IEMS Vol. 1, No. 1, pp. 73-78, December 2002.

A New Constrained Parameter Estimation Approach in Preference Decomposition

Kim Fung Lam†
Department of Management Sciences
City University of Hong Kong, 83 Tat Chee Avenue, Hong Kong
Fax: +852-2788-8560, E-mail: msblam@cityu.edu.hk

Jane W. Moy
Department of Management
Hong Kong Baptist University, Kowloon, Hong Kong
Tel: +852-3411-7575, E-mail: jmoy@hkbu.edu.hk

Abstract. In this paper, we propose a constrained optimization model for conjoint analysis (a preference decomposition technique) to improve parameter estimation by restricting the relative importance of the attributes to an extent as decided by the respondents. Quite simply, respondents are asked to provide some pairwise attribute comparisons that are then incorporated as additional constraints in a linear programming model that estimates the partial preference values. This data collection method is typical in the analytic hierarchy process. Results of a simulation study show the new model can improve the predictive accuracy in partial value estimation by ordinal least squares (OLS) regression.

Keywords: conjoint analysis, linear programming, multi-criteria decision making, preference decomposition

1. INTRODUCTION

In multi-criteria decision-making (MCDM), the preferences of a set of discrete alternatives are evaluated with respect to a finite number of criteria. In the additive preference function model, the overall preference value for each alternative is estimated by the sum of partial values of the criteria that characterize the alternatives. The partial values represent the contribution of the criteria to the overall preference values. In studying consumer preferences in marketing and consumer research, researchers have long been using a preference decomposition technique, named conjoint analysis. Conjoint analysis has proven to be a powerful and popular tool for predicting multi-attribute choice decisions. From rapidly evolving consumer products, like word-processing software (Nataraajan, 1993), and sport shoes (Moy *et al.*, 1994) to timeless goods such as wine (Gil and Sanchez, 1997) and eggs (Ness and Gerhardy, 1994), conjoint analysis is seen being used. Services, such as dental (Chakraborty *et al.*, 1993), auditing (Hermanson *et al.*, 1994), banking (Mihelis *et al.*, 2001), and restaurant services (Tucci and Talaga, 1997) can all be evaluated and assessed by conjoint analysis predicting the consumers preference decision.

Although typically conjoint analysis is used for predicting consumers preferences for a wide range of products and services, applications of conjoint analysis have been seen in areas as diverse as Hong Kong politics in her 1997 reversion to China (Young, 1993) and UK beef retailing (Hobbs, 1996). Not only have the academic literature grown, but commercial application also has increased substantially (Wittink *et al.*, 1994).

Advantages of using conjoint analysis include its capacity to incorporate both qualitative and quantitative physical attributes, and allow estimation of preferences at the individual level to account for heterogeneity in preferences. Major roles of conjoint analysis are: new product design (Gomez Arias, 1996), predicting market shares of new products (Green and Srinivasan, 1978) and market segmentation. Green and Srinivasan (1978, 1990) provide a good introduction to and review of the approach.

† : Corresponding Author

In standard conjoint analysis, respondents are asked to give pairwise comparisons of alternatives; in this paper, the data collection method used in the analytical hierarchy process (AHP) (Saaty, 1990) will also be adopted to obtain the pairwise comparisons of attributes to be used by an optimization model for better partial value estimation. In spite of the high applicability of conjoint analysis, any improvement in the accuracy of partial preference value estimation will be useful to decision maker, especially when the cost of obtaining additional information from respondents is relatively small. The pairwise comparison of attributes can be obtained from the pairwise comparison ratio matrix of attributes in AHP, which is already a well established, popular approach in MCDM.

2. LITERATURE REVIEW

Multicriteria decision making techniques are to facilitate decision-making in finding the best solution to a particular problem from a set of alternatives. In finding the best solution, preferences on each of the selected set of alternatives are evaluated on how well each of the alternatives satisfies a finite number of criteria. Often, criterion weights or partial values are used in evaluating the overall preferences of the alternatives (Stewart, 1990). Many criteria weighting methods are available, including the AHP (Saaty, 1990), linear goal programming models, LINMAP (Srinivasan and Shocker, 1973), and ordinary least squares regression (OLS). Jacquet-Lagreze and Siskos (2001) provided a through review of preference disaggregation in MCDM.

In the AHP, the decision-maker makes comparisons between pairs of alternatives through evaluation of the set of criteria. These criteria are weighted individually at every level relative to one another, so that prioritization of alternatives can be obtained. Some linear goal programming models (Bryson, 1995; Cook and Kress, 1988; Hashimoto, 1994) determine the priority vector with minimum sum of logarithmic absolute error. An overview of different methods for deriving the prioritizing vectors can be seen in Fichtner (1986).

LINMAP (Srinivasan and Shocker, 1973) uses ordinal scaled comparisons of pairs of alternatives. Lam and Choo (1995) extend the approach by allowing ratio scaled comparisons of pairs of alternatives to derive the criteria weights (partial values) of each alternative.

Using the pairwise comparisons technique to collect preference data for a set of products with respect to the product's criteria is typical in marketing, especially in consumer behavioral researches. A well-selected set of pairwise comparisons is crucial to conjoint analysis (Green and Srinivasan, 1990) in deriving reliable partial values that, in turn, provide an accurate evaluation of potential alternatives.

3. MODEL FORMULATION

According to the part-worth (partial value) function model (Green and Srinivasan, 1978), preference for an alternative j, S_j, is equal to the sum of n partial values in n attributes. A partial value can be interpreted as the preference value of a level in an attribute. If an attribute is the color of telephones, then the levels can be white, gray, and red. The partial value for the color red is a respondents preference value towards this color. Let $\boldsymbol{v}$ and $\boldsymbol{x}$ be the estimated overall preference values of alternatives and values of partial values, respectively; then the part-worth function model posits that the preference value of alternative j,

$$v_j = \sum_{p=1}^{n} \sum_{t=1}^{g_p} x_{pt} y_{pt}^j \tag{1}$$

where n is the number of attributes, g_p is the number of levels in attribute p, and y_{pt}^j, a zero one variable, captures the presence (=1) or absence (=0) of the ith level partial value in the pth attribute for the jth alternative.

Let Ω denote the results of comparing some selected pairs of alternatives, and (j, k, t_{jk}) represent that alternative j is at least t_{jk} times preferred to alternative k. We expect the following:

$$v_j - t_{jk} v_k \geq 0, \quad (j,k,t_{jk}) \in \Omega \tag{2}$$

Rewriting (2) as LP constraints, we have:

$$\sum_{p=1}^{n} \sum_{t=1}^{g_p} x_{pt} y_{pt}^j - t_{jk} \left(\sum_{p=1}^{n} \sum_{t=1}^{g_p} x_{pt} y_{pt}^k \right) + e_{jk}^- - e_{jk}^+ = 0, \quad (j,k,t_{jk}) \in \Omega \tag{3}$$

where e_{jk}^+ and e_{jk}^- are deviation variables to incorporate inconsistencies. Deviation variables also capture the surplus and slack in equation (2).

Next, similar to the AHP in obtaining information of attribute pairwise comparisons, let Φ be the set of pairwise comparisons between the attributes obtained from pairwise comparison ratio matrix in the AHP. The importance of an attribute depends on the extended range of its partial values, that is, the difference between the maximum and the minimum partial values among the levels within an attribute. The more important an attribute, the larger this range should be. For instance, consider that an attribute has two partial values that are equal to 10 and 11, respectively. This attribute will have less influence on the overall preference value (of an object) than another attribute that has two partial values that are equal to 1 and 3, respectively. What only matters is the range of the partial values, rather than their absolute values.

With respect to the above argument, we can construct the constraints as below. Let x_{pa} and x_{pb} be the partial values of the most preferred level and the least preferred level, respectively in attribute p, then $(x_{pa}-x_{pb})$ will be the magnitude of the largest difference between the partial values in attribute p. Furthermore, let Φ be the set of pairwise comparisons between the attributes obtained from the respondents, (r, s, t_{rs}) represents that attribute r is at least t_{rs} times preferred to attribute s. Then the constraints comparing attributes can be stated as follows:

$$(x_{ra}-x_{rb})-t_{rs}(x_{sa}-x_{sb})+d_{rs}^{-}-d_{rs}^{+}=0,(r,s,t_{rs})\in\Phi, \quad (4)$$

where d_{rs}^{+} and d_{rs}^{-} are the deviation variables which measure the inconsistencies in the ordering of the attributes.

Both $\sum_{(j,k)\in\Omega}(e_{jk}^{-}+e_{jk}^{+})$ and $\sum_{(r,s)\in\Phi}(d_{rs}^{-}+d_{rs}^{+})$ are badness of fit to the pairwise comparisons in Ω and Φ, respectively. Our constrained parameter goal programming (CPGP) model can be define as follows:

$$Min \quad C_1\{\sum_{(j,k)\in\Omega}(e_{jk}^{-}+e_{jk}^{+})\}+C_2\{\sum_{(r,s)\in\Phi}(d_{rs}^{-}+d_{rs}^{+})\} \quad (5)$$

s.t.

$$\sum_{p=1}^{n}\sum_{i=1}^{g_p}x_{pi}y_{pi}^{j}-t_{jk}(\sum_{p=1}^{n}\sum_{i=1}^{g_p}x_{pi}y_{pi}^{k})+e_{jk}^{-}-e_{jk}^{+}=0$$

$$(j,k,t_{jk})\in\Omega \quad (6)$$

$$(x_{ra}-x_{rb})-t_{rs}(x_{sa}-x_{sb})+d_{rs}^{-}-d_{rs}^{+}=0,(r,s,t_{rs})\in\Phi, \quad (7)$$

$$\sum_{p=1}^{n}\sum_{i=1}^{g_p}x_{pi}\geq 1, \quad (8)$$

where all variables are non-negative. C_1 and C_2 are the coefficients of the deviational variables in the objective function. They represent the penalties of two different kinds of inconsistancies, namely, inconsistancy in preference orderings of alternatives and inconsistancy in preference orderings of attributes. Inequality (8) is a normalization constraint to avoid the trivial solution: $x_{jk}=0$ for all j and k.

4. MODEL DISCUSSION

There are two points about the model that are worth noting. The magnitude between C_1 and C_2 would depend on the consistency of the overall values (of attributes) versus the partial values (of levels). Decision-makers could try different sets of C_1 and C_2 using the training sample and decide on the one that achieves the best results in the trials. Typically, a result is said to be satisfactory if the correlation between the respondents' input preferences and the estimated preferences is high, or when the estimated k best alternatives and the actual k best alternatives are the same or very similar.

Srinivasan, Jain and Malhortra (1983) suggested using linear constraints to impose the relative preference of the levels within the the same attribute. If level a is preferred to level b in attribute p, then they suggested adding the following constraint,

$$x_{pa}-x_{pb}+d_{ab}^{p}\geq 0, \quad (9)$$

where d_{ab}^{p} is a deviational variable.

Moy *et al.* (1997) include in their estimation the pairwise comparisons of the levels within an attribute. Their model thus collects similar information as that used in the AHP, where respondents are asked to compare levels in each attribute. Their constraint can be stated as follows:

$$x_{pa}-t_{ab}^{p}x_{pb}+e_{ab}^{p}\geq 0, \quad (10)$$

where e_{ab}^{p} is a deviational variable, and t_{ab}^{p} can be obtained from the pairwise comparison ratio matrices in the AHP suggested by Saaty (1990).

Since constraints like those introduced by Srinivasan *et al.* (1983), and Moy *et al.* (1997), which only compare attribute levels, cannot be used to impose the relative importance of the attributes, a new type of constraint, like (7), has to be developed.

When there are many attributes, comparing alternatives (obtaining t_{jk} in Ω) will become more difficult, constraints (7) might play a more important role since it considers comparing attributes (obtaining t_{uv} in Φ), which are more easily provided by respondents. Consequently, minimizing inconsistencies in Φ becomes more important or a higher C_2 value might be more appropriate under this or similar circumstances.

5. SIMULATION EXPERIMENT

In our simulation experiment, we evaluate the performance of OLS, the goal-programming model (GP) by Lam and Choo (1995), and CPGP. We generate four attributes, each of which has three levels. All partial values are generated from a normal distribution, $N(9,1)$. With the three levels in each of the four attributes, 81 alternatives can be generated (i.e. $3^4=81$). We use orthogonal arrays (Green, 1974) to choose nine alternatives for the development sample, while the remaining 72 alternatives form the holdout sample. For each of the 81 alternatives, the overall preference value is computed by using the part-worth function model. In order to simulate errors made by the respondent while comparing the alternatives, a random error is added to each of the nine overall preference values in the development sample. The random error has zero mean and its variance, σ_e^2, is computed from the following formula (Wittink and Cattin 1981):

$$E=\sigma_e^2/(\sigma_e^2+\sigma_s^2) \quad (11)$$

where σ_e^2 is the error variance and σ_s^2 is the sample variance of the overall preference values, S_j, before the error terms are added. Hence, equation (11) expresses the ratio of error variance to the total variance. Notice that, if $E=0.1$, then $\sigma_e^2=0.11\ \sigma_s^2$, and if $E=0.2$, then $\sigma_e^2=0.25\ \sigma_s^2$. In this experiment, we use 0.1, 0.2 and 0.3 as the values for E. We call this set of E values $\{E_\Omega\}$.

Simulating comparisons between attributes from respondents, we first compute the range of the partial values in each attribute, and then add a random error to each of the four ranges of partial values to represent the error made during each comparison. These distorted ranges will be used as inputs for constraint (7) in CPGP. The random error, σ_e^2, has zero mean and variance computed from formula (11) above and σ_s^2 is the sample variance of the largest difference between the partial values in an attribute. The set of E values used in this experiment includes 0.1, 0.2 and 0.3. We call this set of E values $\{E_\Phi\}$.

In each of $\{E_\Omega\}$ and $\{E_\Phi\}$, there are three different E values. As a result, there are nine different cases (3×3) in this simulation experiment. We randomly generate 100 data sets for each of these nine cases; hence, we use a total of 900 data sets in this experiment. The perturbed values of the nine overall preference values in each of these data sets are used as inputs in conjoint analysis and solved by OLS, GP and CPGP. We use LINDO (Schrage, 1989) to solve all linear programming problems.

Moreover, CPGP has two types of deviational variable, (e_{jk}^+, e_{jk}^-) and (d_{rs}^+, d_{rs}^-). e_{jk}^+ and e_{jk}^- capture inconsistencies in the orderings of the overall preferences, while d_{rs}^+ and d_{rs}^- capture inconsistencies in the preference orderings of the attributes. Thus CPGP becomes a multi-objective goal-programming problem. We assign three penalty patterns to minimize the objective function in CPGP. We choose $(C_1 : C_2)=(1{:}1)$, (1:3), and (1:5). The results obtained from the different methods are reported in Table 1 and Table 2, which show the average Spearman rank correlation coefficient and average Pearson correlation coefficients, respectively between the estimated and original preference values of the alternatives from the holdout sample. The higher the correlation coefficients, the better the estimates will be.

Naturally, the higher the E_u, the weaker the correlation between the original and estimated preference values, as seen in Table 1. Moreover, note that when we choose $(C_1 : C_2)=(1{:}1)$, the deviational variables, e_{jk}^+ and e_{jk}^-, would have a much greater impact on CPGP than the

Table 1. The average spearman rank correlation coefficients[a] between the estimated and original preference values of the alternatives from holdout samples.

			E_Ω		
Method			0.1	0.2	0.3
OLS[b,c]			0.9189 (0.057)	0.8346 (0.133)	0.7597 (0.168)
GP			0.9199 (0.057)	0.8348 (0.134)	0.7596 (0.168)
	E_Φ	$C_1 : C_2$			
CPGP	0.1	1 : 1	0.9204 (0.057)[d]	0.8353 (0.133)	0.7605 (0.167)
		1 : 3	0.9286 (0.057)[e]	0.8465 (0.138)[e]	0.7801 (0.181)[e]
		1 : 5	0.9343 (0.056)[e]	0.8551 (0.133)[e]	0.7954 (0.175)[e]
CPGP	0.2	1 : 1	0.9204 (0.057)[d]	0.8353 (0.133)[d]	0.7605 (0.167)
		1 : 3	0.9273 (0.056)[e]	0.8470 (0.138)[d]	0.7781 (0.182)[d]
		1 : 5	0.9317 (0.054)[e]	0.8529 (0.133)[e]	0.7919 (0.174)[e]
CPGP	0.3	1 : 1	0.9205 (0.057)[d]	0.8351 (0.133)[d]	0.7604 (0.167)
		1 : 3	0.9261 (0.054)[d]	0.8466 (0.138)[e]	0.7788 (0.179)[d]
		1 : 5	0.9270 (0.054)	0.8513 (0.132)[e]	0.7853 (0.180)[e]

[a] Values in brackets are standard deviations.
[b] H_o : There is no difference between the average correlation coefficient of OLS and the correlation coefficient of CPGP.
[c] H_a : The correlation coefficient of CPGP is greater than the correlation coefficient of OLS.
[d] Reject H_o at $\alpha=0.05$ level (Paired t-test).
[e] Reject H_o at $\alpha=0.01$ level (Paired t-test).

Table 2. The average pearson correlation coefficients[a] between the estimated and original preference values of the alternatives from holdout samples.

			E_Ω		
Method			0.1	0.2	0.3
OLS[b,c]			0.9289 (0.052)	0.8439 (0.131)	0.7734 (0.164)
GP			0.9289 (0.052)	0.8440 (0.131)	0.7733 (0.164)
	E_Φ	$C_1 : C_2$			
CPGP	0.1	1 : 1	0.9295 (0.051)	0.8445 (0.131)	0.7743 (0.163)
		1 : 3	0.9366 (0.051)[e]	0.8558 (0.136)[e]	0.7907 (0.179)[d]
		1 : 5	0.9419 (0.051)[e]	0.8646 (0.133)[e]	0.8052 (0.179)[e]
CPGP	0.2	1 : 1	0.9295 (0.052)	0.8444 (0.131)	0.7743 (0.163)
		1 : 3	0.9351 (0.050)[d]	0.8554 (0.136)[d]	0.7890 (0.177)[d]
		1 : 5	0.9392 (0.049)[e]	0.8622 (0.133)[e]	0.8020 (0.178)[e]
CPGP	0.3	1 : 1	0.9294 (0.051)	0.8443 (0.130)	0.7743 (0.163)
		1 : 3	0.9340 (0.048)[d]	0.8547 (0.136)[d]	0.7900 (0.173)[d]
		1 : 5	0.9348 (0.048)	0.8602 (0.132)[e]	0.7954 (0.182)[d]

[a]Values in brackets are standard deviations.
[b]H_o : There is no difference between the average correlation coefficient of OLS and the correlation coefficient of CPGP.
[c]H_a : The correlation coefficient of CPGP is greater than the correlation coefficient of OLS.
[d]Reject H_o at $\alpha = 0.05$ level (Paired t-test).
[e]Reject H_o at $\alpha = 0.01$ level (Paired t-test).

deviational variables, d_{rs}^+ and d_{rs}^-. The reason is that the number of deviational variables, e_{jk}^+ and e_{jk}^-, in CPGP are usually much greater than the number of deviational variables, d_{rs}^+ and d_{rs}^-. As a result, constraints (7) should have very little impact on CPGP when $(C_1 : C_2) = (1 : 1)$ and the performance of CPGP and GP should be very similar. This expectation is confirmed by the results in Table 1 and Table 2. That is why we do not try smaller C_2 values in this simulation experiment. Furthermore, when we gradually increase the value of C_2, CPGP becomes more influenced by constraints (7) and has better performance, as seen in Table 1 and Table 2.

In Table 1 and Table 2, CPGP obtains higher correlation coefficients than those obtained from GP and OLS. Furthermore, in most cases these coefficients are statistically significant. According to the results in Table 1 and Table 2, the proposed new constraints can improve the predictive ability of GP. Moreover, CPGP performs better than OLS in this experiment. Our new constraints require pairwise comparisons of attributes similar to those obtained by AHP. This piece of additional information, intuitively, should ensure more accurate estimation of partial values and confirm the value of our constrained optimization approach in conjoint analysis.

In conjoint analysis, the relative importance of the attributes in the part-worth function model is usually measured by the magnitude of the difference between the largest estimated partial value and the smallest estimated partial value in the same attribute. Since pairwise comparisons of the relative importance of attributes can be obtained directly from respondents, as in the AHP, we put these pairwise comparisons into a set of linear constraints and add these constraints to a linear programming model. The results of the simulation experiment show that the additional constraints or information, at a relative low cost to decision-makers, can improve the predictive accuracy of the linear programming model GP. Furthermore, the linear programming model with the new constraints has better performance than ordinary least squares regression in this experiment.

ACKNOWLEDGMENT

The work described in this paper was fully supported by a grant from the Research Grants Council of the Hong Kong Special Administration Region, China [Project No. CityU 1159/00H].

REFERENCES

Bryson, N. (1995) A goal programming method for generating priority vectors, *Journal of the Operational Research Society*, **46**, 641-648.

Chakraborty, G., Gaeth, G. J. and Cunningham, M. (1993) Understanding consumers preferences for dental service, *Journal of Health Care Marketing*, **13**, 48-58.

Cook, W. D. and Kress, M. (1988) Deriving weights from pairwise comparison ratio matrices: An axiomatic approach, *European Journal of Operational Research,* **37**, 355-362.

Fichtner, J. (1986) On deriving priority vectors from matrices of pairwise comparisons, *Socio-Economic Planning Sciences,* **20**, 341-345.

Gil, J. M. and Sanchez, M. (1997) Consumer preferences for wine attributes: a conjoint Approach, *British Food Journal*, **99**, 3-11.

Gomez Arias, J. T. (1996) Conjoint-based preferential segmentation in the design of a new financial service, *International Journal of Bank Marketing*, **14:3**, 30-32.

Green, P. E. (1974) On the design of choice experiments involving multi-factor Alternatives, *Journal of Consumer Research*, **1**, 661-678.

Green, P. E. and Srinivasan, V. (1978) Conjoint analysis in consumer research: Issues and Outlook, *Journal of Consumer Research,* **5**, 103-123.

Green, P. E. and Srinivasan, V. (1990) Conjoint analysis in marketing: New developments with implications for research and practice, *Journal of Marketing*, **54**, 3-19.

Hashimoto, A. (1994) A note on deriving weights from pairwise comparison ratio Matrices, *European Journal of Operational Research,* **733**, 144-149.

Hermanson, R. H., Plunkett, L. M. and Turner, D. H. (1994) A study of the importance of certain attributes to clients initial selection of audit firms: A longitudinal and stratified approach, *Journal of Applied Business Research*, **10:1**, 101-107.

Hobbs, J. E. (1996) A transaction cost
analysis of quality, tracebility and animal welfare issues in UK beef retailing, *British Food Journal*, **98:6**, 16-26.

Jacquet-Lagreze, E. and Siskos, Y. (2001) Preference disaggregation: 20 years of MCDA experience, *European Journal of Operational Research*, **130**, 233-245.

Lam, K. F. and Choo, E. U. (1995) Goal programming in preference decomposition, *Journal of Operational Research Society,* **46**, 205-213.

Mihelis, G., Grigoroudis E., Siskos, Y., Politis, Y. and Malandrakis, Y. (2001) Customer satisfaction measurement in the private bank sector, *European Journal of Operational Research,* **130**, 347-360.

Moy, J. W., Li, K. and Lam, K. F. (1994) Using conjoint analysis to study consumer preference in sport shoes, *Proceedings of the Fourth Conference of the Operational Research Society of Hong Kong*, Hong Kong, 167-175.

Moy, W. J., Lam, K. F. and Choo, E. U. (1997) Deriving the partial values in MCDM by goal Programming, *Annals of Operations Research*, **74**, 277-288.

Nataraajan, R. (1993) Prediction of choice in a technically complex, essentially intangible, highly experiential, and rapidly evolving consumer product, *Psychology & Marketing,* **10**, 367-379.

Ness, M. R. and Gerhardy, H. (1994) Consumer preferences for quality and freshness attributes of eggs, *British Food Journal*, **96:3**, 26-34.

Saaty, T. L. (1990) *Multicriteria Decision Making: the Analytic Hierarchy Process,* RWS Publication, Pittsburgh, Pennsylvania.

Schrage, L. (1989) *Users Manual:Linear, Integer and Quadratic Programming with LINDO*, Scientific Press, New York.

Srinivasan, V., Jain, A. K. and Mallhortra, N. K. (1983) Improving predictive power of conjoint analysis by constrained parameter estimation, *Journal of Marketing Research*, **20**, 433-438.

Srinivasan, V. and Shocker, A. D. (1973) Linear programming techniques for multidimensional analysis of preferences, *Psychometrika*, **38**, 337-69.

Stewart, T. J. (1990) A critical survey on the status of multiple criteria decision making theory and practice, *Omega*, **20**, 569-586.

Tucci, L. A. and Talaga, J. (1997) Service guarantees and consumers' evaluation of services. *Journal of Services Marketing*, **11:1**, 10-18.

Wittink, D. R. and Cattin, P. (1981) Alternative estimation methods for conjoint analysis: a Monte Carlo study, *Journal of Marketing Research*, **18**, 101-106.

Wittink, D. R., Vriens, M. and Burhenne, W. (1994) Commercial use of conjoint analysis in Europe: results and critical reflections, *International Journal of Research in Marketing*, **11**, 41-52.

Young, K. Y. (1993) Political risk under 'One country two systems': A conjoint analysis, *Journal of Asian Business*, **9:1**, 39-54.