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Calibrating Price in ACA: The ACA Price Effect and How to Manage It

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CALIBRATING PRICE IN ACA: THE ACA PRICE EFFECT AND HOW TO MANAGE IT

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ABSTRACT

The tendency of ACA to underestimate the importance of price has been widely recognised over the last few years. Dual conjoint methodologies have been developed to address this issue. This paper proposes an alternative to dual conjoint. This new technique overcomes the "ACA price effect" by integrating ACA utility scores with the output of a series of explicit holdout choices.

Preference segments are developed from explicit choices made by respondents. A weighting factor for price utility is calculated for each segment. This is achieved by adjusting price utility so that ACA simulations closely align with holdout results.

Unadjusted ACA utilities match holdout responses very well for price insensitive respondents. However, significant adjustments are required for more price sensitive preference segments.

INTRODUCTION

Objectives

This paper has three objectives:

- To provide a brief description of the pricing problems that occur in ACA and to discuss potential methodologies for countering them
- To introduce a new method of adjusting ACA utility data to compensate for any inaccurate price signals that may exist
- To provide a starting point for further work and discussion

THE ACA PRICE EFFECT

Conjoint analysis has been utilised for a wide range of market research purposes over the last twenty years. One of its main applications has been to predict the potential demand for new products or services, and to establish the price that customers are willing to pay for them (Wittink et al, 1994).

A very popular conjoint technique is Adaptive Conjoint Analysis (ACA). ACA was introduced by Sawtooth Software in 1987 (Johnson, 1987), and is used extensively by marketing professionals in both the USA and Europe (Wittink et al, 1994).

One of the main advantages of ACA is that it allows the researcher to study more attributes than a respondent can evaluate at one time. This avoids the problem of "information overload" which can occur in full-profile studies when the number of attributes is greater than five or six (Green and Srinivasin, 1990). A typical ACA study uses between eight and fifteen attributes (Orme, 1998).

One of the most important outputs of a conjoint study is related to price. Understanding price utility allows researchers to:

- Forecast the effect of changes in price on customer demand for either a new or an existing product or service
- Quantify in dollar terms the benefits that individual product or service features provide to customers, and compare these with the cost to provide them

Over the last few years researchers have found that the importance of price is underestimated in many ACA studies (Pinnell, 1994; Orme, 1998). This is obviously of great concern, and a number of methods have been developed to counter this effect (hereafter referred to as the "ACA price effect").

Most pricing studies make use of either traditional full-profile conjoint (for example Sawtooth Software's CVA package) or choice-based conjoint (for example Sawtooth Software's CBC package) techniques. However neither of these techniques is appropriate when the number of attributes to be studied is greater than about five or six. This problem has left researchers with a challenge to find a technique that has the ability to investigate large numbers of attributes, and still obtain accurate information about price utility.

A possible solution to the problem involves the use of dual conjoint methodologies (Pinnell, 1994; Sawtooth Software, 1999). If two conjoint studies are conducted in the one interview, then the first section can use ACA to obtain information about a large number of attributes, and the second section (utilising another conjoint methodology) can be used to obtain information about price and two to three other key attributes.

This paper proposes an alternative form of conjoint which integrates ACA utility scores with the outputs from a series of choice-based holdouts (CBH). The result of this is a set of calibrated utility scores that have had their price utilities adjusted to overcome the ACA price effect.

Overview of Proposed Methodology

The study methodology is based on the combination of ACA and CBH. In this paper it is applied to a ten attribute study of approximately 1000 respondents which was completed for an electricity distributor. The decision process was highly involved and required respondents to carefully consider the impact that their decisions would have over both the short and long term. Interviews were strictly managed at central locations so that all respondents received a thorough introduction to the concepts and components of the questionnaire. This ensured that respondents carefully considered their options and made meaningful decisions. The prices of some options offered were significantly more than the respondents were currently paying.

ACA is best used when:

- The number of attributes involved in the study is larger than six
- The decision process being investigated is one in which consumers use substantial depth of processing (Huber et al, 1992)
- The number-of-levels effect needs to be minimised (Wittink et al, 1999)
- Individual level analysis is required

The study highlighted in this paper met all of these criteria. However due to the ACA price effect, ACA alone was not sufficient.

CBH (which is a series of explicit holdout choices) was structured so that the ACA price utility could be calibrated. As well as being the measure against which ACA was judged, it was also used to identify preference segments and to display results in a stand-alone manner.

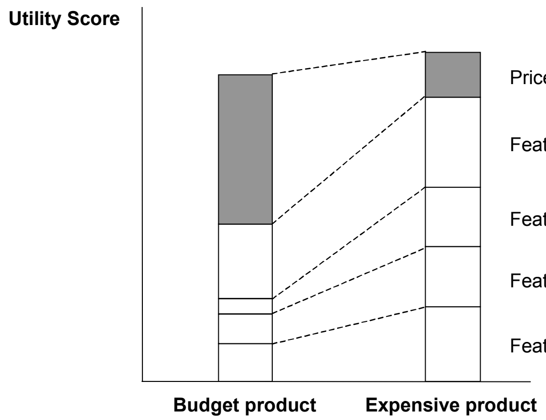
Since the core structure of CBH was for a client-specific purpose, the results presented in this paper are not as open to generalisation as would otherwise be the case. However many of the ideas behind the techniques demonstrated are still applicable in other situations, and could be used for calibrating "pure" dual conjoint studies. (This study is not a "pure" dual conjoint study, as utilities cannot be calculated from CBH in isolation.)

WHAT IS THE ACA PRICE EFFECT?

Recognising the ACA Price Effect

The clearest evidence of the ACA price effect is a simulation that severely over-predicts share for a feature-rich product (Pinnell, 1994). For a respondent who always tends to select the cheapest product available, the amount of extra utility that they place on a low price over a higher price level must exceed the utility from all the extra features that accompany the higher priced products. If it does not, then a simulation will incorrectly predict that the respondent will select the feature-rich product at a higher price.

As shown below, at the individual level the output of an ACA simulation may indicate that a respondent prefers the expensive feature-rich product to the budget product. However, this is a problem if the respondent actually selected the budget product when presented with an explicit choice. While the price level in the budget product has a significant amount of utility, it is not enough to counter the combined impact of the added features in the expensive product.



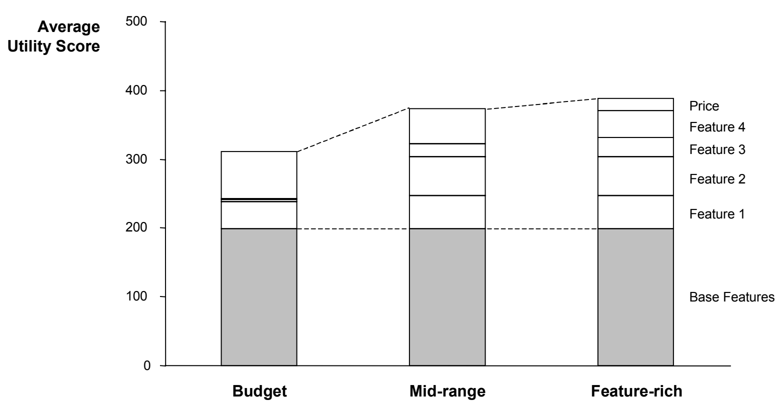
Holdout choices are an excellent means of identifying price underestimation. Both internal consistency and the underestimation of price utility by ACA can be examined by comparing ACA predictions with actual holdout choices (Johnson, 1997).

The ACA price effect can be best illustrated through the use of an example. An ACA simulation was compared with results from a holdout choice (consisting of three options) administered after the ACA questions were completed.

Example:

The three options consisted of a top-of-the-range feature-rich (expensive) product, a mid-range (mid-priced) quality product, and a budget-priced basic product. The results below show that while the simulation predicts that 66% of respondents would select the feature-rich product, only 20% of respondents actually did when presented with that holdout choice.

For this example, it is clear that using the results of ACA in isolation would result in an incorrect conclusion being drawn from the analysis, and ultimately would lead to flawed strategy development.



	Budget	Mid-range	Feature-rich
Simulated Choice:	3.7%	30.4%	65.9%
Holdout Choice:	18.1%	61.4%	20.5%

What Causes It?

There are a number of theories as to why the ACA price effect occurs. These include:

- Inadequate framing during importance ratings
- Lack of attribute independence
- Equal focus on all attributes
- Restrictions on unacceptable levels

Inadequate Framing During Importance Ratings

Perhaps the most difficult part of an ACA interview for respondents to understand and answer accurately is the section known as "importance ratings". In this section, respondents are asked to indicate the level of importance they place on the difference between the highest and lowest levels of each attribute included in the study. The purpose of doing this is to refine the initial utility estimates before the trade-off section begins.

Assigning importance ratings to attribute levels in this way can be a difficult task – particularly when respondents do not know what other product attributes will be offered.

If an attribute related to the reliability of electricity supply has levels ranging from one blackout per annum to three blackouts per annum, then the respondent may rate the difference between one and three blackouts as being very important. If the next attribute tested is price, with levels ranging from $0 to $1,000 per annum, then the difference of $1,000 would almost certainly be assessed as very important as well.

However, if both attributes are rated as very important, then ACA would initially assign utilities to these attribute levels consistent with the respondent being prepared to pay $1000 to reduce blackout incidence from three to one per annum. Clearly if the importance of different attributes is to be captured accurately, respondents must be provided with some context so that they can frame their responses correctly.

If the respondent knew in advance that the next question was going to ask them about a large price difference, then they would probably realise that the number of blackouts per annum is not as important as they might otherwise have thought.

It can also be beneficial to order the importance rating questions so that they are structured in a similar manner to the "calibrating concepts" section. Therefore, the researcher may show what they believe is the most important attribute first and the least important attribute second.

While respondents should not be told this (as everybody may have different opinions), at the very least this ordering will help to better define the boundaries of what "importance" means. This "framing" will also help to ensure that the initial pairwise trade-offs are meaningful.

Lack of Attribute Independence

If an ACA study is conducted on the price, performance and colour of cars, then a respondent who rates the colour "red" highly because they believe that red cars go faster (ie. superior performance), has contravened the main-effects assumption. When a simulation is run, the effect of performance is double-counted because the respondent has attributed performance-related utility to both the colour and performance attributes.

This error serves to underestimate the importance of price. However, the effect can also work in reverse. If the respondent assigns a low rating to performance because they believed that a high performance car would always come at a high price, then the effect of price is effectively being double-counted, and its importance will be overstated.

Either way, these errors are preventable and should be countered by clear explanations and examples at the beginning of the questionnaire. For a very difficult questionnaire it may be worth including a short dummy conjoint exercise at the start that is not used for utility calculation. The extra time that this takes could well be insignificant compared with the increased efficiency with which the main exercise is completed.

Equal Focus on All Attributes

The partial-profile design of ACA forces respondents to consider all attributes. In a full-profile study, respondents may well focus on only those attributes that are more important to them (and take less notice of those attributes that are less important). Respondents are less likely to be able to employ simplification strategies such as this with ACA. Consequently, the importance of each attribute is likely to be more similar with ACA (Pinnell, 1994) than with full-profile techniques.

For example, if the price range tested is quite large, then price will naturally be one of the most important attributes. If ACA forces respondents to place more focus on other attributes than they would have in full-profile, then this will serve to underestimate the importance of price.

Restrictions on Unacceptable Levels

ACA permits the respondent to narrow the focus of a study by indicating which attribute levels are unacceptable. For most studies it is not appropriate for the researcher to allow price levels to be deemed unacceptable. In others it may be important to permit levels to be deemed unacceptable, but there is a risk that in doing this errors will be introduced.

It is difficult to ask respondents to rate a price level as unacceptable or not if they are not fully aware of the benefits of the product they are evaluating. This is particularly true in the case of new products or services. Many respondents may be quite clear about the maximum that they would pay for a new car or personal computer. However, it is much harder for them to put a limit on the price they would pay for products or services that they have never been exposed to, or that they have not been asked to consider before – such as value-added services provided by utility companies.

The problem for the researcher is two-sided. It is clearly undesirable for a respondent to be permitted to rate a large number of attribute levels as unacceptable at the start of the survey – particularly when demand for new or unfamiliar products or services is being studied. Nevertheless if respondents are not given the right to deem a particular price level to be unacceptable, then they may be forced to consider price levels that in reality they would never be prepared to pay.

If a respondent is not allowed to rate a price level as unacceptable, then this level will receive more utility than if it was rated as unacceptable. This will serve to understate the importance of price.

OVERCOMING THE ACA PRICE EFFECT

Quantifying the ACA Price Effect

The key to overcoming the ACA price effect is to be able to quantify it. Since the price utility calculated by ACA may be suspect, another methodology must be used which accurately assesses the impact of price.

One method for achieving this is through the use of "dual conjoint". Dual conjoint can be described as two consecutive conjoint studies utilising different methodologies to obtain information on the same subject.

The first study may use ACA, with the second study usually focussing on price and two or three other key attributes. The first study enables the researcher to collect detailed information on a variety of attributes (which may or may not include price), while the second study can be used to calculate accurate pricing information.

Full-profile methodologies are often used as the second study in dual-conjoint projects. These methodologies include:

- Traditional full-profile conjoint (eg. CVA)
- Choice-based conjoint (eg. CBC)

The two studies can be either compared, or the results can be combined or calibrated to form one set of utilities. It must be noted that on many occasions researchers undertake dual conjoint studies to compare the different perspectives offered by ratings/rankings-based versus choice-based techniques. As each technique has different strengths and weaknesses, many researchers (if time and money permit) employ both techniques to "cover their bases". However this usage of dual conjoint is not addressed in this paper.

This paper focuses specifically on the use of holdout choices ("Choice Based Holdouts" or CBH) for the second study. While CBH is not actually a conjoint methodology, it is used to calibrate conjoint utility scores from ACA. This differs from standard holdout choices which are purely used to check the predictive ability of the conjoint model.

At a general level, there are three advantages to selecting CBH as a method for countering the ACA price effect.

- CBH allows full control over the choices presented to respondents. It is undesirable to have restrictions (prohibited pairs) on the attribute levels that can appear when using traditional full-profile or CBC techniques. However restrictions are hard to avoid if certain combinations of attribute levels naturally tend to be associated with one another (eg. higher quality products should appear with higher prices so that the choices make sense to respondents). CBH allows the researcher to present realistic choices that may exist in the marketplace (Johnson, 1997). CBH cannot be used to calculate utilities, but can be used to calibrate those generated by ACA.
- CBH can be used in its own right. If the researcher is able to formulate choices that are realistic and meaningful, then the output from the choice questions can be presented (ie. results such as "when presented with three options, 28% of respondents selected option A"). While some managers may never really come to terms with the somewhat abstract

nature of “utility” derived from ACA, CBH is something that they can view as unambiguous. However such analysis is obviously restricted to the choices shown in the questionnaire, and the flexibility provided by ACA to simulate a variety of potential product offers is not available. If CBH is used as the primary method of research, ACA can be used to help explain why respondents made the choices that they did.

- The nature of CBH means that it is less time-consuming (and therefore cheaper) and less complex than many dual conjoint methodologies. Depending on the nature and purpose of the research, this factor may have a strong influence on the choice of methodology.

METHODS FOR CALIBRATING PRICE UTILITY

Introduction

In the absence of an actual purchase decision, most studies use CBH as a proxy for customer behaviour. Therefore any conjoint model which produces results significantly different to CBH has a problem. For example, if a CBH question has three options (feature-rich, mid-range, and budget), then an ACA simulation with three products should produce a similar outcome (assuming a “none” option is not appropriate). If the simulation severely over-predicts the share for the feature-rich product (relative to CBH), then the ACA price effect exists.

A number of methodologies for calibrating price utilities can be used:

- Compare the share predicted by ACA and CBH and apply a single weight to all respondents’ price utilities so that the ACA simulation and CBH results match at the aggregate level
- Identify utility importance segments using cluster analysis and use the method above to adjust each segment
- Use regression to adjust each respondent’s price utility individually to better predict their CBH results

However, there are a number of problems with each of these methodologies.

Comparing overall ACA simulations with CBH aggregate results does not identify any lack of internal consistency within the questionnaire. It is possible for the overall ACA simulation to match CBH results (to a satisfactory degree of accuracy), but at the individual level for the predictive validity to be much lower.

For example, in a study of 140 respondents, both ACA and CBH may predict that 100 respondents prefer product A, and 40 respondents prefer product B. A problem exists if the two methodologies do not agree on which respondents would select each product. If ACA and CBH only overlap in their prediction of preference for product A by 80 respondents, then the two methodologies only match for 80% of choices for product A, and for only 50% of choices for product B (the model performs no better than a simple coin toss).

Identifying segments that are influenced differently by the ACA price effect using utility importance is a difficult task. Not only do different respondents have different sensitivities to price, they may also be influenced differently by the ACA price effect. This makes identifying a homogenous segment very difficult.

Calibrating price at the individual level is theoretically the best way to align ACA and CBH. However the presence of any reversals (such as when a respondent appears to prefer a higher price level to a lower one) in the data makes calibration difficult.

If a weighting factor is applied to price utilities that are in the wrong order, then the magnitude of the reversal will increase. When these respondents are combined with other "clean" respondents, then aggregate utilities will appear more distorted than before the calibration took place. While the reversals could be artificially removed before calibration, this approach has implications that are beyond the scope of this paper.

Using CBH Segments

A potential segmentation methodology involves the use of CBH data. Examining the pattern of CBH responses can identify the importance of price to respondents.

A respondent who consistently chooses high-priced feature-rich products in CBH is unlikely to have the importance of price underestimated by ACA. Quite simply, price isn't particularly important to them. However, a respondent who makes all their choices based upon the cheapest price available is a strong candidate for the ACA price effect. Unless the lower price levels have extremely high utility, then simulations may predict that the respondent would choose a more expensive option if it contained enough features. If the mid-priced option is one price level more expensive than the cheap option, then the difference in utility between these two price levels must exceed the total difference in utility for each attribute that is enhanced in the mid-priced option.

A simple criterion for identifying price sensitivity segments is to count the number of times that the respondent chooses an option at a certain price (assuming that multiple CBH questions are asked on similar products). If each choice contains a high-priced (H), mid-priced (M) and low-priced (L) option, then a respondent may be considered relatively price insensitive if they choose the high priced option the majority of times. This allows the H segment to be identified. Similarly, respondents who choose the other two options the majority of times may be characterised as belonging to either the M or L segments.

Once segments have been identified, an extremely important check is to calculate the average utility importance for each one. If there is no obvious difference in utility importance between segments, then the study has very little internal consistency between ACA and CBH, and is of questionable value.

The main focus is to examine the ability of ACA to predict CBH results for each of the three price segments. When evaluating ACA's predictive ability, the most important factor to monitor is the percentage of respondents for whom ACA correctly predicts the CBH response. If the hit rate is high, it automatically follows that the predicted market shares will be similar. However, if the predicted shares are similar, it does not necessarily follow that the hit rate (ie. the internal consistency) is high.

The predictive ability of ACA for each of the segments is likely to be quite different. The H segment is not price sensitive, and will probably require little or no adjustment to the ACA utilities. Some adjustment will need to be made to the M segment, and it is likely that substantial adjustment will need to be made to the L segment. For the L segment, the utility for low price levels will have to be high enough so that it outweighs all the extra utility available from more expensive options.

The above methodology is best illustrated through the use of a simple example.

Example:

Segments were identified by analysing the overall pattern of respondent preference to nine of the holdout choices presented. Of the ten attributes in the study, each of the nine key holdout choices presented comprised only five of these attributes. The remaining attributes were set to be equal (and were examined in separate holdouts not detailed in this paper). The utility importance determined using ACA for each of the three segments is shown below (using Points scaling).

The number of respondents in each segment was 231 in H, 592 in M, and 146 in L.

The utility importance of each of these five attributes is "pointing in the right direction".

- The price attribute shows that the L segment places the most importance on price
- The importance of attribute 1 is flat across all segments, as attribute 1 was a fundamental attribute that wasn't seen as a luxury
- The importance of attributes 2, 3 and 4 indicates that the H segment values them more than the M segment, which values them more than the L segment. These three attributes are all luxuries, so this trend in the level of importance is to be expected.

	Segment		
Attribute	***H***	***M***	***L***
Price	59	67	77
Attribute 1	45	45	45
Attribute 2	64	58	40
Attribute 3	28	24	21
Attribute 4	59	35	29

Price trend as expected

Similar importance due to common attribute levels

Additionally, of the three options presented in each choice, some of the attribute levels were common. This allowed ACA's predictive ability to be scrutinised further.

For example, of the five attributes in each option, attribute 2 always appeared in the high priced and mid priced options at the best level, while attribute 4 always appeared in the mid priced and low priced options at the worst level.

- As attribute 2 is always set at the best level in the options used to identify the H and M segments, then it would be expected that it is one of the reasons why they chose those options. Respondents who fitted into the L segment would be expected to do so partly because they didn't really value the best level of attribute 2. As can be seen by the similar utility importance for attribute 2 in the H and M segments, ACA supports the preference segments identified.

- A further example of this is provided by attribute 4. Respondents who fitted into the H segment did so because they really valued the top level, while those who chose M or L didn't place as much value on that level. The ACA importance for the M and L segments demonstrates their relative indifference to attribute 4.

The price sensitive respondents (segment L) place more importance on the price attribute and less on the other attributes available. However when a simulation is run which combines price with these attributes, the magnitude of the price importance is not high enough to cancel out the utility available from the other four attributes. The importance of the price attribute reported by ACA is "too flat".

To adjust the utility levels so that the results from a simulation are similar to CBH results, the price utilities must be enhanced by a scaling factor. The factors found to maximise the predictive ability of ACA were:

H: no adjustment needed

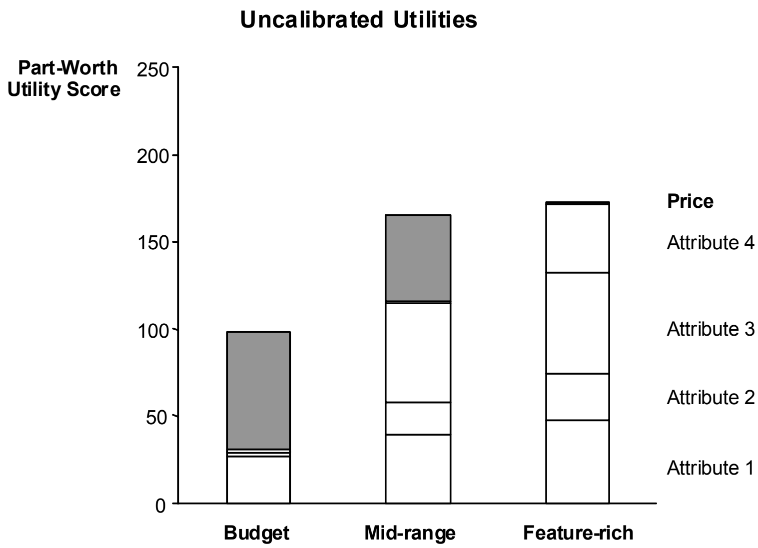
M: scaling factor of 2

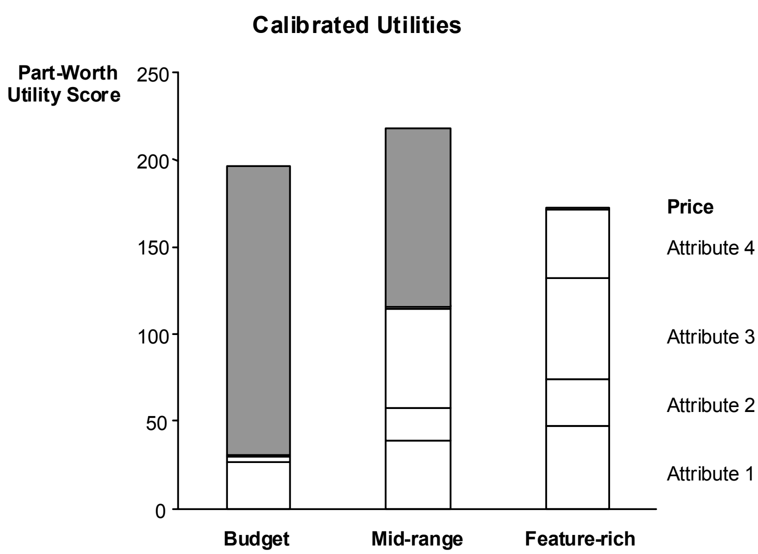
L: scaling factor of 4 (or greater)

These factors were determined by looking at the hit rate of ACA when applied to the nine key CBH questions. The scale factors were adjusted until ACA best predicted (at an individual level) the CBH results for each segment. This process ensured that the integrity of each individual interview was maintained. After the three segments were analysed and calibrated, they were brought together.

The average utility function for one of the simulated CBH questions is shown below – before and after calibration. The average importance of the calibrated price attribute is about two times greater than before calibration. This is obviously significant – especially when calculations based on the dollar value of utility differences are performed.

When checking the validity of ACA simulations with CBH results, it is important to note that some options in CBH will have similar utility when simulated using ACA. If the utility of two options at the individual level is very close, then it is unreasonable to expect ACA to correctly predict the option that each respondent chose. A sensitivity allowance must be built into the calibration model to account for this effect.





Internal Consistency

A useful check of internal consistency is to repeat at least one of the CBH questions (Johnson, 1997). ACA results will not be able to predict CBH results if the CBH results themselves are inconsistent. However much care should be taken when repeating CBH questions. Respondents may detect that questions are doubled up, and therefore become suspicious about the motives of the questionnaire.

While in many cases it is desirable to repeat holdouts before and after the main conjoint task, this is not suitable for the ACA/CBH approach. As ACA relies on respondents making main-effects assumptions, any CBH questions shown before ACA will only serve to confuse them. CBH questions are designed to reflect reality, so they will contain options that have lots of features and high prices, versus others with minimal features and low prices. It is undesirable for respondents to make any associations between levels (such as that a high price implies more features) before undertaking ACA, as this violates main-effects assumptions.

Another extremely important factor to consider is the order of CBH questions. If a respondent who prefers the feature-rich option is shown a choice which has this option at a high price, and then another choice which has the option at a low price, they will probably pick the feature-rich option both times. However, if they are then shown another choice with the feature-rich option at a high price once again, they may not select it, as they know that it is potentially available for the cheaper price. The respondent has had their preference "framed" by the range of prices previously shown.

Other Issues

Four other issues that must be addressed when designing an ACA/CBH survey are:

- Presenting meaningful choices
- The "number of attributes effect"
- The range of CBH questions shown
- Accuracy of utility estimates for non-price attributes

Presenting Meaningful Choices

CBH relies on presenting respondents with meaningful choices. It is obviously easier to construct realistic choices after a study is complete. For this reason, it may be worth running a pilot ACA study that can be used to help formulate choices. When the main ACA research program takes place, the researcher can be sure that the choices that they are presenting are appropriate and will provide meaningful information. Alternatively, the researcher may already have a strong idea of the particular product configurations that they are hoping to test.

Number of Attributes Effect

If the choices used in CBH are not full profile (ie. only contain a subset of the attributes used in the study), then the weighting factor to be applied to the price utilities may be influenced by the number of attributes present in the choice. The weighting factors used in the previous example were based on holdout choices that contained five attributes of varying levels, and five attributes set at a constant level (according to main-effects assumptions). However, the weighting factor would probably be different if only two attributes varied, and eight were kept constant. It is therefore important that CBH is structured to reflect reality as closely as possible.

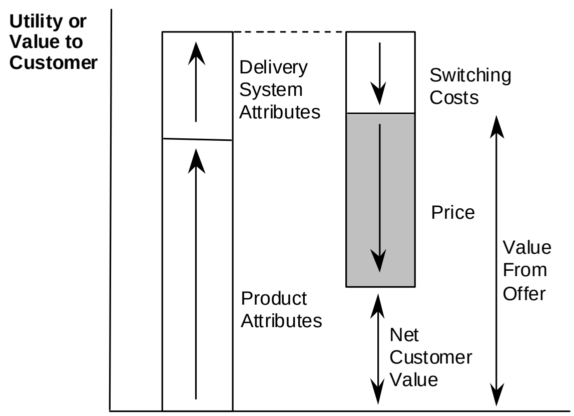
Range of CBH Questions

The range of CBH questions asked must be sufficient so that all price levels are covered. The calibration process effectively turns price utilities into a "plug" which adjusts a simulation so that it matches CBH results. If only one CBH question is asked, then it is possible to apply a weighting factor that implies that the respondent has a really strong preference for a particular option. While ACA is correctly predicting the option that the respondent chose, the calibration process has overwhelmed the fact that the respondent may have only just preferred this option. It is difficult to assess which option the respondent would have chosen if the pricing levels used were slightly different, as a single CBH question gives no sense of how close the respondent was to choosing a different option.

However if multiple CBH questions are asked at different price points, then it is possible to assess the "strength of preference" that they possess for a particular pricing level. If ACA price utilities are calibrated so that simulations accurately predict a variety of CBH questions at different price points, then the researcher can be confident that the price utilities are quite robust.

Accuracy of Utility Estimates for Non-Price Attributes

Many of the problems with ACA that impact on the price utility estimation can also apply to other attributes. However the impact of these problems is likely to be different (and not as damaging) for non-price attributes. Price is a unique component of an ACA study, as in many cases it can be viewed as the only means of "taking utility away" from the respondent.



The product and delivery system attributes may be formulated based on 10-12 features which all add to the utility that the customer derives from a value proposition. If these attributes are enhanced, the net customer value will also increase unless other attributes are made less attractive. In most cases it costs a company money to provide extra product features. The price must be increased to cover this cost. This means that price is usually the only attribute that is used to subtract utility from an enhanced product offer (as switching costs are often too intangible to include).

The price attribute also comes to the fore when performing calculations such as the dollar value of attribute enhancements. The utility of price is the critical factor when converting the utility values of other attributes into more tangible units such as dollars.

While price may not be the only attribute which needs adjustment in an ACA study, it is often the attribute which most needs to be accurate. The effect of incorrectly estimating utility for other attributes is in many cases not likely to significantly impact on the findings of the study (although this of course is dependent on the purpose of the study). It is the unique role of price that makes it such an issue.

Conclusion

While there is much written about the merits of a dual conjoint approach, there is little documentation available on the mechanics of performing this technique. This is unfortunate, as many researchers simply cannot condense the number of attributes to be tested down into a form that can be used exclusively by choice-based or traditional conjoint, and still meet their research aims.

The techniques used in this paper can be summarised as follows:

- In the absence of an actual purchase decision, CBH choices provide a strong basis for predicting respondent choices. By asking the respondent to choose between a range of options, real-world purchase decisions can be simulated. The pricing signals evident from these choices can be used to calibrate pricing signals emerging from the ACA study.
- The dual ACA/CBH approach is useful as it allows the researcher to present managers with the responses from CBH. ACA utility data can then be used to illustrate the drivers of these choices. If ACA is calibrated so that it accurately predicts CBH, ACA can be more confidently used to present results from hypothetical choice simulations that the respondent did not directly evaluate.

The dual ACA/CBH approach was developed to meet a specific aim for a particular project. In many ways it is a "fix", and it may not be suitable for all projects. However as ACA will undoubtedly continue to be used to address projects with large numbers of attributes, it is important that researchers are able to achieve correct pricing signals. The dual ACA/CBH approach enables ACA to be used to develop robust strategies involving many attributes. Until other methodologies are further developed, this approach provides a sound basis for researchers and managers.

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