, Young, and Takane 1976; Young, De Leeuw, and Takane 1976). In fact we can say that, if possible, these optimal transformations *linearize* the relation between full-profile stimulus evaluations and the self-explicated utilities (De Leeuw 1988).

Derivation of Constraints

To derive constraints upon part-worths from the self-explicated model, let's first consider the simple main effects conjoint analysis model for individual k

$$(4) \qquad Y_{h[i_1 i_2 \cdots i_J],k} \cong c_k + \sum_{j=1}^{J} x_{ijk}$$

in which

$x_{ijk} \equiv$ respondent k's part-worth for level i of attribute j,

$c_k \equiv$ to be estimated additive constant, that depends upon the choice of origin for part-worths per attribute.

The part-worths, x_{ijk}, are estimated for instance by OLS-regression or some nonmetric procedure like MONANOVA (Kruskal 1965) or LINMAP (Srinivasan and Shocker 1973a,b). If the model in equation 3 fits perfectly, that is the full-profile stimulus evaluations are indeed a linear transformation of the self-explicated utilities, then the simple main effects conjoint analysis model in equation 4 will also fit perfectly. In that case it will be possible to express each part-worth estimate x_{ijk}, up to an additive constant[2] d_{jk}, in terms of the slope parameter b_k, the self-explicated importance weight w_{jk} and the self-explicated desirability score u_{ijk}[3]. That is

$$(5) \qquad x_{ijk} = d_{jk} + b_k w_{jk} u_{ijk}.$$

If there is random error in the full profile stimulus evaluations and we estimate part-worths from equation 4 these part-worths will be inaccurate because of that random error. Now assume that the model that "true" full-profile stimulus evaluations are a linear function of the

2 The additive constants, d_{jk}, depend upon the choice of origin per attribute and the additive constant a_k. Notice that the sum of the d_{jk}'s should equal a_k minus c_k.

3 If the design matrix is of deficient rank then we may, due to collinearity, obtain part-worths that can not be expressed, up to an additive constant, in terms of b_k, w_{jk} and u_{ijk}. However in that case we can always find another set of part-worths, without decrease of fit in equation 4, such that equation 5 holds.

self-explicated utilities is right and in addition we know people's "true" attribute level desirabilities and attribute importance weights. In that case, restricting part-worth estimates, while fitting equation 4, to be a linear transformation of the $w_{jk}\ u_{ijk}$'s as in equation 5 will yield better part-worth estimates, in terms of predictive validity, than part-worth estimates we would obtain from fitting equation 4 without these constraints. Notice that fitting equation 4 under the constraints in equation 5 is essentially equivalent to fitting equation 3.

However, if any alternative or modified model is the "true" model or if the self-explicated measures of attribute level desirability and attribute importance are no accurate interval level estimates of people's "true" desirabilities and importances, then constraining part-worths according to equation 5 will give biased part-worth estimates.

Now, if our goal is to improve the predictive validity of our part-worth estimates, then our interest lies in avoiding any possible introduction of bias. This can be accomplished to a large extend using order information only from the self-explicated data. That is, we estimate part-worths from equation 4 subject to the restriction that we must be able to express these part-worths as

$$(6) \qquad x_{ijk} \quad = g_{jk} + v_{jk}\, e_{ijk}$$

in which for each individual k

the v_{jk}'s are monotonically related to the w_{jk}'s,
the e_{ijk}'s are monotonically related to the u_{ijk}'s,
in comparison to equation 5 there is no slope parameter because it can be absorbed either in the v_{jk}'s or in the e_{ijk}'s, and
the g_{jk}'s are additive constants that depend upon the choice of origin for part-worths per attribute and the choice of normalization for the v_{jk}'s and e_{ijk}'s.

This is equivalent to fitting

$$(7) \qquad Y_{h[i_1 i_2 \cdots i_J],k} \cong \sum_{j=1}^{J} v_{jk}\, e_{ijk}$$

for each individual. Notice that in comparison to equation 4 there is no additive constant because it can be absorbed in the e_{ijk}'s. The products $v_{jk}e_{ijk}$ are completely determined by equation 7, although the v_{jk}'s and e_{ijk}'s are not[4]. After fitting equation 7 the x_{ijk}'s are found by adding constants g_{jk} to the $v_{jk}e_{ijk}$'s (see equation 6) in order to meet the choice of origin for the part-worths per attribute. In addition to monotonicity constraints we can impose nonnegativity constraints upon the v_{jk}'s if we think that any coding of self-explicated importance weights should be positive-unipolar, assuming that within each attribute higher self-explicated desirabilities correspond to higher part-worth estimates.

Fitting equation 7 we use only ordinal information from the self-explicated data. Therefore, with respect to the second issue raised, it is the reliability of the order among self-explicated desirability ratings and among self-explicated importance ratings that matters, not the ratings themselves. Since the v_{jk}'s need to be only monotonically related to the w_{jk}'s the constraints do not introduce bias into part-worth estimates if some individual's "true" model turns out to be the equal weights model or the lexicographic model, as these models can be represented by transformations of the w_{jk}'s. As noted, the noncompensatory nature of conjunctive and disjunctive models can not be fully represented by any choice of e_{ijk}'s and v_{jk}'s. Therefore, if "completely unacceptable" attribute levels are assumed to have a noncompensatory conjunctive influence upon full-profile stimulus evaluations such that full-profile stimuli containing at least one attribute level judged "completely unacceptable" always gets the lowest evaluations regardless of the desirabilities of its levels on remaining attributes (Srinivasan 1988), then one might consider to fit equation 7 leaving out these stimuli. However as noted by Green, Krieger, and Bansal (1988) and Klein (1986) one should be cautious about the noncompensatory nature of "completely unacceptable" attribute levels (also see Mehta, Moore, and Pavia 1989). Including stimuli with noncompensatory "totally unacceptable" levels in fitting equation 6 is likely to result into comparably very low e_{ijk}'s for "totally unacceptable" levels, which to some extend imitates the noncompensatory nature of these levels. Bias due to nonlinear monotonic relations between self-explicated utilities and full-profile evaluations can in part be accounted for by estimates of the v_{jk}'s and e_{ijk}'s (besides, as noted, by monotonic transformations of the Y's).

Summarizing, we conclude that fitting equation 7 at the individual level circumvents some issues regarding self-explicated models raised in the past. As such we expect that the

4 Multiplying the v_{jk}'s by an arbitrary factor and dividing the e_{ijk}'s by the same factor will leave both the fit of equation 7 and the $v_{jk}e_{ijk}$'s unaffected.

constraints upon the v_{jk}'s and e_{ijk}'s introduce a relative small amount of bias into part-worth estimates. Furthermore, we hope that any bias introduced will be outweighted by a reduction in variance in part-worth estimates. We want to stress here that our method does not assume that any of the issues mentioned applies equally to each individual. That is, individual differences in "true" models, scale use and so on do not introduce bias into the part-worth estimates. In the next paragraph we describe a cross-validation study to shed some light on the empirical validity of our constraints.

EMPIRICAL COMPARISON OF CROSS-VALIDITIES

To assess the validity of our method, we compared cross-validition results for it with cross-validation results for some alternative methods, using data from a study by Green and Schaffer (1989).

Description of the Data

The stimuli in Green and Schaffer's (1989) experiment were full-profile privately offered, unfurnished apartment descriptions. Attributes and levels used in their conjoint design are shown in Table 1.

[Insert Table 1 about here]

Green and Schaffer collected data from 177 business students in four phases.

> In the first phase of their data collection respondents gave acceptability ratings for each attribute level on a 0-10, equal-interval rating scale, ranging from completely unacceptable to completely acceptable. In addition each respondent was asked to rate importance values of attributes in a constant sum procedure in which 100 points had to be allocated across the six attributes.
>
> In the second phase respondents evaluated 18 full-profile cards from a fractional factorial orthogonal main effects design. Evaluations were given on a likelihood of renting scale ranging from 0 to 100. Respondents were asked to assume that they were in need of an apartment within walking distance of the university.

In the third phase respondents evaluated 16 full-profile cards from a second orthogonal design utilizing levels 1 and 3 of the attributes only. Evaluations were given on the same likelihood of renting scale as in the second phase.

In the fourth phase respondents were asked to evaluate 16 full-profile cards from a nonorthogonal design. These cards were easier to judge than the cards in phase II and phase III since they consisted of two highly desirable profiles (where five out of six attributes were at their highest levels), two extremely poor profiles (only one of the six attributes at its highest level) and twelve intermediate profiles (each with three attributes at their highest level and three attributes at their lowest level).

Phase I through III were completed in one sitting. Data collection in phase IV took place two weeks later.

Design of the Comparative Study

First we estimated part-worths for each individual in a calibration sample, phase II full-profile stimulus evaluations, using various methods (including ours) and secondly, for each of these methods and for each individual, we used the estimated part-worths to predict full-profile evaluations in two different cross-validation samples, phase III and phase IV full-profile stimulus evaluations. Cross-validated product moment correlations between predicted and actual full-profile evaluations and percentages of first choice hits then are taken as measures of the internal validity of each method. The counterpart of internal validity is external validity which relates to the extend in which each method can predict actual choice behavior (cf. Green 1984). Though in practice external predictive validity is the most important criterion for the performance of different methods we did not assess external predictive validity in this study.

There are three methods against which we compared our method on internal validity. Two of these three methods were applied twice using different models. Methods and models are listed below.

I 1. Conjoint analysis using a main-effects-only model.

II 1. Computation of self-explicated part-worths using the self-explicated model including importance weights, that is we set x_{ijk} equal to $w_{jk}u_{ijk}$.

2. Computation of self-explicated part-worths using the self-explicated model without importance weights, that is we set x_{ijk} equal to u_{ijk}.

III 1. Conjoint analysis using the main-effects-only model with *a priori* within-attribute order constraints upon part-worths as proposed by Srinivasan, Jain, and Malhotra (1983). The *a priori* constraints are given in Table 1. Notice that this is not the only choice of *a priori* constraints that could have been made. However, Srinivasan, Jain, and Malhotra (1983) do not give guidelines for the specification of constraints except for that one should use constraints only after being convinced that the imposed structure is likely to be valid for almost all individuals. We think that our *a priori* constraints are valid for almost all individuals.

2. Conjoint analysis using the main-effects-only model with idiosyncratic within-attribute order constraints upon part-worths derived from self-explicated desirability ratings as also proposed by Srinivasan, Jain, and Malhotra (1983).

We applied our method to estimate part-worths with the three different options listed below.

IV 1. Assuming that individuals implicitly include their importance weights into their self-explicated desirability ratings, each x_{ijk} should be representable as e_{ijk}, where the e_{ijk}'s are monotonically related to the u_{ijk}'s for each individual. That is we exclude the importance weights from the self-explicated utility model.

2. Assuming that importance weights can be negative as well as positive, that is bipolar, each x_{ijk} should be representable as $v_{jk}e_{ijk}$, where the e_{ijk}'s are monotonically related to the e_{ijk}'s and the v_{jk}'s to the w_{jk}'s for each individual.

3. Assuming that importance weights are nonnegative, that is unipolar, each x_{ijk} should be representable as $v_{jk}e_{ijk}$, with e_{ijk}'s and v_{jk}'s monotonically related to the u_{ijk}'s and w_{jk}'s respectively for each individuals and, in addition, all v_{jk}'s nonnegative.

Part-Worth Estimation

We treated the full-profile stimulus evaluations which were obtained as ratings on a 0-100 rating scale metrically, assuming approximately interval scale properties (Green and Srinivasan 1978, p.111). Because the data for one business student contained a missing value we analyzed the data of a total of 176 business students. To estimate part-worths in metric conjoint analysis we used OLS regression. To estimate part-worths in method III we used the MORALS procedure (Young, De Leeuw, and Takane 1976). Because we treat the full-profile evaluations metrically and because stimuli in the calibration set are generated by an orthogonal design, the MORALS procedure guarantees global optimal estimates in the present application. The self-explicated desirability ratings used in model 2 may contain ties. That is two (or more) levels from one attribute may receive the same self-explicated desirability rating from individual *k*. In that case part-worths for these levels were constrained to be equal to each other. This is the so-called the secondary approach to ties (Kruskal 1964).

The problem of fitting equation 7 at the individual level under the appropriate constraints is equivalent to the nonlinear multiple regression problem with common scale predictor variables and restrictions upon regression weights formulated by Van der Lans (1989). He uses alternating least squares as a general strategy to solve the particular regression problem (see also, Van der Lans and Heiser 1988). Alternating least squares procedures have been extensively used in various techniques for nonlinear multivariate analysis (see among others, Gifi 1990; Young 1981). For a description of the computational steps we refer to the appendix. Because this algorithm does not guarantee a global optimal solution, we computed nine (three in case of model 1) different solutions using nine (three) different strategies to generate start configurations. For each individual then we used the part-worths found in the solution with the highest fit. We used the secondary approach to ties if there were ties in either the self-explicated desirabilities or the self-explicated importance weights.

Fitting Results

As measures of fit for each model we look at average Pearson correlations between actual full-profile evaluations and predicted full-profile evaluations in the calibration sample. Of course methods imposing less constraints on part-worth estimates should yield higher fits than methods imposing more constraints. This turns out indeed to be the case. The most restrictive models are the model 1 and 2 under method II. Average Pearson correlations for these models can also be interpreted measures of the convergent validity of self-explicated utilities and full-profile evaluations (Bateson, Reibstein, and Boulding 1987). Their values, .712 and .679 respectively, are rather high compared to values found in studies by Green, Goldberg, and Wiley (1982) (.34), Akaah and Korgaonkar (1983) (.25), and Cattin, Hermet, and Pioche (1982) (.53) though compatible to the value found by Cattin, Gelfand, and Danes (1983) (.70), and Agarwal and Green (1989) (.70). Overall the current sample of business students demonstrates relative high convergent validity.

Metric conjoint analysis poses the least constraints upon part-worth estimates. The fit of metric conjoint analysis, an average Pearson correlation of .914, is the highest in this study and comparable to fits found in other studies. Akaah and Korgaonkar (1983) for instance found an average multiple correlation of .911 and Cattin, Gelfand, and Danes (1983) an average squared multiple correlation of .892 (the average squared multiple correlations amounts to .838 in our calibration sample).

Fits for models under methods III and IV are in between these two extremes. Method III gives average Pearson correlations of .888 for model 1 and .882 for model 2. Average Pearson correlations for method IV models 1, 2, and 3 are .800, .830, and .825 respectively. They latter ones are, as they should be since the models are more restrictive, smaller than the average Pearson correlation for method III model 2. The order among the fits of the models under method IV corresponds to what it should be, model 1 being the most and model 2 being the least restrictive. As mentioned before, average Pearson correlations for method IV model 1, 2, and 3 were obtained by selecting for each respondent the highest fit over different starts. This procedure is no guarantee for finding a global optimum. However for method IV model 3 the difference between lowest and highest fit was less than .001 for 173 out of 176 respondents and less than .01 for all respondents. This may reassure us about the algorithm's performance in finding global optimal solutions.

Cross-Validation Results

Cross-validation results are shown in Table 2. First it may catch our eye that for each method the average cross-validated correlation and percentage of first choice hits is higher in phase IV than in phase III. This is probably due to the construction of the stimulus sets, the stimuli in phase IV being easier to judge. With regard to the average cross-validated correlations we see that differences between methods and models are relatively small, average cross-validated correlations for the self-explicated models being the lowest ones.

[Insert Table 2 about here]

Comparing the models from method III (within-attribute constraints) we can conclude that *a priori* constraints yield higher cross-validated correlations. The difference between the two models though is small, because most respondents have within-attribute orders among their self-explicated desirabilities that are equivalent to the *a priori* orders, which supports the *a priori* constraints chosen. Concentrating on models from method IV (across-attribute constraints) we see that model 3 (unipolar weights) outperforms both model 1 (equal weights) and model 2 (bipolar weights). Apparantly, the assumption that any coding of self-explicated importance weights should be unipolar is a valid one.

To assess the relative performances of methods I, II, III, and IV we selected the best model from each method. In the phase III cross-validation sample method III gives the highest average cross-validated Pearson correlation. The difference between conjoint analysis and method III is significant as are the differences between method II and all other methods. Neither the difference between method IV and conjoint analysis nor the difference between method IV and method III is significant. In the phase IV cross-validation sample method IV gives the highest average cross-validated correlation. The differences with conjoint analysis are significant for both method III and method IV. Moreover, the difference between method II and method IV is significant. The difference between methods III and IV is reversed and, though larger than in the phase III cross-validation sample, not significant.

Percentages of first choice hits show, as we saw, the same pattern as average cross-validated Pearson correlations in the sense that the percentages of first choice hits in the phase IV cross-validation sample are considerably larger than the ones in the phase III cross-validation sample. In addition, comparisons within each method give the same results as for the average cross-validated Pearson correlations. Method IV gives the highest percentage of first choice hits in the phase III cross-validation sample. Method II, closely followed by method IV, gives the highest percentage of first choice hits in the phase IV cross-validation sample. Conjoint analysis performs worst in both samples. Differences in the phase III cross-validation sample are not significant. In the phase IV sample both method II and method IV differ significantly from conjoint analysis.

We conclude that, at least using the data from the Green and Schaffer (1989) study, constrained part-worth estimation improves upon the cross-validity of conjoint analysis, though the improvements are small and not significant in the phase III cross-validation sample. Comparisons with the self-explicated utility model and within-attribute constraints as proposed by Srinivasan, Jain, and Malhotra (1983) give mixed results, constrained estimation with across-attribute constraints as proposed in this paper performing marginally, and for the most part not significantly, better or at least as good as these methods dependent upon the measure of cross-validity used.

DISCUSSION

Our proposal for constraining part-worths across attributes using the self-explicated model improves upon the cross-validity of conjoint analysis. The magnitude of the improvement is small but comparable to improvements in cross-validity reported in other studies (see for instance, Cattin 1981; Srinivasan, Jain, and Malhotra 1983). Comparisons with the self-explicated utility model and Srinivasan, Jain, and Malhotra's (1983) method are less univocal. The self-explicated utility model is outweighted by our constrained part-worth estimation method if we look at cross-validated Pearson correlations. They are about equal on percentages of first choice hits. On the other hand, Srinivasan, Jain, and Malhotra's method is outweighted, though slightly and not significantly, by our method when we look at percentages of first choice hits. They are about equal on cross-validated Pearson correlations.

Given the data set used one should be cautious in drawing conclusions from this study. Privately offered apartments were used as product class and business students as population of interest. With respect to desirability the within-attribute order of part-worths was more or less obvious. This presumably favoured the constrained estimation methods (method III and IV), in comparison to situations in which these orders are less clear-cut and therefore more difficult to specify for either the researcher or the respondents. Furthermore, within-attribute orders of part-worths could reasonably be assumed to be equal across individuals. This enabled us to impose a large number of *a priori* constraints. When there are no such a priori orders likely to be valid for all individuals we have to use self-explicated (idiosyncratic) orders. In this study idiosyncratic constraints worsened the performance of Srinivasan, Jain, and Malhotra's method slightly when compared with *a priori* constraints. This might be due to the secondary approach to ties used in estimation, self-explicated desirability ratings containing ties for some individuals.

Also, the construction of cross-validation samples using only levels one and three from each attribute may have influenced our results. In addition, where Tashchian, Tashchian, and Slama (1981) found higher validity of conjoint analysis for higher educated individuals, we expect that the education level of business students has had some influence upon our findings. We just have to remember the relative high convergent validity between self-explicated utilities and full-profile evaluations, indicating that overall the business students were able to give numerical ratings of desirabilities and importances that are valid with regard to the model in equation 3. It remains to be seen whether this ability is shared by other people. However, our method is invalidated only if people show a disability to give valid ordinal self-explicated measures of desirability and importance. Further research is needed to assess the generalizability of current results to other product classes and populations. We expect to benefit most from our method in comparison with other methods when: 1- individuals differ from each other with respect to within-attribute desirability orders, 2- individuals differ from each other with respect to the model they use to arrive at self-explicated utilities, 3- individuals are able to give reliable ordinal measures of desirability and importance, whereas their ability to give reliable interval or ratio scaled measures is much lower, and 4- there is no interaction between attributes.

A major drawback of our method is that self-explicated data should be collected in addition to full-profile evaluations. Therefore, in practical situations, one may raise questions about the value of possible small improvements in predictive validity compared to the increased demands upon respondents. These issue is even more relevant when we consider the fact that most marketers are primarily interested in predicting market share instead of individual preferences (Hagerty 1986). For instance, improvements in percentages first choice hits evidently give only an upper bound to the improvement in market share prediction when using the first choice rule in a conjoint simulator.

In the empirical study we compared the internal validity of our constrained part-worth estimation method with some other methods. Future research should also be directed towards an assessment of the comparative external predictive validity. Another research question concerns the comparative reliability of the constrained part-worths estimates. Especially, refering to the kinds of reliability distinguished by Bateson, Reibstein, and Boulding (1987), its reliability over time, using self-explicated data collected at two different points in time, and its reliability over data collection procedures, using different procedures to collect the self-explicated data, seem interesting. With regard to the latter, data collection procedures should perhaps involve explicit comparisons of attribute level desirabilities across attributes though across-attribute comparisons are certainly more difficult than within-attribute comparisons and may invoke implicit incorporation of importance weights into attribute level desirabilities. Note that the latter does not necessarily impair our method since the v_{jk}'s are permitted to be equal. One can also think of more precise and valid definitions of attribute importance (Srinivasan 1988). Thus, future research should aim at data collection procedures that maximize the validity of orders among attribute level desirabilities and among attribute importances.

Extensions of our Method

We tried to present our method in a straightforward manner without mentioning too many possible modifications or combinations with other methods. We use this last paragraph to point out some of them.

First, we can modify our method by using the primary approach to ties instead of the secondary approach to ties in estimating optimal v_{jk}'s and e_{ijk}'s. That is, attribute importances or attribute level desirabilities rated equally do not necessarily obtain equal v_{jk}'s or e_{ijk}'s. Doing so, we impose less constraints which reduces the bias in part-worth estimates but at the same time increases variance due to inaccuracy in estimating the correct part-worths. Again it depends upon the trade-off between these two whether this will lead to an improvement in predictive validity.

In the second place, we can readily combine our method with Hagerty's (1985) method aggregating responses across individuals in a two-stage procedure as recommended by Hagerty (o.c., p.182). Transformed full-profile evaluations from Hagerty's method can serve as input to our method. Pooling information across individuals with similar full-profile evaluations may theoretically and empirically lead to higher predictive accuracy as shown by Hagerty (1985). In an empirical study however, Green and Helsen (1989) did not find an improvement in predictive accuracy over the traditional conjoint analysis model. Of course, we can compute the eigenvalue decomposition, see also Hagerty's (1985) Q-type factor analysis, of the correlation matrix of all respondent's vectors of part-worths, as obtained by our constrained estimation method, or apply some clustering procedure to all these vectors of part-worths to gain some insight into similarities and dissimilarities in part-worths between individuals.

Though our method, requiring self-explicated data, brings along additional demands upon respondents it can be used to lower the number of full-profile stimuli to be evaluated. Suppose that an individual gives the same self-explicated desirability ratings to two or more attribute levels. Then in setting up an fractional factorial orthogonal design we can, in principle, leave out all these attribute levels but one. That is, somehow similar to adaptive conjoint analysis (Johnson 1987), the set of stimuli to be presented to a respondent depends upon the respondent's self-explicated responses. Subsequently, we estimate v_{jk}'s and e_{ijk}'s from which we can compute part-worth estimates for all attribute levels. Thus, in this procedure we use, similar to hybrid conjoint analysis (Green 1984), self-explicated data to reduce the number of full-profile stimuli to be evaluated. We have to take care that in leaving out attribute levels at least two attribute levels should remain with each attribute in order to be able to estimate meaningful v_{jk}'s. Whether this procedure will prove useful in practice remains to be seen. We expect that, if the traditional self-explicated model shows high convergent validity, as in the present study, reducing the number of full-profile evaluations will result into constrained part-worth estimates that perform worse than self-explicated part-worths computed from the traditional self-explicated model using no full-profile evaluations at all.

The last extension we mention is a combination of our method with hybrid conjoint analysis. Here we compute optimal v_{jk}'s and e_{ijk}'s, monotonically related to the w_{jk}'s and u_{ijk}'s respectively, in the first fitting stage and (sub)group level conjoint part-worth estimates for the residuals in the second fitting stage (cf. Green 1984). We can choose between different monotonic relations for different individuals, in which case we just fit our model at the individual level, or similar monotonic relations across individuals. Unfortunately, the latter approach brings back the issue of how to normalize the self-explicated data within individuals. Furthermore, we loose the possibility to account for individual differences in model use, which we regard as one of the most attractive features of our current method. We also note that the algorithm given in the appendix has to be adapted to deal with different importance weights per attribute, when estimating equal transformations of the w_{jk}'s across individuals.

All in all, our method for constrained part-worth estimation seems to be interesting enough, judged by its current performance as well as by its possible extensions, to instigate further research.

APPENDIX A

The objective of finding individual level constrained part-worth estimates that minimize the sum of squared residuals in equation 7 can be formulated in terms of minimization of the following loss function

(A1) $\sigma(\mathbf{E},\mathbf{v}) = (\mathbf{q} - \mathbf{JEv})'(\mathbf{q} - \mathbf{JEv})$

for each individual. Notice that, dealing with one individual at a time, we dropped index k.

$\mathbf{q}$	$\equiv$	an H-vector with standardized scores for full profile stimuli 1,2,...H,
$\mathbf{J}$	$\equiv$	an HxH idempotent matrix known as the centering operator. We have $\mathbf{J} = \mathbf{I} - \mathbf{t}(\mathbf{t}'\mathbf{t})^{-1}\mathbf{t}'$, where $\mathbf{I}$ is the HxH identity matrix and $\mathbf{t}$ an H-vector with all its elements equal to 1,
$\mathbf{E}$	$\equiv$	an HxJ-matrix of scores for full profiles 1,2,...,H, on attributes 1,2,...,J,
$\mathbf{v}$	$\equiv$	a J-vector of scores for attributes 1,2,...J.

The loss function in equation A1 is minimized subject to the following constraints

(I)	$q_h = f(Y_h)$	
(II)	if $u_{hj} < u_{h'j'}$ then $e_{hj} \leq e_{h'j'}$,	$\forall\ h,h' \in 1,2,...,H$, and $j,j' \in 1,2,...,J$,
(III)	if $u_{hj} = u_{h'j'}$, then $e_{hj} = e_{h'j'}$,	$\forall\ h,h' \in 1,2,...,H$, and $j,j' \in 1,2,...,J$, (this characterizes the secondary approach to ties),
(IV)	if $w_j < w_j'$ then $v_j \leq v_j'$,	$\forall\ j,j' \in 1,2,...,J$,
(V)	if $w_j = w_j'$ then $v_j = v_j'$,	$\forall\ j,j' \in 1,2,...,J$, (this characterizes the secondary approach to ties), and
(VI)	$0 \leq v_j$	$\forall\ j \in 1,2,...,J$, (only with unipolar weights)

in which

q_h	$\equiv$	h th element of $\mathbf{q}$,
f	$\equiv$	linear or monotonic function dependent upon whether we assume the full profile stimulus evaluations Y_h to have interval scale or ordinal scale properties,

u_{hj}	$\equiv$	self-explicated desirability rating for level i_j of attribute j that, among others, characterizes full profile stimulus h,
e_{hj}	$\equiv$	element in h th row and j th column of $\mathbf{E}$.

We minimize the loss function in equation A1 iteratively, performing two steps in each iteration.

Step 1 In the nth iteration we find $\mathbf{v}^{(n)}$ as the vector that minimizes the function in equation A2 over all $\mathbf{v}$ subject to the constraints on $\mathbf{v}$.

(A2) $\xi(\mathbf{v}) = (\mathbf{q} - \mathbf{JE}^{(n-1)}\mathbf{v})'(\mathbf{q} - \mathbf{JE}^{(n-1)}\mathbf{v})$.

The right-hand side can be written as

(A3) $(\mathbf{q} - \mathbf{JE}^{(n-1)}\mathbf{v}^{*(n)})'(\mathbf{q} - \mathbf{JE}^{(n-1)}\mathbf{v}^{*(n)}) + (\mathbf{v}^{*(n)} - \mathbf{v})'\,\mathbf{E}^{(n-1)'}\mathbf{JE}^{(n-1)}(\mathbf{v}^{*(n)} - \mathbf{v})$

in which $\mathbf{v}^{*(n)}$ is the unconstrained minimizer of the loss function in equation A2, that is $\mathbf{v}^{*(n)} = (\mathbf{E}^{(n-1)'}\mathbf{J}\,\mathbf{E}^{(n-1)})^{-1}\mathbf{E}^{(n-1)'}\mathbf{q}$. In case $(\mathbf{E}^{(n-1)'}\mathbf{J}\,\mathbf{E}^{(n-1)})$ has deficient rank we can take a generalized inverse of $(\mathbf{E}^{(n-1)'}\mathbf{J}\,\mathbf{E}^{(n-1)})$ like the Penrose-Moore generalized inverse.

The left-hand term in equation A3 is constant and therefore the function in equation A2 is minimized by minimizing the right-hand term in equation A3. This term can be majorized using the Rayleigh quotient (cf. Heiser 1987; Van der Lans and Heiser 1988) and therefore equation A3 can be minimized by successive minimizations of

(A4) $\phi(\mathbf{v}) = (\mathbf{v} - \hat{\mathbf{v}}^{(n,t)})'(\mathbf{v} - \hat{\mathbf{v}}^{(n,t)})$

subject to the constraints on $\mathbf{v}$ given above and in which

$\hat{\mathbf{v}}^{(n,t)}$	$=$	$\mathbf{v}^{(n,t-1)} + \beta^{-1}\mathbf{E}^{(n-1)'}\mathbf{J}\,\mathbf{E}^{(n-1)}(\mathbf{v}^{*(n)} - \mathbf{v}^{(n,t-1)})$, with β being the largest eigenvalue of $\mathbf{E}^{(n-1)'}\mathbf{J}\,\mathbf{E}^{(n-1)}$
t	$\equiv$	the iteration number for the inner iterations, and
$\mathbf{v}^{(n,0)}$	$=$	$\mathbf{v}^{(n-1)}$.

We define $\mathbf{v}^{(n,t)}$ as the vector that minimizes the function in equation A4, that is $\mathbf{v}^{(n,t)}$ is the projection of $\hat{\mathbf{v}}^{(n,t)}$ onto the region defined by the constraints. This projection is split into a projection onto the subspace of the equality constraints followed by projection onto the cone of the inequality constraints (using monotonic regression) which is - if necessary - followed by a projection onto the cone of the nonnegativity constraints. If the difference between the value of function ξ for $\mathbf{v}^{(n,t)}$ and $\mathbf{v}^{(n,t-1)}$ is smaller than some convenient small number ε we set $\mathbf{v}^{(n)}=\mathbf{v}^{(n,t)}$.

Step 2 We find $\mathbf{E}^{(n)}$ as the matrix that minimizes the function in equation A5 over all $\mathbf{E}$ subject to the constraints.

(A5) $\psi(\mathbf{E}) = (\mathbf{q} - \mathbf{JEv}^{(n)})'(\mathbf{q} - \mathbf{JEv}^{(n)})$

Using indicator matrices $\mathbf{G}_j$ (see for instance Gifi 1990) that carry both the equality and inequality constraints among the e_{hj}'s, minimization of the function in equation A5 is equivalent (see Van der Lans 1989) to the minimization of

(A6) $\mu(\mathbf{e}) = (\mathbf{e} - \mathbf{e}^{*(n)})\ \mathbf{G_v}^{(n)\prime}\mathbf{G_v}^{(n)}\ (\mathbf{e} - \mathbf{e}^{*(n)})$

in which $\mathbf{G_v} = \mathbf{J}\sum_{j=1}^{J} v^{(n)}{}_j\mathbf{G}_j$.

To minimize μ we can use the same majorization approach as in step 1. After convergence we find $\mathbf{E}^{(n)}$ as $(\mathbf{G}_1\mathbf{e}^{(n)} \mid \mathbf{G}_2\mathbf{e}^{(n)} \mid \ldots \mid \mathbf{G}_J\mathbf{e}^{(n)})$.

We alternate between step 1 and step 2 until convergence of the loss function in equation A1. Before starting the iterations we have to define $\mathbf{E}^{(0)}$ and $\mathbf{v}^{(0)}$, the initial values. Any choice of initial values obeying the constraints is permitted. The computer program by Van der Lans (1989) allows one to specify the initial values, $\mathbf{v}^{(0)}$, oneself, or to take random values, or to have all values in $\mathbf{v}^{(0)}$ to be equal to 1. With regard to the initial values $\mathbf{E}^{(0)}$ one can specify them, take random values, or let all initial values be equal to 0. Three final comments on the algorithm deserve attention here. In the first place, the centering operator $\mathbf{J}$ is included only to speed up convergence. If the full profile evaluations are ratio scaled measures and thus the intercept term in equation 7 is of interest then we can compute it afterwards. Secondly, if the Y_h's are ordinal or even nominal scale measures we have to perform an additional step that computes the optimal f in each iteration. A last comment concerns a simplification of the algorithm if stimuli are obtained from an orthogonal design. In that case $\mathbf{E}^{(n-1)\prime}\mathbf{J}\ \mathbf{E}^{(n-1)}$ will be diagonal and we can easily solve the problem in equation A3 without using majorization.

If we choose Srinivasan and Shocker's (1973a,b) criterion of fit, C^*, then we can alternate between two linear programming problems, the first one of which is the minimization of

$$\text{(A7)} \quad \kappa(\mathbf{v}) = \sum_{(h,h')\in\Omega} \{(\mathbf{e}^{(n-1)}{}_h - \mathbf{e}^{(n-1)}{}_{h'})'\mathbf{v}\}^-$$

in which

Ω ≡ the set of dominance pairs (h,h') such that h is evaluated higher than h',

$\mathbf{e}^{(n-1)}{}_h{}'$ ≡ the hth row in $\mathbf{E}^{(n-1)}$,

$\{(\mathbf{e}^{(n-1)}{}_h - \mathbf{e}^{(n-1)}{}_{h'})'\mathbf{v}\}^- = 0$ if $\mathbf{e}^{(n-1)}{}_h{}'\mathbf{v} \geq \mathbf{e}^{(n-1)}{}_{h'}{}'\mathbf{v}$,

$\{(\mathbf{e}^{(n-1)}{}_h - \mathbf{e}^{(n-1)}{}_{h'})'\mathbf{v}\}^- = (\mathbf{e}^{(n-1)}{}_h - \mathbf{e}^{(n-1)}{}_{h'})'\mathbf{v}$ if $\mathbf{e}^{(n-1)}{}_h{}'\mathbf{v} < \mathbf{e}^{(n-1)}{}_{h'}{}'\mathbf{v}$, and

$\sum_{(h,h')\in\Omega} \{(\mathbf{e}^{(n)}{}_h - \mathbf{e}^{(n)}{}_{h'})'\mathbf{v}\} = 1.$

and the second one of which is the minimization of

$$\text{(A8)} \quad \lambda(\mathbf{e}) = \sum_{(h,h')\in\Omega} \{(\mathbf{g}_{\mathrm{v}}{}^{(n)}{}_h - \mathbf{g}_{\mathrm{v}}{}^{(n)}{}_{h'})'\mathbf{e}\}^-$$

in which

$\mathbf{g}_{\mathrm{v}}{}^{(n)}{}_h{}'$ ≡ the hth row in $\mathbf{G}_{\mathrm{v}}{}^{(n)}$,

$\{(\mathbf{g}_{\mathrm{v}}{}^{(n)}{}_h - \mathbf{g}_{\mathrm{v}}{}^{(n)}{}_{h'})'\mathbf{e}\}^- = 0$ if $\mathbf{g}_{\mathrm{v}}{}^{(n)}{}_h{}'\mathbf{e} \geq \mathbf{g}_{\mathrm{v}}{}^{(n)}{}_{h'}{}'\mathbf{e}$,

$\{(\mathbf{g}_{\mathrm{v}}{}^{(n)}{}_h - \mathbf{g}_{\mathrm{v}}{}^{(n)}{}_{h'})'\mathbf{e}\}^- = (\mathbf{g}_{\mathrm{v}}{}^{(n)}{}_h - \mathbf{g}_{\mathrm{v}}{}^{(n)}{}_{h'})'\mathbf{e}$ if $\mathbf{g}_{\mathrm{v}}{}^{(n)}{}_h{}'\mathbf{e} < \mathbf{g}_{\mathrm{v}}{}^{(n)}{}_{h'}{}'\mathbf{e}$, and

$\sum_{(h,h')\in\Omega} \{(\mathbf{g}_{\mathrm{v}}{}^{(n)}{}_h - \mathbf{g}_{\mathrm{v}}{}^{(n)}{}_{h'})'\mathbf{e}\} = 1.$

Although this algorithm converges, it also does not guarantee global optimal estimates.

Table 1

APARTMENT ATTRIBUTES, LEVELS AND CONSTRAINTS

Attribute name		*Levels*	*A priori constraints*
I.	Walking time to classes	1. 10 minutes 2. 20 minutes 3. 30 minutes	$1 \geq 2 \geq 3$
II.	Noise level of apartment house	1. Very quiet 2. Average noise level 3. Extremely noisy	$1 \geq 2 \geq 3$
III.	Safety of apartment location	1. Very safe location 2. Average safety 3. Very unsafe location	$1 \geq 2 \geq 3$
IV.	Condition of apartment	1. Newly renovated troughout 2. Renovated kitchen only 3. Poor condition	$1 \geq 2 \geq 3$
V.	Size of living/dining area	1. 24 by 30 feet 2. 15 by 20 feet 3. 9 by 12 feet	$1 \geq 2 \geq 3$
VI.	Monthly rent (utilities included)	1. $540 2. $360 3. $225	$1 \leq 2 \leq 3$

Table 2

COMPARISON OF CROSS-VALIDATION RESULTS

	Phase III		*Phase* IV	
Method	*Average Pearson corre-lations*[a]	*Percen-tages first choice hits (%)*[b]	*Average Pearson corre-lations*[a]	*Percen-tages first choice hits (%)*[b]
I 1. Conjoint analysis	0.762	42.7	0.766	65.0
II 1. Self-explicated model (weighted)	0.721	45.3	0.760	<u>79.6</u>
2. Self-explicated model (equal weights)	0.646	27.7	0.700	77.2
III 1. Within-attribute constraints (*a priori*)	<u>0.774</u>	45.6	0.783	73.5
2. Within-attribute constraints (idiosyncratical)	0.771	43.4	0.779	73.2
IV 1. Across-attribute constraints (equal weights)	0.753	44.2	0.774	75.7
2. Across-attribute constraints (bipolar weights)	0.753	45.4	0.779	77.2
3. Across-attribute constraints (unipolar weights)	0.767	<u>47.5</u>	<u>0.793</u>	79.4

a) In each column the highest average Pearson correlation is underlined. Differences between methods, taking the best model from each method, were tested, after a Fisher's Z transformation of the correlations, using a paired samples t-test (two-tailed, $\alpha = .01$) (see Snedecor and Cochran 1967, p. 93). In the phase III cross-validation sample significant differences were found between method II and each of the other methods, as well as between methods I and III. In the phase IV cross-validation sample significant differences were found between method I and III, method I and IV, and method II and IV.

b) In each column the highest percentage first choice hits is underlined. Differences between methods, taking the best model from each method, were tested using McNemar's test for correlated proportions (two-tailed, $\alpha = .01$) (see Snedecor and Cochran 1967, p. 213). In the phase III cross-validation sample no significant differences were found. In the phase IV cross-validation sample significant differences were found between method I and II, and method I and IV.

REFERENCES

Agarwal, Manoj K. and Paul E. Green (1989), "Adaptive Conjoint Analysis versus Self-Explicated Models: Some Empirical Results," Working Paper 90-158, The School of Management, State University of New York, Binghamton (December).

Akaah, Ishmael P. and Pradeep K. Korgaonkar (1983), "An Empirical Comparison of Predictive Validity for Self-Explicated, Huber-Hybrid, Traditional Conjoint and Hybrid Conjoint Models," Journal of Marketing Research, 20 (May), 187-97.

Arnolds, Hugh J. and Martin G. Evans (1979), "Testing Multiplicative Models Does Not Require *Ratio* Scales," Organizational Behavior and Human Performance, 24, 41-59.

Bateson, John E. G., David Reibstein, and William Boulding (1987), "Conjoint Analysis Reliability and Validity: A Framework for Future Research," in Review of Marketing, M. J. Houston, ed. Chicago: MI, American Marketing Association, 451-81.

Cattin, Philippe (1981), "Some Findings on the Estimation of Continuous Utility Functions in Conjoint Analysis," in Advances in Consumer Research, Vol. 9, A. Mitchell, ed. St. Louis: MO, Association for Consumer Research, 367-72.

____________, Alan E. Gelfand, and Jeffrey Danes (1983), "A Simple Bayesian Procedure for Estimation in a Conjoint Model," Journal of Marketing Research, 20 (February), 29-35.

____________, Gerard Hermet, and Alan Pioche (1982), "Alternative Hybrid Models for Conjoint Analysis: Some Empirical Results," in Analytical Approaches to Product and Market Planning: The Second Conference, R. Srivastava and A. Shocker, eds. Cambridge, MA: Marketing Science Institute, 142-52.

Coombs, Clyde H. (1964), A Theory of Data, New York: Wiley.

De Leeuw, Jan (1988), "Multivariate Analysis with Linearizable Regressions," Psychometrika, 53 (December), 437-54.

__________, Forest W. Young, and Yoshio Takane (1976), "Additive Structure in Qualitative Data: An Alternating Least Squares Method with Optimal Scaling Features," Psychometrika, 41 (December), 505-29.

Gifi, Albert (1990), Nonlinear Multivariate Analysis, New York: Wiley.

Green, Paul E. (1984), "Hybrid Models for Conjoint Analysis: An Expository Review," Journal of Marketing Research, 21 (May), 155-69.

__________, J. Douglas Carroll, and Frank J. Carmone (1976). "Superordinate Factorial Designs in the Analysis of Consumer Judgments," Journal of Business Research, 4 (November), 281-95.

__________, Stephen M. Goldberg, and Mila Montemayor (1981), "A Hybrid Utility Estimation Model for Conjoint Analysis," Journal of Marketing, 45 (Winter), 33-41.

__________, Stephen M. Goldberg, and James B. Wiley (1982), "A Cross-Validation Test of Hybrid Conjoint Models," in Advances in Consumer Research, Vol. 10, R. P. Bagozzi and A. M. Tybout, eds. Ann Arbor, MI: Association for Consumer Research, 147-50.

__________ and Kristiaan Helsen (1989), "Cross-Validation Assessment of Alternatives to Individual-Level Conjoint Analysis: A Case Study," Journal of Marketing Research, 26 (August), 346-50.

__________, Abba M. Krieger, and Pradeep Bansal (1988), "Completely Unacceptable Levels in Conjoint Analysis: A Cautionary Note," Journal of Marketing Research, 25 (August), 293-300.

__________ and Vithala R. Rao (1971), "Conjoint Measurement for Quantifying Judgmental Data," Journal of Marketing Research, 8 (August), 355-63.

__________ and Catherine M. Schaffer (1989), "Importance Weight Effects on Self-Explicated Preference Models: Some Empirical Findings," Working Paper, Wharton School, University of Pennsylvania (August).

__________ and V. Srinivasan (1978), "Conjoint Analysis in Consumer Research: Issues and Outlook," Journal of Consumer Research, 5 (September), 103-23.

__________ and __________ (1989), "A Bibliography on Conjoint Analysis and Related Methodology in Marketing Research," Working Paper, Wharton School, University of Pennsylvania (September).

Hagerty, Michael R. (1985), "Improving the Predictive Power of Conjoint Analysis: The Use of Factor Analysis and Cluster Analysis," Journal of Marketing Research, 22 (May), 168-84.

__________ (1986), "The Cost of Simplifying Preference Models," Marketing Science, 5 (Fall), 298-319.

Heiser, Willem J. (1987), "Correspondence Analysis with Least Absolute Residuals," Computational Statistics & Data Analysis, 5, 337-56.

Huber, George P. (1974), "Multi-Attribute Utility Models: A Review of Field and Field-Like Studies," Management Science, 20 (June), 1393-1402.

Johnson, Richard M. (1987), "Adaptive Conjoint Analysis," Sawtooth Software Conference on Perceptual Mapping, Conjoint Analysis, and Computer Interviewing, Ketchum, ID: Sawtooth Software, 253-65.

Kamakura, Wagner A. (1988), "A Least Squares Procedure for Benefit Segmentation for Conjoint Experiments," Journal of Marketing Research, 25 (May), 157-67.

Klein, Noreen M. (1986), "Assessing Unacceptable Attribute Levels in Conjoint Analysis," in Advances in Consumer Research, Vol. 14, M. Wallendorf and P. Anderson, eds. Association for Consumer Research, Provo: UT, Association for Consumer Research, 154-8.

Krishnamurthi, Lakshman and Dick R. Wittink (1989), "The Part-Worth Model and Its Applicability in Conjoint Analysis," Working Paper, College of Business Administration, University of Illinois (September).

Kruskal, Joseph B. (1964), "Multidimensional Scaling by Optimizing Goodness of Fit to a Nonmetric Hypothesis," Psychometrika, 29 (March), 1-28.

____________ (1965), "Analysis of Factorial Experiments by Estimating Monotone Transformations of the Data," Journal of the Royal Statistical Society, Series B, 27, 251-63.

Mehta, Raj, William L. Moore, and Teresa M. Pavia (1989), "An Examination of Unacceptable Levels in Conjoint Analysis," Working Paper, Salt Lake City, UT: Graduate School of Business, the University of Utah (November).

Mitchell, Terence R. (1982), "Expectancy-Value Models in Organizational Psychology," in Expectations and Actions: Expectancy-Value Models in Psychology, N. T. Feather, ed. Hillsdale: Erlbaum, p. 293-312.

Moore, William L. (1980), "Levels of Aggregation in Conjoint Analysis: An Empirical Comparison," Journal of Marketing Research, 17 (November), 516-23.

Nickerson, Carol A. and Gary H, McClelland (1989), "Across-Persons Versus Within-Persons Tests of Expectancy-Value Models: A Methodological Note," Journal of Behavioral Decision Making, 2 (4), 261-70.

Orth, Bernard (1987), "Lineare und Bilineare Modelle für Verhältnis- und Intervallskalierte Variablen [Linear and Bilinear Models for Variables Measured on Ratio and Interval Scales]," Psychologische Beiträge, 29 (2/3), 442-57.

Pekelman, Dov and Subrata K. Sen (1979), "Improving the Prediction in Conjoint Analysis," Journal of Marketing Research, 16 (May), 211-20.

Schmidt, Frank L. (1973), "Implications of a Measurement Problem for Expectancy Theory Research," Organizational Behavior and Human Performance, 10, 243-51.

Shepard, Roger N. (1964), "On Subjectively Optimum Selection among Multiattribute Alternatives," in Human Judgment and Optimality, M. W. Shelley, II and G. L. Bryan, eds. New York: Wiley, 257-81.

Snedecor, George W. and William G. Cochran (1967), Statistical Methods, sixth edition. Ames, IA: The Iowa State University Press.

Srinivasan, V. (1988), "A Conjunctive-Compensatory Approach to the Self-Explication of Multiattributed Preferences," Decision Sciences, 19, 295-305.

____________, Arun K. Jain, and Naresh K. Malhotra (1983), "Improving Predictive Power of Conjoint Analysis by Constrained Parameter Estimation," Journal of Marketing Research, 20 (November), 433-8.

____________ and Allan D. Shocker (1973a), "Linear Programming Techniques for Multidimensional Analysis of Preferences," Psychometrika, 38 (September), 337-69.

____________ and ____________ (1973b), "Estimating Weights For Multiple Attributes in a Composite Criterion using Pairwise Judgments," Psychometrika, 38 (December), 473-93.

Tashchian, Armen, Roobino O. Tashchian, and Mark E. Slama (1981), "The Impact of Individual Differences on the Validity of Conjoint Analysis," in Advances in Consumer Research, Vol. 9, Andrew Mitchell, ed. St. Louis: MO, Association for Consumer Research, 363-6.

Van der Lans, Ivo A. (1989), "Common Scale Quantifications and Restrictions upon Regression Weights in Nonlinear Multiple Regression," paper presented at the Sixth European Meeting of the Psychometric Society, Leuven, Belgium (July).

____________ and Willem J. Heiser (1988), "Nonlinear Multiple Regression Analysis with Common Scale Transformation across Predictor Variables," Working Paper RR 88-10, Department of Data Theory, University of Leiden, The Netherlands.

Wilkie, William L. and Edgar A. Pessemier (1973), "Issues in Marketing's Use of Multi-Attribute Attitude Models," Journal of Marketing Research, 10 (November), 428-41.

Wittink, Dick R. and Philippe Cattin (1989), "Commercial Use of Conjoint Analysis: An Update," Journal of Marketing, 53 (July), 91-6.

Young, Forest W. (1981), "Quantitative Analysis of Qualitative Data," Psychometrika, 46 (December), 357-88.

____________, Jan De Leeuw, and Yoshio Takane (1976), "Regression with Qualitative and Quantitative Variables: An Alternating Least Squares Method with Optimal Scaling Features," Psychometrika, 41 (December), 505-29.