

# Choice Adapted Predictive Modelling

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## Background

The use of conjoint techniques in pharmaceutical market research presents its own set of issues affecting the choice of conjoint design. These are:

- ◆ The high unit cost of interviews leading to generally smaller than ideal sample sizes.
- ◆ Complex product offerings often requiring a larger number of product attributes than is allowed by some commercially available conjoint paradigms.
- ◆ Problems in defining “the customer” leading to a need to include both physician and patient exercises, which then need to be integrated.
- ◆ Complex patterns of product use with poly-pharmacy being a common feature of many markets – yet it is single product offerings that our clients are developing and we are asked to research.
- ◆ A highly variable, non-symmetrically distributed assessment of the performances of current products by physicians.

The last mentioned issue, we believe, contributes as much as (if not more than) the question asked of respondents when faced with a conjoint task, to the well recognized over-estimation of new product share in market simulations<sup>(1)</sup>. Consequently, it is an important focus of this paper.

Our hypothesis is that the predictive power and simulation realism of choice-based designs can be equaled (or even improved on) through full profile ranking (or rating) exercises with the addition of a ‘choice threshold’ question after the ranking exercise has been completed. This means that smaller sample sizes can be utilized than would be recommended for discrete choice paradigms such as Choice based Conjoint (CBC) but that the benefits of such paradigms can be included.

We have used the data so gathered to generate utility scores using standard multinomial logit (MNL) analysis, at the individual respondent level. Through then maintaining true individual choice thresholds (analogous to the ‘none’ option in CBC) throughout the simulation exercise, we are able to conduct market simulations that better reflect realistic market structures. They may, therefore, have validity advantages compared to discrete choice paradigms as, unlike most discrete choice simulation modules, these simulations preserve true individual level choice thresholds throughout the simulation. They certainly offer an advantage on a per unit cost basis.

This paper forms a progress report on our ongoing approach to testing the hypothesis above and to adding realism to market simulations. This has reached the stage where we now have a fully tested conjoint simulation module (CAPMOD) which has been used successfully for a number of clients.

We use data collected on behalf of one of these clients and also data generated from an extension to this funded by Adelphi exclusively for this paper.

## The experiment

### Background

Our client had a product in development for the treatment of a common chronic disorder in which acute episodes can occur. Market research was required to assist in future development (clinical trial) decisions. In particular, the relative importance of selected clinical drivers and the trade offs that physicians are prepared to make among these when making treatment decisions.

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The data for this study were gathered in March 1999. The experiment described here included these data (made suitably anonymous to preserve confidentiality) plus data gathered during the Adelphi-funded study conducted in March 2000. The starting point (attribute and level grid) was common to both. They differed in terms of the conjoint methodology used thus enabling comparisons to be made.

### The conjoint exercises

Both the 1999 and 2000 conjoint designs were based on a matrix with nine attributes each with two, three or four levels.

| Attributes                                    | Levels                                   |   |  |  |
|---|--|---|--|--|
| Sustained improvement in efficacy attribute 1 | Less than market leader                  | Equal to market leader  | Some improvement over market leader        | Great improvement over market leader                               |
| Sustained improvement in efficacy attribute 2 | No improvement                           |   | Some improvement                           | Great improvement  |
| Sustained reduction in efficacy attribute 3   | No reduction                             |   | Some reduction                             | Great reduction  |
| Quality of life data                          | No evidence of improvement (and no data) | Evidence of clinically significant quality of life improvements |  | Evidence and approved claim/label for quality of life improvements |
| Maintenance dose regimen                      | 4 times daily                            |   | 3 times daily                              | 2 times daily  |
| Additional dosing above maintenance dose      | Not indicated for this use               |   | Indicated. Slight increase in side effects | Indicated. No increase in side effects                             |
| Prevention of accelerated decline in function | No evidence                              |   |  | Evidence   |
| Side effect profile                           | Worse than existing class                |   | Similar to existing class                  | Improvement over existing class                                    |
| Reduction in number of acute attacks          | No                                       |   |  | Yes  |

**Table 1 Attribute & level grid used for conjoint design**

Also common to both designs was the conjoint question setting. Physicians were asked to complete the exercises in the context of the last patient seen suffering from the condition for which it was anticipated the new drug would be indicated. We selected this question setting, rather than presenting a patient pen picture or using “a typical patient” or “the last 20 patients” for example, as we wanted to ensure that:

- ◆ The focus of the physician was on an actual patient and his/her treatment decision. This ensured that the respondent would know all the extra information about the patient necessary to make the conjoint exercise more accurate.
- ◆ We wanted a representative sample of treatment decisions so that the source of any new business could be identified and profiled in our simulation process. Having either “the last 20 patients” or a sample of patients typical for each respondent, which is far from a representative (or typical) sample of patients presenting with the condition, would not have allowed this.

## Choice Adapted Predictive Modelling

The two conjoint studies can be summarised as follows:

|                      | March 1999  | March 2000   |
|----------------------|---|--|
| Paradigm             | Classic "Full Profile"  | CBC (Sawtooth)   |
| Sample Size          | 75  | 50   |
| Stimulus Material    | Full Profile, Cards   | Full Profile, Cards  |
| Conjoint Task        | Ranking   | Choice Sets of 3 Cards   |
| Number of Tasks      | 28 cards  | 15 choice tasks  |
| Hold Out             | 3 cards   | 1 choice task  |
| Analysis Method      | OLS   | MNL  |
| Utility Output Level | Individual  | Aggregate  |
| Simulation Methods   | a) 1 <sup>st</sup> Past the Post<br>(Conjoint Analyser - Bretton Clark)<br>b) Probabilistic (Simgraf – Bretton Clark) | Share of Preference in CBC Simulation Module<br>a) with no-buy option<br>w/o no-buy option |

**Table 2** Summary of the two conjoint studies

### Comparisons of the two conjoint studies

The two studies can be considered as alternative conjoint approaches to a common problem. We therefore made comparisons between them using three standard measures on which comparisons were possible: attribute relative importance based on overall attribute/level utility scores, holdout analysis and market simulation results.

### Relative importance of attributes

- ◆ Comparisons of results from the two MNL-based analyses (CBC with and without the 'no-buy' option and the OLS-based analysis (Conjoint Analyser) are shown in Table 3. Simgraf is a simulation module that uses output from Conjoint Analyser and, therefore, the concept of attribute relative importance is not applicable.

| Attribute   | Aggregate Level Probability Model (MNL) (CBC with no-buy) | Aggregate Level Probability Model (MNL) (CBC w/o no-buy) | Individual Preference Ranking (OLS) 1stPP (Conjoint Analyser) | Individual Preference Ranking (OLS) Probabilistic Model (Simgraf) |
|-------------|---|--|---|---|
| Attribute 1 | 25.1%   | 24.4%  | 27.3%   | n.a.  |
| Attribute 2 | 8.6%  | 9.2%   | 11.2%   | n.a.  |
| Attribute 3 | 9.4%  | 10.2%  | 9.3%  | n.a.  |
| Attribute 4 | 13.0%   | 13.3%  | 10.5%   | n.a.  |
| Attribute 5 | 7.4%  | 5.6%   | 3.4%  | n.a.  |
| Attribute 6 | 3.5%  | 3.3%   | 2.0%  | n.a.  |
| Attribute 7 | 14.4%   | 15.5%  | 15.2%   | n.a.  |
| Attribute 8 | 9.9%  | 9.3%   | 9.3%  | n.a.  |
| Attribute 9 | 8.7%  | 9.1%   | 11.7%   | n.a.  |

**Table 3** Relative importance of attribute ranges – based on overall utility scores

### Hold out analysis

We compare (Table 4) the predicted results for the hold out cards with their actual shares (occasions each was chosen during the interviews) with those predicted by three of the simulation modules:

- ◆ Individual level, OLS, 1<sup>st</sup> past the post (Conjoint Analyser)
- ◆ Individual level, OLS, probabilistic model (Simgraf)
- ◆ Aggregate level, MNL, probability model (CBC) - only that without the 'no-buy' option can be included.

| Holdout Set within CBC exercise  | Actual Share (CBC) <sup>1</sup> | Aggregate Level Probability Model (MNL) (CBC w/o no-buy) | Actual Share (individual pref ranking) <sup>2</sup> | Individual Preference Ranking (OLS) 1stPP (Conjoint Analyser) | Individual Preference Ranking (OLS) Probabilistic Model (Simgraf) |
|--|---------------------------------|--|---|---|---|
| Holdout Card 1   | 58.0%                           | 65.7%  | 81.3%   | 70.7%   | 45.4%   |
| Holdout Card 2   | 2.0%                            | 10.2%  | 0.0%  | 1.3%  | 20.7%   |
| Holdout Card 3   | 40.0%                           | 24.1%  | 18.7%   | 28.0%   | 33.9%   |
| <sup>1</sup> % of occasions each card selected as the preferred within 3-card holdout set<br><sup>2</sup> % of occasions each card was the preferred of the three within total set |                                 |  |   |   |   |

**Table 4** Hold out analysis

**Market simulations**

- ◆ The predicted 'shares of preference' for all four simulations are shown in Table 5.

| Product               | Aggregate Level Probability Model (MNL) (CBC with no-buy) | Aggregate Level Probability Model (MNL) (CBC w/o no-buy) | Individual Preference Ranking (OLS) 1stPP (Conjoint Analyser) | Individual Preference Ranking (OLS) Probabilistic Model (Simgraf) |
|-----------------------|---|--|---|---|
| Prod 1                | 12.5%   | 17.0%  | 18.7%   | 20.0%   |
| Prod 2                | 2.1%  | 5.1%   | 1.3%  | 4.5%  |
| Prod 3                | 2.8%  | 5.6%   | 1.3%  | 1.8%  |
| Prod 4                | 14.6%   | 19.5%  | 13.3%   | 20.3%   |
| Prod 5                | 47.2%   | 53.3%  | 66.7%   | 53.4%   |
| 'stay as is' (no buy) | 20.9%   | n.a.   | n.a.  | n.a.  |

**Table 5 Market simulation results (share of preference)**

It is impossible to draw an overall conclusion on which is the best predictive model relying solely on these results. We can observe that, based on the usual relative importance measure, they give broadly similar results. We also have no basis for an evaluative assessment of any differences. The hold out analyses favour the aggregate level MNL (CBC) and 1<sup>st</sup> past the post OLS models in that, in this case at least, they are superior to the probabilistic OLS model. The market simulations for the aggregate MNL (CBC) and probabilistic OLS models are similar. In this comparison, the 1<sup>st</sup> past the post OLS model differs from the other two.

It is tempting to conclude that as the MNL model (CBC) has appeared to be superior on two measures and the two OLS models each on only one, that the MNL model is the best. However the data are limited and we would like to see more direct comparisons being made. (It is also our belief that the notion of a universally best conjoint paradigm is a contradiction in terms). It could also be argued that what really matters performance in simulations of current markets and, most importantly, in future market predictions.

## Predicted vs. actual market shares from conjoint methods

### Observations

The 1999 experiment described above was designed solely to establish priorities and trade offs among a specific list of product attributes. The list was known to be inappropriate for actual marketplace simulations. The elapsed time is also too short for any new product entry to have occurred. We therefore turn to previously published data to illustrate the point (well accepted among pharmaceutical researchers) that ‘off the shelf’ conjoint paradigms severely over-estimate in pharmaceutical markets. (1, 2)

Data from an Adelphi paper published in 1997<sup>(2)</sup> are reproduced in Table 6 and Table 7.

| Product/<br>Product Class | Actual Market Share<br>(current at time of<br>study) | Simulated Share<br>OLS probabilistic<br>(Simgraf) |
|---------------------------|--|---|
| Established products      | 58%  | 56.5%   |
| Recent Entrant ‘A’        | 21%  | 21.1%   |
| Recent Entrant ‘B’        | 13%  | 13.0%   |
| Recent Entrant ‘C’        | 8%   | 9.4%  |

**Table 6** Example of current market simulation

| Product/<br>Product Class | Actual<br>Market Share<br>(2 years after study) | Predicted Share<br>OLS probabilistic<br>(Simgraf) |
|---------------------------|---|---|
| Established products      | 63.5%   | 50.0%   |
| Recent Entrant ‘A’        | 16.3%   | 15.1%   |
| Recent Entrant ‘B’        | 12.2%   | 8.9%  |
| Recent Entrant ‘C’        | 5.0%  | 6.4%  |
| New Product #1            | 1.4%  | 4.2%  |
| New product #3            | 0.9%  | 7.0%  |
| New Product #3            | 0.7%  | 8.4%  |

**Table 7** Example of future market prediction

### Conclusions

In our experience, these findings are not uncommon. It is often possible to replicate the current market - and probabilistic methods may improve the likelihood of this. Future predictions for new product entries are very frequently over-stated. The reasons for this include brand effect, the degree of innovation associated with the new product, number in therapy class launch sequence and time to market as well as volume and quality of promotional spend.

Most efforts among pharmaceutical researchers to correct this have focused on correction (discount) factors<sup>(3)</sup>. Our belief is that the realism of the simulation, and the implications of this for earlier steps in the paradigm, should first be examined more closely.

### **Issues and solutions in market simulations**

In order to make then product profiles we enter into market simulations more realistic, we obtain profiles of current products on the attribute and level grid on which the conjoint stimulus material is based. This also has the added benefit of making respondents very familiar with the attributes and their ranges that they will see in the conjoint cards.

Our experience is that there is a wide range in the perceptions that physicians have for the same products. The distributions of these perceptions are also often skewed with both positive and negative skews being found. It is also a feature of some pharmaceutical markets that products with very similar images can have quite different market shares.

Currently available conjoint simulators use perceptions of products entered in the simulation that are common to each individual respondent – even those that use individual level utility scores. Because of the image distribution problem referred to above, this could lead to very misleading results. In methods that rely on aggregate level data throughout, the problem is of particular concern. This has always been a major concern to us with the use of discrete choice methods. The recent introduction of Hierarchical Bayes analysis with CBC (CBC/HB) is therefore a particularly exciting development.

These issues indicate the need for analysis **and** simulation capability at the individual level throughout. It also seems appropriate to allow current products to be “as is” in terms of their images for individual physicians. In this way, we maintain the reality of individual preferences and choices throughout the entire exercise. This is very different from how the ‘no buy’ option is treated within discrete choice paradigms. In CBC, for example, the ‘no buy’ option is, in effect, treated as a null profile. ‘None’ becomes an attribute with its own utility. This means that, if the number of products in a simulation differs from the number of alternatives in the choice tasks presented to the respondent, the estimates produced by the simulation will not be correct<sup>(4)</sup>. In CBC, the use of the ‘no buy’ option is recommended for considerations of question realism; it is not recommended for inclusion in simulations<sup>(4)</sup>, thus often making simulating a whole pharmaceutical market extremely difficult.

## Choice adapted predictive modelling (CAPMOD)

### Introduction

CAPMOD is a simulation module that can be applied to any conjoint analysis output (utility scores) provided that a choice threshold question (or question set) has been asked of all respondents. This concept can be applied to either preference- or choice-based data collection and analysis methods. With choice-based methods we prefer analysis be done at the individual respondent level such that individual respondents' utility sets can be used throughout the simulation exercises, although this is not essential.

### An example of CAPMOD in practice

The CAPMOD choice threshold question was used in the 1999 conjoint study described above. The question sequence is illustrated in Figure 1 and Figure 2. This shows how a choice question is applied to a "classic" full profile, OLS conjoint design. The objective is to obtain a threshold, the product profiles above which would have been prescribed had they been available and, importantly, below which none would have been prescribed even though preferences among them can be established. The logic here is that new product 'A' might be preferred to new product 'B' (and this information is utilized for utility score calculations) but neither would be purchased – a first essential step towards market share. By ranking all alternatives, including those below the choice threshold, the amount of comparative information per profile per respondent is maximized. This in turn leads to more robust calculations of utility scores than are possible with conventional discrete choice designs.

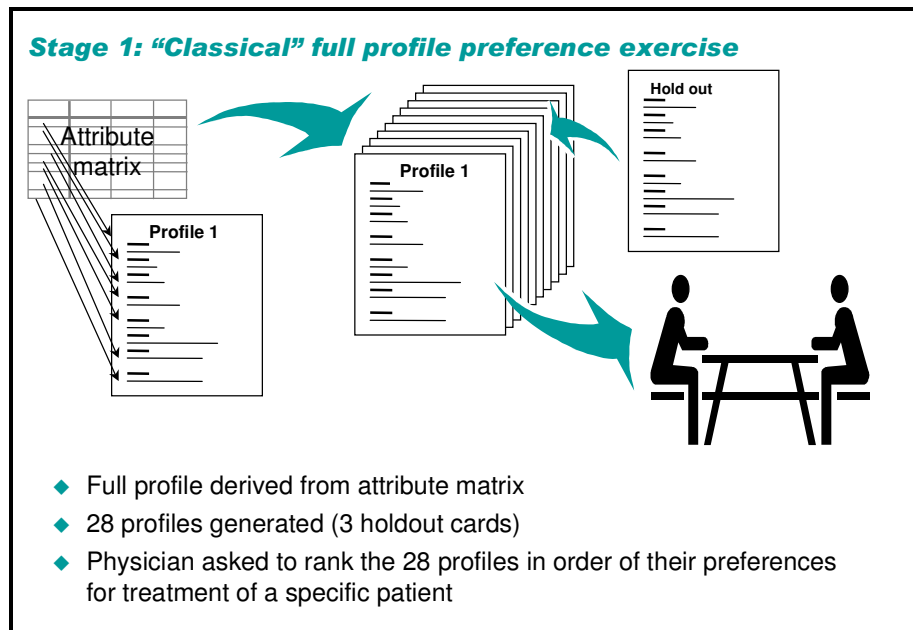
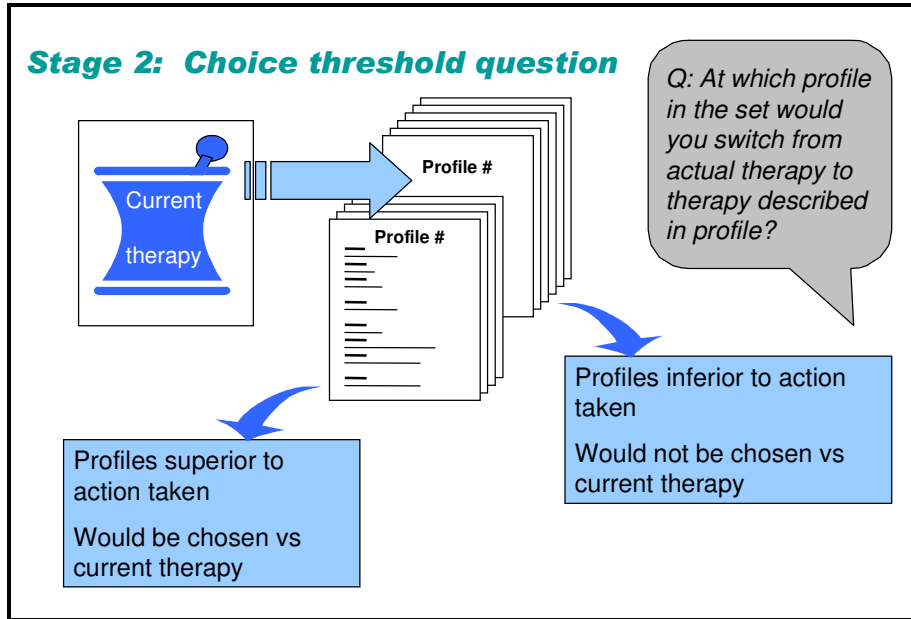


Figure 1 The conjoint interview: Stage 1



**Figure 2 The conjoint interview: Stage 2**

Using the choice question also allows market expansion through new product introductions to be calculated. The question shown can be worded to include whether the products in the set above the threshold would be prescribed in addition to current therapy or to replace it. In both cases non-drug therapy can be included.

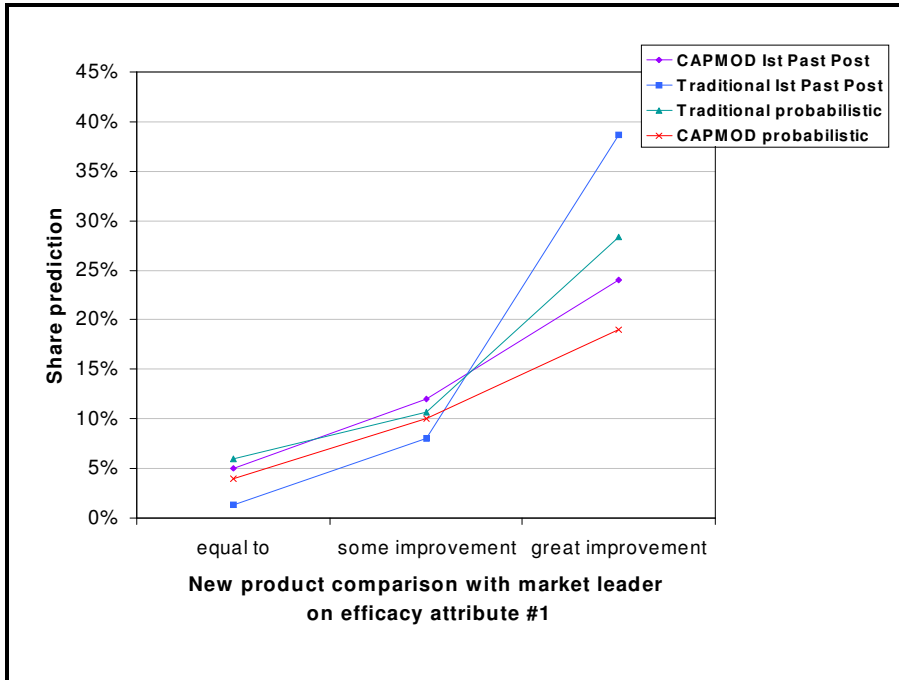
Results of CAPMOD simulations are included in Table 8. We have taken a series of alternative possible outcomes for a new product and introduced each into the five-product market simulated above (Table 5). We have added the new product to the market simulation obtained from six different models.

- ◆ preference ranking, individual level OLS, 1st past the post market model
- ◆ preference ranking, individual level OLS, probability model
- ◆ discrete choice, aggregate level MNL model (CBC w/o the 'no-buy' option)
- ◆ discrete choice, aggregate level MNL CBC w/o 'no-buy' option) modified to recognize individuals' differing images of current products
- ◆ CAPMOD (preference ranking + choice threshold, OLS, 1st past the post)
- ◆ CAPMOD (preference ranking + choice threshold, OLS, probabilistic).

| Method   | Share Prediction for New Products |            |            |
|--|-----------------------------------|------------|------------|
|  | Product #1                        | Product #2 | Product #3 |
| Individual level OLS (pref ranking, 1 <sup>st</sup> PP)                            | 63.5%                             | 34.0%      | 4.0%       |
| Individual level OLS (pref ranking, probabilistic)                                 | 51.2%                             | 25.5%      | 4.8%       |
| Aggregate level MNL (CBC w/o no-buy in simulation)                                 | 56.5%                             | 28.8%      | 9.8%       |
| Aggregate level utilities MNL/CBC) + individual profiles of current product choice | 49.5%                             | 24.1%      | 7.9%       |
| CAPMOD (pref ranking +choice threshold, OLS, 1stPP)                                | 40.5%                             | 28.0%      | 6.0%       |
| CAPMOD (pref ranking + choice threshold, OLS, probabilistic)                       | 37.6%                             | 21.3%      | 4.8%       |

**Table 8 Comparisons of alternative new product share predictions**

These results highlight a common problem with first past the post models (e.g CVA, ACA from Sawtooth and Conjoint Analyser, Simgraf from Bretton-Clark). They tend to over-state share for superior products and under-state share for inferior products when used to simulate current markets. There is every reason to be concerned with this when new products are being simulated. This is illustrated in Figure 3. In this case we are using out 1999 data to simulate the situation of a company having a new product in development and being confident about the eventual profile other than on one dimension. This happens to be an attribute that the conjoint study has shown to be important. The final outcome on this attribute will have a major effect on uptake. The traditional OLS based, first past the post model (Conjoint Analyzer) under-estimates at the low (inferior) outcome but, more importantly severely over-estimates relative to other simulation models at the high (superior) outcome. Amending the model to be probabilistic, rather than 1<sup>st</sup> past the post, reduces this low/high difference. However, we believe that, in this market, both share estimates are unrealistic. Maintaining the individual level focus throughout (from data collection, through data analysis to simulation) produces share estimates that appear to have greater basis of reality credibility, and are, intuitively more believable.



**Figure 3 Comparisons of simulation results given alternative outcomes in new product profile**

The CAPMOD simulation module, in this example, maintains individual level data throughout. All analysis and simulations are conducted at the individual level. This is not the case with pseudo thresholds such as the 'no-buy' option in discrete choice models such as CBC. Consequently, not only is the Independence of Irrelevant Attributes (IIA) problem not an issue but also that the source of new product share – in terms of current competitors, individual physician and patient types - can be identified. This principle can be applied to any conjoint design provided the choice threshold question has been appropriately worded.

## **Conclusions**

Our early work comparing alternative simulation methods within conjoint models led to two main conclusions:

- ◆ We cannot identify a clear “winner” from the standard preference/OLS and choice/MNL model comparisons. Even if all the limitations of and caveats that must be applied to our experiment were to be removed, we doubt whether this would ever change. So much must also depend on the situation.
- ◆ New product predictions in pharmaceutical markets lack credibility due to an over-estimation apparent to the experienced marketeer on presentation and confirmed post launch.

Through applying choice thresholds at the individual level we can:

- ◆ Allow perceptions of current products to be “as is” for each respondent
- ◆ Eliminate (or substantially reduce) reliance on external adjustment factors which, whatever the experience brought to their estimation, must have a substantial arbitrary element and, therefore, be questionable.
- ◆ Remove the need to profile other than new products in simulations of new product introductions.

We also believe that as the basis is more realistic, the resulting new product predictions to be more reliable.

Additional research and experience is required to further test our hypothesis and the predictive capability of the CAPMOD concept. We are sufficiently encouraged by our experience over the last two years that we have committed to the ongoing development of the model and are currently applying it to a number of data sets including choice sets simulated from rank order data analyzed through CBC/HB. This allows for individual level utilities to be estimated for both main effects and interactions at the individual respondent level and, hence, capturing much of the best of traditional OLS- and MNL-based models with the added realism of individual current product images and maintained individual level choice thresholds.

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