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USING CONJOINT ANALYSIS IN PRICING STUDIES: IS ONE PRICE VARIABLE ENOUGH?

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ABSTRACT

When conjoint analysis is used in pricing studies, it is important to measure the brand x price interaction. In this study, a "choice modelling" approach is used to measure the effects of brand name and price, and neglecting that interaction would have produced incorrect conclusions.

INTRODUCTION

Among conjoint practitioners, it is commonly accepted that one should be alert for the presence of interactions, but that they are not likely to occur in practice, and if they do, they probably won't be very serious.

Conjoint attributes are often described using categories such as "high," "medium," and "low." Such attributes don't often provide enough detail for interactions to be detected. However, for attributes with financial implications, such as price, the situation is different. In a pricing study, the client may want to know how the market would respond differently to price increases of, say, 5% versus 10%. In pricing studies, the level of precision desired is often much greater than in other applications, and one must be very specific about price levels. For this reason, interactions are more likely to occur in pricing studies than in many other applications.

THE BASIC MAIN-EFFECTS-ONLY APPROACH

The simplest way to handle price in a conjoint study is with a single price variable. Here is an example of an attribute list with a single price attribute:

Brand A Brand B Brand C
\$1.39 \$1 69 \$1.99

If these were the only attributes, one could compose nine product concepts by crossing the attributes with one another, and get responses to each concept. Using a main-effects-only model, one would solve for part worths for each brand and each price. But, this would be to assume that the same set of part worths for price applied to each brand.

However, it's conceivable that the "shape" of the part worths could be different for each brand. For example, when considering Brand A, a respondent could be indifferent to price; when considering Brand B, price could be very important; and the respondent might be more likely to choose Brand C at a higher rather than a lower price!

INCLUDING INTERACTIONS

Of course, interactions can be handled in conjoint analysis. Finkbeiner and Lim (1991) discussed that subject at the recent Sawtooth Conference. Another approach is to use compound attributes; one could combine brand and price like this:

Brand A at $1.39
Brand A at $1.69
Brand A at $1.99
Brand B at $1.39
Brand B at $1.69
Brand B at $1.99
Brand C at $1.39
Brand C at $1.69
Brand C at $1.99

(This can only be done if there are other attributes against which to compare the compound attribute.) Since nine part worths would be determined, they could assume whatever shape might be required to account for the data. This approach is facilitated by Sawtooth Software's CVA System. However, there are reasons to be wary of this approach:

> Many-leveled attributes can result in interviews that are taxing for the respondent, and if there are more than a very few attributes of this complexity, the data are likely to be unusable.
>
> The evidence reported by Dick Wittink and his coauthors at this conference shows that when some attributes have few levels and others have many, the many-leveled attributes are likely to emerge as seeming more important than they should.

We'd like to describe two practical approaches to this problem, one from the early 1970's, and the other quite recent. The earlier one "should have" worked, but didn't very well. The new one, derived from it, seems to work well. Neither is really an example of conjoint analysis, instead being a particularly simple example of "discrete choice" analysis. Both methods share the property that every brand has its own price variable, which is to say that they capture the brand-by-price interaction. We'll show that one can reach the wrong conclusions in a pricing study if that interaction is neglected.

A METHOD FROM THE 1970'S

In 1972, Market Facts, Inc. published a paper by one of the authors describing a technique for measuring respondent sensitivity to price. It was also described more accessibly by Frank Jones in Journal of Marketing (1975). The data collection and analysis procedures were extremely simple. Consider four brands, each with four possible prices. Just to emphasize that the prices need have nothing in common, brands A and B are shown with low prices and brands C and D with higher prices. For example, A and B could be in six-packs, and C and D in 12-packs.

Brand A	Brand B	Brand C	Brand D
$1.25	$1.33	$2.50	$3.45
$1.50	$1.67	$2.99	$4.56
$1.75	$2.00	$3.99	$5.67
$2.00	$2.33	$4.99	$6.78

If we had a respondent's rank order of preference for these 16 combinations of brand and price, then we could predict which he should choose, given any competitive set of them.

The data collection procedure was to show the respondent four stacks of cards, one stack for each brand. The top card on each stack, and the only one visible, showed that brand's lowest price, as found in the first row of the table above. The respondent was asked which he would prefer from among the four, if each brand were priced as shown. When the respondent chose a brand, that card was removed from its stack, and the next price "popped up." The respondent was then asked a similar question for the modified array of product concepts, one of whose prices was now higher.

This process could continue until all cards had been selected, or could terminate if the respondent declared he would no longer purchase any of the products, or if all cards for the brands of interest had been selected. The respondent might have to make as many as 15 selections, but probably fewer.

The method of analysis was extremely simple. Given any array of brands, each at a specific price, as well as the respondent's rank order of preference for all combinations, one can predict which he should choose. By specifying a constant competitive set, one can count how many respondents should prefer the brand of interest if it were at each price level.

For example, suppose we are interested in Brand A, and the rank orders of preference collected for the 16 combinations are as shown below:

Brand A	Brand B	Brand C	Brand D
$1.25 1	$1.33 2	$2.50 3	$3.45 12
$1.50 4	$1.67** 5	$2.99** 6	$4.56** 13
$1.75 7	$2.00 8	$3.99 11	$5.67 14
$2.00 9	$2.33 10	$4.99 15	$6.78 16

If the competitive products were those with asterisks, for example, then this respondent should choose brand A when at its first or second price level, both of which have preference ranks more favorable than those for any other product. However, this respondent should prefer brand B if Brand A were at its third or fourth price levels. By cumulating over respondents it is easy to produce a curve showing how share of choices should vary as a function of price, given any specified set of competitive prices.

This technique enjoyed mixed success. It was easy for the respondent, inexpensive, and simple for the field personnel. Unfortunately, however, the results were disappointing. The interview was so obviously concerned with measuring the respondent's sensitivity to price increases that respondents soon became self-conscious. Some, apparently regarding it as an intelligence test, meticulously chose the lowest price each time. Others, apparently regarding it as a challenge to their brand loyalty, remained faithful to their preferred brand, even as its price increased to unreasonable levels.

At about that same time conjoint analysis burst upon the scene, offering many advantages. One important advantage for pricing studies was conjoint analysis permitted additional attributes to be included, thus disguising the researcher's intent. This method was therefore appropriately forgotten, although Mahajan, Green, and Goldberg (1982) did draw upon it.

RESURRECTION IN THE 1990's

Recently the authors (with John Fiedler of POPULUS) had the opportunity to work together on a pricing study for which a modern-day version of this technique seemed appropriate. The products of interest were consumer packaged goods sold in several different types of retail outlets.

Interest was focussed on brand name, price and volume. We needed to quantify the effect of price changes on market share and sales volume. Standard conjoint analysis did not seem appropriate for these reasons:

Since there were no other attributes of interest (a rare occurrence in conjoint studies!) it seemed that a conjoint interview with just two attributes would be too obvious in its purpose.

There was a wide range of prices within each category, making it hard to come up with a single pricing variable for each category.

It was essential to capture any brand-by-price interaction, but that is most easily done when there are other attributes with which to compare a compound brand-by-price attribute.

Accordingly, a modern-day version of the older technique was utilized. A critical development had occurred since the early 1970's: the invention and proliferation of the personal computer. With a computer as an interviewing device, it is easier to ask repetitive "pick one from n" questions, and to have enough else going on that the respondent is not so aware of the purpose.

Consider a screen like this:

You stop at a convenience store to buy a newspaper while driving home from work, and just happen to remember that you're out of milk. The store offers four choices. Which will you buy?

TYPE THE NUMBER OF YOUR CHOICE

1	2	3	4	5
Meadosweet quart $1.00	Ajax half gallon $1.90	Goodpasture quart $1.25	Darigood pint $.60	NONE: I'd get milk another time

The top of the screen shows a "prolog," a scenario to add variety and put the respondent in a concrete frame of mind. The four products are arranged in random order, just as they would be on the store shelf. The respondent answers by pressing a key, 1 through 4 to select a product, or 5 to indicate no purchase. If a product is selected, then the respondent may optionally be asked how many units would be purchased. The screen is then replaced by another featuring a different prolog, and with the products arranged in different order and priced differently.

Varying the prologs helps keep the respondent interested in task. We found that several such questions can be answered without choice behavior degenerating into obvious patterns.

The desire was not so much for detailed information about each specific product category as for generalizable results that might apply across categories. Seven product categories were selected as representative of the broader range of the client's business. Fieldwork was done in eight geographically dispersed cities. Respondents were intercepted in shopping malls, qualified with respect to product category usage, and then seated at computers which conducted the interviews.

Each respondent was interviewed about a single product category, represented by four brands. Each respondent first saw 8 1/2 x 11 color photographs of the front and back of each brand's actual container; all text was clearly legible, including instructions and suggestions for usage.

The particular brands presented, as well as their base prices, differed from city to city to reflect regional usage patterns and competitive activity. Each was presented in the interview at four price levels, consisting approximately of current price, current price less 10%, and current price plus l0% and plus 20%.

We interviewed 525 respondents, and each respondent completed 12 choice tasks, so 6,300 choice events were available for analysis. The design of the choice tasks was balanced; each brand appeared equally often at each price level, and for each pair of brands, all 16 combinations of price levels appeared together approximately the same number of times.

The interviews were equally distributed among the seven product categories, so 900 choice events were available per product category. Since a quarter of the choice tasks presented each brand at each of its price levels, there were 225 choice events involving each price level for each brand.

Although these data provide a fascinating opportunity to study many details of consumer choice, the basic questions that motivated the project can be answered just by counting. We need only count the percentage of times a brand is selected when presented at each price level. Shares of choices are presented the table below for representative brands in three categories.

Share Of Choices At Each Price

Category	-10%	current	+10%	+20%	Max/Min
X	39.11	35.09	32.61	29.69	1.32
Y	50.22	37.28	25.55	22.12	2.27
Z	46.22	18.67	12.50	7.96	5.80

The categories differ considerably in price sensitivity. The last column contains the ratio for each representative brand's maximum and minimum shares. In Category X there is a share change of only about 32% as the price moves from +20% to -10%, but in Category Z the share change is approximately five-fold!

Here are results for three products in Category Z:

Share Of Choices At Each Price

Brand	-10%	current	+10%	+20%	Max/Min
A	46.22	18.67	12.50	7.96	5.80
B	34.09	19.74	15.42	7.56	4.50
C	54.30	30.53	19.91	18.94	2.87

Even brands within the same category behave differently from one another. Brands A and B have similar shares as their prices increase, but A has a much larger increase than B when its price drops. Brand C is much more robust in the face of price increases than either A or B.

These results show that brands within a category can behave differently in response to changing prices. It would be a serious error to attempt to measure price sensitivity, using conjoint analysis or any other method, without taking the brand-by-price interaction into account.

HOW REALISTIC ARE THE RESULTS?

These results show some products to be very price sensitive and others to be much less so. This tends to confirm existing knowledge about these product categories.

In conjoint analysis applications, the researcher should caution the user that the results are only shares of preference -- not shares of market. The same caution is required here. The interview is conducted in a laboratory environment where all products are available at controlled prices, and where the respondent has been made familiar with all of them. In the real world many other factors influence purchase behavior:

Prices are not always as intended by the manufacturer.
Customers may be less aware of price in the store.
Not all products are available everywhere.
There are temporary out-of-stock conditions.
In-store personnel may create point-of-sale effects.
Purchase behavior can be influenced by displays.
Purchase behavior can be influenced by on-pack rebates.
Local advertising may change perceptions of products.

These factors have the net effect of decreasing responsiveness in the market, compared to what is observed in the laboratory.

The user of such data therefore shouldn't expect to see as much responsiveness to price in the real market as in the laboratory, but should expect to see a similar pattern. The products and categories that are most responsive in the laboratory should be those that are most responsive in the market. And the price points that result in particularly large increases or decreases in share in the laboratory should also be the critical ones in the market.

EFFECTS OF LEARNING AND FATIGUE

When similar questions are asked repetitively, respondents sometimes adopt stereotyped ways of responding. Past experience has shown that this can be a particular problem in pricing studies if respondents are aware of the purpose.

Conjoint analysis can minimize this by including other attributes to disguise the purpose of the study. Here, instead, we varied the situational context with a variety of "prologs." We weren't sure how successful this would be, and were prepared to discard data from tasks later in the interview if they turned out to display results of learning, fatigue, or other distortion.

We examined this question by conducting separate analyses of data from the first six and the last six choice tasks, counting the number of times the client's products were selected at each price level. Across all categories and price levels, results from the first six tasks and the last six tasks were correlated .939. Further search for patterns in the results detected no evidence of difference between them. We concluded that we had been successful in generating sufficient respondent interest to obtain data of high quality.

ANALYSIS AT THE INDIVIDUAL LEVEL

In most applications of discrete choice analysis, the analysis must be done at the aggregate level. However, in the case where there are only two attributes, much can be done at the individual level.

In our example, there were only four brands, each at four prices. Neglecting "NONE" as a category, only 16 stimulus objects were presented to a respondent during the interview. Each time he made a choice he indicated an explicit preference for one of those over three others.

However, if we assume that lower prices should be preferred to higher prices, we can infer a good deal more. With that assumption, if A is chosen over B, we can also infer that any lower price level would be preferred to B at any higher price level. For illustration, suppose that a choice task presents brands A, B, C, and D, each at the second of four price levels, and that A is chosen. We know that A at price level 1 and A at price level 2 should he preferred to B, C, or D, each at price levels 2, 3, and 4. By this single choice, the respondent indicates a total of 2 x 3 x 3 = 18 order relationships among his preferences for the 16 underlying objects.

This suggests four types of within-individual analysis:

> One could use a nonmetric regression algorithm to estimate individual respondent utilities from the data provided by his choices. If each task produced an average of 18 order relations, twelve tasks would provide a total of 216 order relations among only 16 parameters.

We may regard this as a repeat-measures paired comparison preference study, and use standard Thurstone or Bradley-Terry methods to estimate “utilities” for the 16 underlying concepts.

Using either of the above approaches, one may develop a “consistency” measure for each respondent. Suppose a respondent provides a total of 216 pairwise preference relationships among the 16 stimulus objects shown him. A simple consistency measure would be the percentage of those that are not contradicted by others. Such a measure was used in the present study to compare data for categories with one another, as well as data originating from different cities.

Similarly, it is easy to provide a measure of each individual's relative sensitivity to price. This can be done just as in conjoint analysis, by comparing the range of utilities for price to the range of utilities for brand. In the present study, such a price sensitivity measure was strongly correlated with several other self-report measures of attitude and behavior.

SUMMARY

We have reviewed ways price can be handled in conjoint analysis, and argued that in pricing studies it is essential to capture interactions of brand and price. We have described a simple method of doing so, which is in the tradition of “discrete choice” methods, but which, like conjoint analysis, also permits analysis at the level of the individual respondent. We have presented actual data using this method to demonstrate that different product categories, and different brands within a category, respond differently to price changes.

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