Perfect Union

CBCA marries the best of conjoint and discrete choice models.

By Steven H. Cohen

Interest in discrete choice models as applied to choice-based conjoint analysis has grown considerably over the past several years, for good reason. People make choices when purchasing products and services and, consequently, the opportunity to develop in-depth knowledge of the drivers of choice is very attractive. While its popularity is on the rise, the history and advantages of choice-based conjoint analysis (CBCA) are not well understood. Such information can help marketing managers and researchers do a better job of designing research, analyzing and interpreting the results, and using them to make more-informed business decisions.

First of all, we need to clear up some confusion: Discrete choice models and CBCA are *not* the same thing. In conjoint analysis, the respondent reacts to experimentally designed product or service descriptions, called "profiles." These evaluations are typically ranking or rating tasks, or paired comparisons. CBCA uses the basic ideas and designs of conjoint analysis, but instead asks the respondent to choose one option from several competing product or service alternatives. Discrete choice models are a particular type of statistical analysis—specifically, logit and probit analysis—that can be applied to the choice data collected in a CBCA study.

In short, conjoint analysis is a research technique for systematically collecting data on preferences or choices using experimental designs, and discrete choice models are statistical methods for analyzing choice responses. CBCA joins the two technologies to help the manager understand the drivers of choice. Just as a conjoint analysis study is not limited to collecting data on respondents' choices, the use of discrete choice models is not limited only to the analysis of conjoint experiments.

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Traditional Conjoint Analysis

Conjoint analysis was originally introduced to market researchers in the early 1970s as a means to evaluate the importance of product or service attributes and price as they predict consumer preferences. By systematically manipulating the product or service descriptions shown to a respondent with an experimental design, conjoint analysis allows decision makers to understand preferences in an enormous range of potential market situations. Although analysis of conjoint data can be undertaken in aggregate or at the level of predefined market segments, the typical researcher develops a utility equation for each respondent and the results are summed across people to predict market shares (using a share simulator).

Conjoint analysis has demonstrated its usefulness and staying power for a long time. Over the past several years, however, some researchers have begun to question some of its basic assumptions and methods and look for alternatives that would retain its best points while overcoming its deficiencies.

Problems Areas

Several concerns arise in traditional conjoint analysis. First, as researchers, we believe that research tasks that closely mimic what people do in the real world will produce more valid and reliable results than tasks which do not. So while conjoint analysis asks people to provide rankings or ratings, we know that people do something very different when selecting or purchasing products or services: they make *choices*.

Second, conjoint analysis generates values for each product or service attribute that explain people's preferences. To obtain estimates of market share—which are just the sum of individual choices—the preference results from conjoint analysis must be used in a share simulator. Simulators are built on rules that translate the preference values into a predicted choice. Unfortunately, there are many different share simulator rules and they do not yield the same answer. The analyst must select which set of rules he or she likes best for the situation at hand. Thus, the traditional two-stage conjoint procedure—estimate preferences and then simulate shares—can yield different results, depending on the whim of the analyst.

Third, performing the analysis for each individual assumes that we have measured the drivers of each consumer's preferences with certainty. The results from the conjoint task uniquely define what that person will do under any situation. Diligent analysts often note the sizable variability found in the utility coefficients across respondents. Not only is the variability substantial, but incorrect signs (price is positive rather than negative) and switched magnitudes (luxury car buyers prefer small cars over large cars) are often found when looking carefully at individual respondents' results.

By estimating at the individual level, we also relinquish the opportunity to test for statistical differences across predefined groups. Is the price sensitivity of men different from that of women? Does a particular feature attract experienced, knowledgeable consumers more than the inexperienced? Only when statistical analysis is performed in aggregate or at the segment level can traditional conjoint analysis address this issue.

Fourth, when performing benefit segmentation, cluster analysis is used to group people with similar feature utilities. Depending on the type of cluster analysis used, and even depending on the order in which the data are sorted, you will get different results.

Fifth, interaction effects are ignored in most traditional conjoint analysis studies because including interactions increases the number of profiles that must be evaluated. Without interaction effects, for example, people are assumed to be equally price-sensitive to every brand in the category. Incorporating a brand-by-price interaction effect permits a test of this assumption, thereby allowing us to understand whether consumers are less sensitive to changes in the price of the category leader than they are to changes in the price of other brands. Conjoint analysis estimated at the individual level includes interaction effects only in the very simplest circumstances.

Sixth, what if specific product features, or levels of specific product features, are unique to a brand or unique to products at a price point? For example, what if an 8X zoom lens can only be used on a camera that costs over $250, but you want consumers to evaluate cameras costing from $75-$400? Traditional conjoint analysis will not accommodate this restriction without eliminating unacceptable profiles. Doing so, however, will cause problems like nonorthogonality and lack of balance, which might invalidate the results.

Finally, how does low purchase intent or a low ranking translate into non-purchase? Conjoint analysis simulations assume a share model in which everyone will buy. But what if some people do not wish to purchase at all, especially in those situations where the product is not fully featured or costs too much? Incorporating demand into a traditional conjoint model requires ad hoc assumptions about how a low-purchase-intent rating or ranking will translate into inaction.

Discrete choice models

About the same time that conjoint analysis was being introduced in marketing, transportation planners were grappling with understanding why people chose particular modes of transportation to travel to work. In the early 1970s, the government was funding research to understand how to get people out of their cars and onto mass transit. These studies were the beginnings of work applying discrete choice models to understanding behavior.

In transportation mode studies, people are asked detailed questions about the alternative methods of getting to work: the travel time, the fares or costs, the convenience, and so on. People also report the *one* way that they do use to go to work. This one choice from a series of alternatives, a discrete choice, contains the data that is analyzed. These studies assume that something about the characteristics of the choice—their fares, travel time, convenience—and something about the characteristics of the person—age, income, and so on—make the chosen alternative more attractive than others.

Exhibit 1

Simple CBCA task: Which checking account would you choose?

Services included with all four accounts	• ATM card with free unlimited use of your bank's ATM machines • Unlimited free check writing with no per-check charges • Unlimited free access to automated account information over the telephone

	Account #1	Account #2	Account #3	Account #4
Monthly fee and minimum balance required	No minimum balance required Pay a monthly fee of $10 if your account balance drops below $0	Maintain a $500 minimum checking balance to avoid a $10 monthly fee	Maintain a $1,500 minimum checking balance to avoid a $10 monthly fee	Maintain a combined balance at least $15,000 in your checking and savings accounts to avoid a $25 monthly fee
Competitive interest paid on checking accounts	No	No	Yes	Yes
Use of other banks' ATM machines	$1.50 for each ATM visit	$1 for each ATM visit	$1 for each ATM visit	Free
Priority access telephone number	No	No	No	Yes
Choose the one account you prefer ☞	❑	❑	❑	❑

❑ None of these

Transportation mode choice studies illustrate the key features of data that are analyzed with discrete choice models:

- A competitive set of alternatives (bus, train, car, etc.).

- Characteristics or features of each alternative, which may exist for one alternative (the consumer pays maintenance costs for his or her car, but does not for public transport) or all alternatives (the amount of time it takes to get to work).

- Characteristics of the people making the choices (white- or blue-collar workers, men or women).

- A unique choice made by each person from the discrete set of alternatives.

Note that, in this case, discrete choice models are applied to survey data. No experimentation or testing of alternative product features or pricing is included, as in conjoint analysis. In fact, discrete choice models can be applied to any kind of data where there are competing alternatives and people make a choice. Survey data and scanner data, for example, have been analyzed successfully using discrete choice models.

Mode choice surveys, however, suffer from a major deficiency. Transportation researchers found that fares, for example, varied little within the geographic area studied. Accordingly, the effect of fare on choice was very limited in its explanatory power. Not only did this make it difficult to find statistically significant effects, but the narrow range of fares observed hampered the ability of planners to generalize the results to other geographic areas, time periods, or changes in fare policy.

Choice-Based Conjoint Analysis

The best features of discrete choice models and conjoint analysis are married in CBCA. Much of the credit for this union goes to J.J. Louviere, now a professor at the University of Sydney, Australia, and his colleagues. The advantages are particularly exciting because CBCA overcomes the major deficiencies of either technique when taken alone.

Exhibit 1 shows an example of a CBCA task disguised from a study investigating the design of retail checking accounts. In this example, consumers have five choices available. Account No. 1 (on the far left) is a no-minimum, no-fee account. Interest is not paid on the account and a fee is always charged for the use of another bank's ATM. Account No. 4 (on the far right) is a "relationship" account. By keeping at least $15,000 in the account, interest accrues and the use of other banks' ATMs is free. A priority access telephone number is available to holders of this account.

In between are checking accounts that require intermediate amounts on deposit. Interest is included with one account and not with the other. The use of another bank's ATM machines is free for the first four transactions and is fee-based thereafter. No priority access number is available, however. The fifth and final choice displays a unique feature of CBCA: The consumer can choose one of the four accounts or "none of these."

In a study using CBCA, respondents will evaluate several choice situations, with fees, account minimums, and other benefits varying across them.

Exhibit 2 shows another type of choice situation, this time requiring an allocation. Allocations are a type of choice behavior, except that 100% of the respondent's resources are divided among several competing alternatives. In this example, telecommunications managers at large businesses are asked to allocate their company's business telephone lines across competing telephone service suppliers. In contrast to the previous example, type of service vendor or brand now enters into the picture. No vendor offers either a unique feature or a unique level of a feature.

The manager's task is to allocate the company's phone lines across competing service vendors. The manager may decide to purchase all lines from one vendor or, depending on the company's needs, to divide the lines across vendors. Note that, in this case, every manager must "buy" telephone lines; the option for "none of the above" is not available. Again, each manager will complete several of these tasks.

Exhibit 3 on page 16 illustrates another marketing problem that can be addressed with CBCA: product line composition and pricing. In this case, let's suppose that Xerox currently has a more extensive product line and is interested in introducing two new variants, Model 12 and Model 14. At issue is whether to introduce either or both and how to price them. If their introduction does not draw share from competitors and just cannibalizes current models without generating incremental sales or profits, then introducing the new models does not make sense.

In this case, we vary (1) the availability of Models 12 and 14 across choice situations, and (2) the prices of all models. In the choice set shown, the two models are not available for purchase. In other choice sets, one or both models will be available. This will allow us to understand not only how choices change as prices change, but also what effect the availability of the two new models has on product line share.

Advantages

CBCA has several advantages over traditional conjoint analysis:

- In traditional conjoint, each product or service profile is either rated one at a time, ranked in order of preference, or, at best, shown two at a time in a paired comparison. With CBCA, choice is made from a set of competing product or service alternatives. The set of alternatives can be limited, as shown in the exhibits, or extensive, as might confront a buyer of desktop applications software or someone choosing from a restaurant menu.

- In traditional conjoint, few product profiles are seen and evaluated, typically in the range of 10-20, though computer-aided conjoint tasks might require 30-50 judgments. In CBCA, if consumers were to evaluate 10

Exhibit 2

Resource allocation task: How would you allocate your business lines across telecommunications services vendors?

	Service provider			
	Local telephone company	**Long distance telephone company**	**Best out-of-region telephone company**	**Local cable TV company**
Price of monthly service	Same as now	10% less than now	10% more than now	10% less than now
Long distance included	No	Yes	Yes	No
Speed of installation	15 days	30 days	15 days	30 days
Customer service hours	7 a.m.-11 p.m.	24 hours per day	7 a.m.-11 p.m.	7 a.m.-11 p.m.
Billing format	Electronic	Paper	Paper	Paper
Keep your current phone numbers	Yes	Yes	No	No
Trial period	60 days	30 days	30 days	60 days

What is the likely allocation of your business lines 12 months from now, given the information above?

Business lines	______ %	______ %	______ %	______ %

Remember, the total must equal 100%.

Exhibit 3

Product line choice situation: Which copier would you purchase?

Canon		
	Model A	$1,299
	Model B	$2,299
Xerox		
	Model 11	$1,249
	Model 12	This model is not available
	Model 13	$1,449
	Model 14	This model is not available
	Model 15	$1,849
	Model 16	$2,599
Kodak		
	Model M	$1,099
	Model O	$1,599
	Model P	$2,249
Any other midrange copier		

choice situations as in Exhibit 1, they would see and provide choices—or nonchoices—for 40 product descriptions because each situation contains four different checking accounts.

- In traditional conjoint, every product or service must share product features and the levels of those features. With CBCA, features can be unique to one alternative (only the relationship account has priority access, for example) or the levels of a feature can be unique to each alternative (the intermediate accounts have balance requirements in the low thousands, while the relationship account has a balance requirement of at least $15,000).

- In traditional conjoint, every product must be ranked or rated. In CBCA, should none be appealing, the consumer can reject all alternatives and choose "none of the above."

- In traditional conjoint, all features are assumed to have the same effect for each brand under study. With CBCA, price and feature sensitivity can be different for each alternative. For example, we can explicitly test whether telecom managers are less price sensitive to changes in the monthly service fees of their local telephone company and more sensitive to the service fees that might be charged by the local cable TV company.

- In traditional conjoint, only one product or service from each company is evaluated at a time. In CBCA, we can study how product features, prices, and availability affect the composition and market share of a vendor's entire product line in a single task.

- In traditional conjoint, we cannot explicitly test for different types of decision structures. Using a nested logit model with CBCA, we can test whether buyers first choose a vendor and then choose a product within that vendor's line (a nested choice structure) or whether brand plays a role equal to that of product features and price (a nonnested structure).

- When traditional conjoint is used to generate a utility equation for each person, characteristics of the individual cannot be used as predictors in the statistical model. Only when traditional conjoint is estimated at an aggregate or segment level can individual characteristics be explicitly included in the analysis. With CBCA, we can explicitly test for differences in the impact of features or prices across predefined groups.

- In traditional conjoint, simulation of choices and selection of a simulator rule occur independently and *after* the estimation of preference utilities. With CBCA you use the estimation equation directly for simulation. No two-step method is required, nor is there any decision required about which simulator rule to use.

- As noted earlier, one of the disadvantages of traditional conjoint is the use of cluster analysis for benefit segmentation. Until very recently, benefit segmentation could not be performed on choice-based conjoint analysis data because estimation is not performed at the individual level with discrete choice models. Recent work has shown how to derive choice-based benefit segments in CBCA using latent class analysis, and other research has demonstrated that segmentation based on integrated methods such as latent class analysis outperform traditional two-stage conjoint and clustering methods.

Disadvantages

Several limitations of CBCA give some researchers cause for concern:

- Discrete choice models are aggregate statistical techniques that "stack" people in the data matrix. A unique utility equation is not estimated for each person. Most researchers familiar with traditional conjoint are used to getting individual-level results to use in simulation and segmentation.

- Some claim that CBCA does not deliver predictions that are as accurate as individual-level conjoint analysis. The predictions of CBCA have been tested against traditional conjoint and the score seems to be about even. This is remarkable, considering that CBCA does not generate individual-level predictions and the traditional method does. Furthermore, these comparisons have been conducted on a playing field that allows traditional conjoint to participate: relatively few attributes, known directional effects, no significant interaction effects, no unique features or levels, share predictions, and no differences in preference across respondent groups. Since CBCA can cover a wider range of situations, it is not possible to include the traditional mode of analysis in a comparative test which plays to the strengths of CBCA.

- CBCA tasks are difficult to design. Essentially, two experimental designs are necessary: one to generate profiles and another to place the profiles into balanced choice sets. This creates a challenge for the unsophisticated user, or for one accustomed to using canned software. Sawtooth Software has developed its CBC module, which does facilitate conducting discrete choice experiments. More-complex situations, involving high-level interactions, many potential choices, resource allocations, multiple choices from the same choice set, or price or feature dependencies among products in a line require considerable design and analysis expertise.

- Using a logit model in CBCA requires the analyst to be aware of and test for the independence of irrelevant alternatives (IIA) property. IIA assumes that the probability of selecting one alternative from a choice set is not influenced by the presence or absence of other alternatives in the set. IIA usually is not a viable assumption when two competing alternatives are very similar. Violations of IIA can be tested, however, and modifications should be made to the model. Because of its simpler assumptions, traditional conjoint completely ignores IIA and allows no specification tests. Although some commercial software packages allow the analyst to incorporate a correction for product similarity into traditional conjoint simulations, why, when, and how to use these adjustments is entirely ad hoc.

All things considered, CBCA's advantages far outnumber the issues raised by its detractors, and we expect market researchers to apply it for many years to come. ◆

Additional Reading

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