Sawtooth Software

RESEARCH PAPER SERIES

An Overview and Comparison of Design Strategies for Choice-Based Conjoint Analysis

Keith Chrzan,
Maritz Marketing Research
and
Bryan Orme,
Sawtooth Software, Inc.
2000

530 W. Fir St.
Sequim, WA 98382
(360) 681-2300
www.sawtoothsoftware.com

An Overview and Comparison of Design Strategies for Choice-Based Conjoint Analysis

Keith Chrzan, Maritz Marketing Research
Bryan Orme, Sawtooth Software

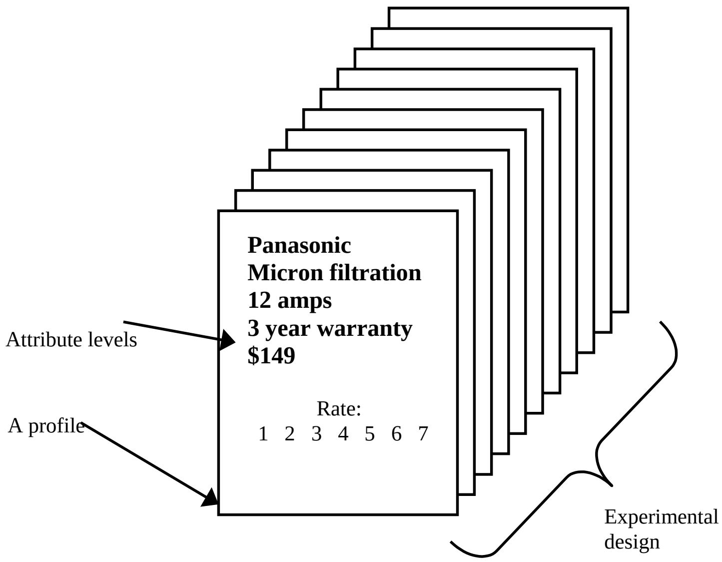
There are several different approaches to designing choice-based conjoint experiments and several kinds of effects one might want to model and quantify in such experiments. The approaches differ in terms of which effects they can capture and in how efficiently they do so. No single design approach is clearly superior in all circumstances.

This paper describes different kinds of design formats (full profile, partial profile), and different methods for making designs (manual, computer optimization, computer randomization) for choice-based conjoint designs. Over and above the plain vanilla generic main effects most commonly modeled in conjoint analysis, there are several types of "special effects" that can be included in choice-based models. The various ways of constructing choice-based designs are compared in terms of their ability to capture these effects. Using simulations and artificial data sets we also assess the statistical efficiency of the various design methods.

Background

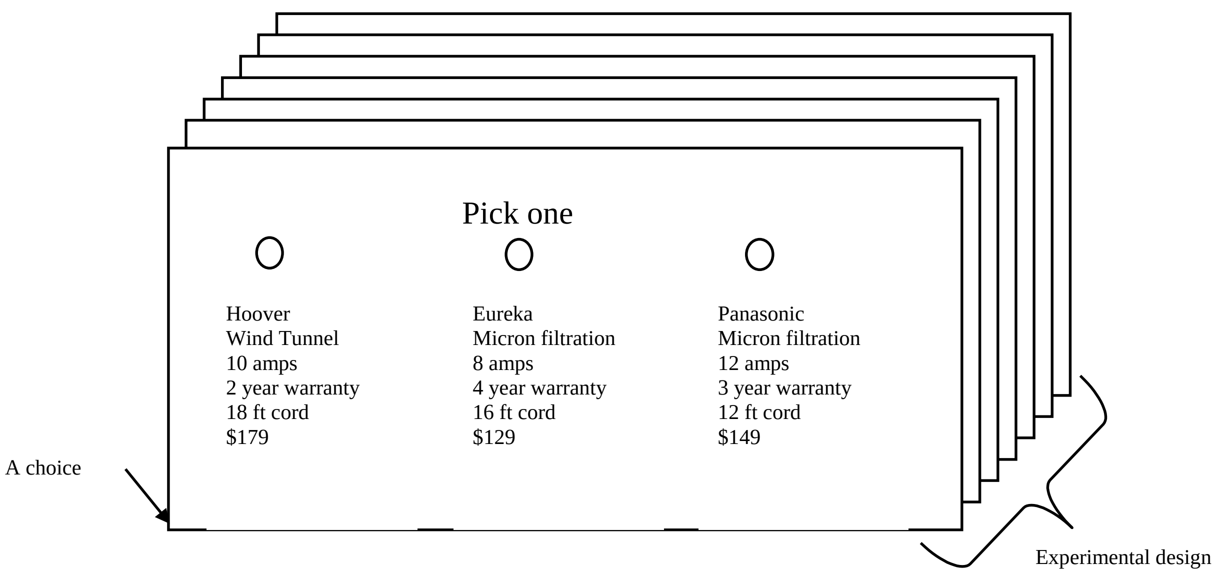
In traditional conjoint analysis (see Figure 1), experimentally controlled combinations of attribute levels called profiles are presented to respondents for evaluation (ratings or rankings). In a multiple regression analysis these evaluations then become the dependent variables predicted as a function of the experimental design variables manifested in the profiles.

Figure 1 - Traditional Ratings-Based Conjoint



In 1983, however, Louviere and Woodworth extended conjoint analysis thinking to choice evaluations and multinomial logit analysis. In the choice-based world, respondents choose among sets of experimentally controlled sets of profiles and these choices are modeled via multinomial logit as a function of the experimental design variables.

Figure 2 - Choice-Based Conjoint Experiment



As you might guess, the greater complexity of the experiment allows the researcher to think about designing and estimating many more interesting effects than the simple main effects and occasional interaction effects of traditional conjoint analysis (Louviere 1988, Anderson and Wiley 1992, Lazari and Anderson 1994).

In addition to focusing on the novel effects choice-based analysis allowed, other topics became important for choice-based analysis. Design efficiency became a topic of research because the efficiency of experimental designs for multinomial logit was not as straightforward as that for traditional linear models and their designs (Kuhfeld *et al*. 1994, Bunch *et al*. 1994, Huber and Zwerina 1995). Finally, still other researchers sought ways to make choice-based experiments easier for researchers to design (Sawtooth Software 1999) or for respondents to complete (Chrzan and Elrod 1995).

Characterizing Experimental Designs

Stimulus Format

In choice-based experiments, stimuli can be either full profile (FP) or partial profile (PP). Full profile experiments are those that display a level from every attribute in the study in every product profile. Partial profile experiments use profiles that specify a level for only a subset (usually 5 or fewer) of the attributes under study. Full and partial profile stimuli for a 10 attribute vacuum cleaner study might look like this:

Figure 3 - Full vs Partial Profile Stimuli

Full

Hoover	Eureka	Panasonic
9 Amps	12 Amps	10 Amps
12 ft cord	16 ft cord	24 ft cord
Dirt sensor	-	-
-	Micron filter	Micron filter
1 yr warranty	2 yr warranty	6 mo warranty
Edge cleaner	Edge cleaner	-
Flex hose	-	Flex hose
-	Height adj.	Height adj.
$249	$199	$299

Partial

Hoover	Eureka	Panasonic
9 Amps	12 Amps	10 Amps
Edge cleaner	Edge cleaner	-

Generating Choice-Based Experiments

Three broad categories of experimental design methods for choice models are a) manual, b) computer optimized, and c) computer randomized.

Manual

Strategies for creating full profile designs start with traditional fractional factorial design plans. Consider a four-attribute conjoint study with three levels each, commonly written as a 3^4 experiment. (Note that this notation reflects how many possible profiles can be constructed: $3^4 = 81$ profiles, representing the full factorial.) The figure below shows a 9 run experimental design from the Addelman (1962) catalog for a 3^4 design, and how it would be turned into 9 profiles in a traditional full profile ratings or rankings based conjoint experiment. In this design plan, each column represents an attribute whose three levels are uncorrelated (orthogonal) with respect to each other. In a traditional conjoint experiment, each row would specify a single profile.

Figure 4

3^4 Addelman Design for Profiles

Profile	V1	V2	V3	V4
1	1	1	1	1
2	1	2	2	3
3	1	3	3	2
4	2	1	2	2
5	2	2	3	1
6	2	3	1	3
7	3	1	3	3
8	3	2	1	2
9	3	3	2	1

For V1, let 1=Hoover, 2=Eureka, 3=Panasonic, and so on

Traditional fractional factorial designs were designed for creating sets of single profiles, so they need to be adapted if they are to be used to generate sets of choice sets. The original (Louviere and Woodworth 1983) methods are no longer in widespread use but there are three adaptations of fractional factorial designs that are.

The simplest of these comes from Bunch *et al.* (1994) and is called “shifting.” Here’s how shifting would work for an experiment with four attributes each at three levels:

1. Produce the 9 run experimental design shown above. These runs define the first profile in each of 9 choice sets.
2. Next to the four columns of the experimental design add four more columns; column 5 is just column 1 shifted so that column 1’s 1 becomes a 2 in column 5, 2 becomes 3 and 3 becomes (wraps around to) 1. The numbers in column 5 are just the numbers in column 1 “shifted” by 1 place to the right (and wrapped around in

Figure 5

3^4 Shifted Design

	Profile 1				Profile 2				Profile 3			
Set	V1	V2	V3	V4	V1	V2	V3	V4	V1	V2	V3	V4
1	1	1	1	1	2	2	2	2	3	3	3	3
2	1	2	2	3	2	3	3	1	3	1	1	2
3	1	3	3	2	2	1	1	3	3	2	2	1
4	2	1	2	2	3	2	3	3	1	3	1	1
5	2	2	3	1	3	3	1	2	1	1	2	3
6	2	3	1	3	3	1	2	1	1	2	3	2
7	3	1	3	3	1	2	1	1	2	3	2	2
8	3	2	1	2	1	3	2	3	2	1	3	1
9	3	3	2	1	1	1	3	2	2	2	1	3

the case of 3). Likewise columns 6, 7 and 8 are just shifts of columns 2, 3 and 4.
3. The four columns 5-8 become the second profile in each of the 9 choice sets. Note that the four rows just created are still uncorrelated with one another and that the value for each cell in each row differs from that of the counterpart column from which it was shifted (none of the levels "overlap")
4. Repeat step 2, shifting from the values in columns 5-8 to create four new columns 9-12 that become the third profile in each of the 9 choice sets.
5. Replace the level numbers with prose and you have a shifted choice-based conjoint experimental design.

Shifted designs are simple to construct but very limited in terms of what special effects they can capture (described later).

A second way of using fractional factorial designs is a "mix and match" approach described in Louviere (1988). A few more steps are involved. For the 3^4 experiment, for example:

1. Use 4 columns from the Addelman design to create a set of 9 profiles. Place those in Pile A.
2. Use those 4 columns again, only this time switch the 3's to 1's in one (or more) of the columns and the 1's to 3s, etc., so that the 9 rows are not the same as in step 1. Create these 9 profiles and place them in Pile B.
3. Repeat step 2 to create a third unique set of profiles and a new Pile C.
4. Shuffle each of the three piles separately.
5. Choose one profile from each pile; these become choice set 1.
6. Repeat, choosing without replacement until all the profiles are used up and 9 choice sets have been created.
7. A freebie: you could have set aside the attribute "Brand" and not included it in the profiles. In step 4 you could label each profile in Pile A "Brand A," each profile in Pile B "Brand B" and so on. The Brand attribute is uncorrelated with any other attribute and is a lucky side benefit of having constructed your design in this way. This freebie also allows designs to support estimation of alternative specific effects described below.

A very general and powerful way to use fractional factorial designs is called the L^{MN} strategy (Louviere 1988). One can use an L^{MN} design when one wants a design wherein choice sets each contain N profiles of M attributes of L levels each. For our small example, let's have N=3, M=4 and L=3 (still the small 3^4 experiment with 4 attributes of 3 levels each). This approach requires a fractional factorial design with N x M columns of L level variables. It turns out that for such an experiment the smallest design has 27 rows (Addelman 1962). Taking 12 of the columns from the Addelman design and placing them three in groups of four each is the hardest part of the design:

Figure 6

3^{12} L^{MN} Design

Set	Profile 1	Profile 2	Profile 3
1	1 2 1 3	2 2 3 1	1 3 3 2
2	3 2 3 1	3 1 3 1	2 3 1 2
3	1 2 3 3	2 3 2 2	2 1 2 3
.	. . . .	. . . .	. . . .
.	. . . .	. . . .	. . . .
.	. . . .	. . . .	. . . .
.	. . . .	. . . .	. . . .
27	3 3 2 1	3 2 1 2	1 1 3 3

The L^{MN} design now requires just one step, because all three profiles come directly from each row of the fractional factorial design: The first 4 columns become the 4 attributes in profile 1, columns 5-8 describe profile 2 and columns 9-12 describe profile 3. No shifting or mix and match are necessary.

The larger 27 choice set design in this example is typical of L^{MN} designs. This cost buys the benefit of being able to support "mother logit" analysis of cross effect designs described below (caution: this is true only if each choice set includes a "none" or "other" response).

For manual generation of partial profile stimuli a design recipe can be used. Design recipes for profiles with 3 or 5 attributes appear in the Appendix of a 1999 Sawtooth Software Conference paper (Chrzan 1999). A new design recipe for partial profiles with just two attributes, and suitable for telephone survey administration is available upon request.

Randomized Designs

Randomized designs are used in Sawtooth Software's CBC product. A random design reflects the fact that respondents are randomly selected to receive different versions of the choice sets. Those choice sets are created in carefully specified ways. CBC allows the user to select one of four methods of design generation:

1. In Complete Enumeration, profiles are nearly as orthogonal as possible within respondents, and each two-way frequency of level combinations between attributes is equally balanced. Within choice sets, attribute levels are duplicated as little as possible (a property called "minimal overlap"), and in this sense this strategy resembles the shifting strategy described earlier.
2. In Shortcut, profiles for each respondent are constructed using the least often previously used attribute levels for that respondent, subject again to minimal overlap. Each one-way level frequency within attributes is balanced.

3. The Random option uses profiles sampled (randomly, with replacement) from the universe of possible profiles and placed into choice sets. Overlap can and does occur, though no two profiles are permitted within a choice set that are identical on all attributes.
4. Finally, the Balanced Overlap approach is a compromise between Complete Enumeration and Random – it has more overlap than the former and less than the latter.

Please see the CBC documentation for a description of these different kinds of randomized designs (Sawtooth Software 1999). Depending on the extent of overlap, these types of randomized designs are differently able to measure special effects and differently efficient at measuring main effects. It turns out that designs with little or no level overlap within choice sets are good at measuring main effects, while designs with a lot of overlap are good at measuring higher-order effects.

Computer Optimization
Kuhfeld *et al.* (1994) discuss how to use computer search algorithms in SAS/QC to assess thousands or millions of potential designs and then pick the most efficient. The authors find substantial efficiency improvements even in traditional conjoint analysis when those designs are asymmetric (when they have different numbers of levels). Computer optimization enables the researcher to model attributes with large numbers of levels or complex special effects. Huber and Zwerina (1996) add the criterion of utility balance to further improve computer optimization of designs. New SAS macros have been added specifically for generating efficient choice experiment designs (Kuhfeld, 2000). Please refer to these papers for further details.

SPSS™ Trial Run can be used to generate computer optimized designs (SPSS 1997) as can Sawtooth Software's CVA (Kuhfeld 1997). Their design strategies are usually suitable for traditional (one profile at a time) conjoint designs, but their capabilities are limited when it comes to designing choice experiments.

Types of Effects

Before comparing these design strategies, the various types of effects on which they are evaluated require explication.

Generic, plain vanilla, main effects
The basic kind of effect in all types of conjoint studies is the utility of each level of each attribute. Designs that produce only main effects are, not coincidentally, called main effects designs. Each main effect measures the utility of that level, holding everything else constant (at the average combination of other levels used in the study). Traditional conjoint analysis typically produces only main effects.

Interactions
Interactions occur when the combined effect of two attributes is different from the sum of their two main effect utilities. For example, being stranded on a deserted island is pretty bad, say it has a utility of -40. Attending a party hosted by cannibals is also a bad thing,

say with a utility of -50. But, attending a party hosted by cannibals on a deserted island could be altogether worse, in grisly sorts of ways (utility -250). Or again, being naked is a modestly good thing (+3) and speaking at the Sawtooth Software Conference is a +10, but speaking naked at the Sawtooth Software Conference is a -37.

<u>Alternative specific effects</u>
When not all of the alternatives (say brands or technologies) in a choice experiment share exactly the same attributes or levels, the non-shared effects are said to be alternative specific. In the simplest case brands may have different levels, so that brands might range in price between $500 and $1,500, say, while generics range from $300 to $700. But, the more complex case may include alternatives having different levels and even different numbers of levels for an attribute.

The other kind of alternative specific effect allows different alternatives to have different attributes altogether. For example, I can walk to work, drive, or ride the train. All three alternatives have transit time as an alternative. Driving myself has gas cost and parking fees as attributes not shared with the other alternatives. Similarly, taking the train involves a wait time and a ticket fare as unique attributes. Driving, walking and taking the train have some attributes in common and some not. The attributes not shared by all three are alternative specific. The advantage of alternative specific effects is that they obviously allow modeling of a much wider range of choice situations than traditional conjoint analysis which requires all profiles to share the same attributes and levels.

<u>Cross-effects</u>
A vendor sells Coke, Sprite, and Miller Beer in 5:3:2 proportion. What happens if Pepsi becomes available and takes 10 share points? According to the simple logit choice rule, it will draw proportionally from each other alternative, taking 5 points from Coke, 3 from Sprite and 2 from Miller. Common sense, however, says that Pepsi is likely to take more share from Coke and very little indeed from Miller. But the multinomial logit model will not allow this unless you trick it, and the trick is to include what are called cross effects. A cross effect in this example would be a part worth utility that penalizes Coke, Sprite and Miller differently when Pepsi is present, so that Pepsi draws proportionally more share (say 8 points) from Coke, and proportionally less (say 2 and 0 points respectively) from Sprite and Miller. These cross effects are also called availability effects.

Cross effects can be used to permit asymmetric share draws from other attributes besides brand. In a study of personal computers, for example, one might expect asymmetric share draws to affect PC brand, price, microprocessor speed, etc.

<u>Comparisons of Design Strategies</u>

Two comparisons of the above design strategies involve identifying which of the above special effects each design strategy can accommodate and quantifying the statistical efficiency of the various design strategies under different conditions.

The capabilities of the various design strategies are compared in Exhibit 1, where an "X" incidates that that design strategy may be used under various conditions or to estimate certain effects.

Exhibit 1 - Comparison of Capabilities

Design Method

	Full Profile								Partial Profile
Effects	FF Shift	FF Mix &Match	FF L^{MN}	CBC Complete Enum.	CBC Shortcut	CBC Random	CBC Balanced Overlap	Computer Optimiz.	Recipe/CBC
Main Effects only	X	X	X	X	X	X	X	X	X
Interactions		X	X	X	X	X	X	X	?
Prohibitions				X	X	X	X	X	?
Alternative Specific Effects		X	X		X	X		X	?
Cross Effects			X			X		X	
Many attributes									X
Telephone administration									X

We assessed the efficiency of the various design strategies via a series of simulation studies. For each, we created data sets whose respondents (n=300) had mean zero vectors of utilities (random responses). We tested the efficiency of alternative manual, computer optimization and computer randomization (CBC software) design methods in estimating the several types of effects. We estimated parameters using CBC and LOGIT (Steinberg and Colla 1998) software.

Exhibit 2 - Comparison of Relative Efficiencies

Design Method

Effects	FF Shift	FF Mix &Match	FF L^{MN}	CBC Complete Enum.	CBC Shortcut	CBC Random	CBC Balanced Overlap	Computer Optimiz.	Recipe
Main effect FP, symmetric [1]	100%	ni	ni	100%	100%	68%	86%	100%	na
Main effect FP, asymmetric [2]	99%	ni	ni	100%	100%	76%	92%	98%	na
Generic partial profile [3]	na	na	na	na	100%	66%	na	ni	95%
FP, few interactions [4]	ne	90%	ni	94%	94%	90%	97%	100%	na
FP, many interactions [5]	ne	81%	ni	80%	80%	86%	88%	100%	na
FP, prohibitions [6]	ni	ni	ni	100%	67%	90%	93%	96%	na
FP, alternative-specific effects [7]	100%	ni	100%	na	100%	85%	na	ni	na
FP, cross-effects [8]	ne	ne	74%	ne	ne	100%	ne	ni	na

[1] 3^4, 18 choice sets in fixed designs, 18 choice sets per respondent, triples
[2] 5 x 4 x 3 x 2, 25 choice sets in fixed designs, 25 choice sets per respondent, triples
[3] 3^{10}, 60 choice sets in fixed designs, 10 choice sets per respondent, triples
[4] 3^4, 8 interactions, 81 choice sets in fixed designs, 27 choice sets per respondent, triples
[5] 3^4, 16 interactions, 81 choice sets in fixed designs, 27 choice sets per respondent, triples
[6] 3^4, 4 prohibitions, 18 choice sets in fixed designs, 18 choice sets per respondent, triples
[7] 3^4 common effects, A: 3^3 B: 3^2 C: 3^1 alternative specific effects, 27 choice sets in fixed designs, 27 choice sets per respondent, triples
[8] 3^4, 36 cross effects, 27 choice sets in fixed designs, 27 choice sets per respondent, triples
ne = effects not estimable
na = design strategy not available or not applicable
ni = not investigated

Efficiency is a measure of the information content a design can capture. Efficiencies are typically stated in relative terms, as in “design A is 80% as efficient as design B.” In practical terms this means you will need 25% more (the reciprocal of 80%) design A observations (respondents, choice sets per respondent or a combination of both) to get the

same standard errors and significances as with the more efficient design B. We used a measure of efficiency called D-Efficiency (Kuhfeld *et al*. 1994). The procedure for computing the precision of a design and D-efficiency using CBC and SPSS software is explained in the appendix.

The relative efficiencies of the different design strategies appear in Exhibit 2. We have scaled the results for each row relative to the best design investigated being 100% efficient. Many of the designs were inestimable because they were inappropriate for the kind of effects included in the design and these are coded ne (not estimable). Other designs simply cannot be constructed by the method shown in the column – these are na. Finally, some results we did not investigate (ni) for reasons noted below.

For main effects estimation, minimal overlap within choice sets is ideal. For this reason strategies like fractional factorial shifting, work best.

When designs are symmetric, the orthogonal catalog-based designs with a shifting strategy (where each level is available once per choice set) produce optimal designs with respect to main effects, as do CBC Complete Enumeration, CBC Shortcut and SAS and CVA optimization. Other fractional factorial methods we did not investigate because they would be inferior in principle to shifting. With asymmetric designs, however, CBC's strategies (Complete Enumeration and Shortcut) can be slightly more efficient. This finding was shown even more convincingly than our particular example in a 1999 Sawtooth Software Conference paper (Mulhern 1999).

For partial profile designs, only four methods are available and one, SAS optimization, we found difficult to program. Of the three remaining, CBC Shortcut performed best, followed closely by the recipe approach and distantly by CBC Random. This confirms earlier findings (Chrzan 1998).

For situations requiring interactions, computer optimization via SAS produces the most efficient designs. Balanced Overlap is the best of the CBC strategies. Interactions can be inestimable when shifting fractional factorial designs and the L^{MN} approach should be about as efficient as the fractional factorial mix and match approach. A practical advantage of using CBC for interactions designs is that the analyst need not accurately predict which interactions will be needed, as in SAS.

The most efficient designs for alternative-specific attributes are CBC Shortcut and a fractional factorial approach that uses shifting for shared attributes and L^{MN} for alternative-specific attributes. Computer optimization using SAS is possible, but we found it difficult to program.

Especially interesting was how poorly the fractional factorial L^{MN} design fared relative to CBC random for estimating a cross-effects design – only 74% as efficient. It is worth noting that the cross-effect design had only 27 total choice sets. Assigning respondents randomly to designs selected in a random manner with replacement results in a very large pool of different profiles and ways those profiles can be assembled in sets. In the limit, it is a full factorial design, both with respect to profiles and the ways they can be combined (without duplication) into sets. When sample size is sufficient (our example used 300 respondents), the naïve way of composing designs in this situation wins out, which may come as a surprise to those who regularly design studies specifically to model cross effects. Again, optimization with SAS is possible, but requires a steep learning curve.

Interesting, too, was how well CBC's random designs fared almost across the board – for all but the "many" interactions designs, one or more of the four CBC strategies is either optimal or near optimal.

If the researcher wants to prohibit combinations of levels from appearing together within profiles, it is very difficult to do with catalog designs. One simple but arbitrary approach has been to discard or alter choice sets that violate prohibitions. Randomized designs can do this automatically and in a more intelligent way, and as long as the prohibitions are modest, the resulting design is often quite good. In our study CBC Complete Enumeration and computer optimization gave the most efficient prohibitions designs. (However, we've seen other cases in which the Shortcut strategy performed better than

Complete Enumeration for CBC, so we caution the reader that these findings may not generalize to all prohibitions designs.)

Interestingly, some prohibitions can actually improve design efficiency, as we will now demonstrate.

Level Prohibitions and Design Efficiency

Sometimes the analyst or the client wishes to prohibit some attribute levels from combining with others when constructing product alternatives. Prohibiting certain attribute combinations ("prohibitions") leads to level imbalance and dependencies in the design, which popular wisdom holds should decrease design efficiency.

For example, consider a four-attribute choice study on personal computers, each with three levels (3^4 design). Further assume that we prohibit certain combinations between two attributes: Processor Speed and RAM. Each attribute has three levels, and we can characterize a particular pattern of level prohibitions between Processor Speed and RAM using the following two-way frequency grid:

	32 Meg RAM	64 Meg RAM	128 Meg RAM
200 MHZ			
300 MHZ			
400 MHZ	**X**	**X**	

In this example, of the nine possible combinations of Processor Speed and RAM, two (the cells containing an "X") are prohibited. Three-hundred respondents are simulated assuming part worths of 0. Error with a standard deviation of unity is added to the utility of alternatives (3 per task for 18 tasks) prior to simulating choices. The design efficiencies reported below are with respect to main effects only and are indexed with respect to the orthogonal design with no prohibitions:

Complete Enumeration	64.50%
Shortcut	43.10%
Random	57.81%
Balanced Overlap	59.81%
Optimized Search	61.82%

Note that we haven't included an efficiency figure for orthogonal catalog plans. For main effect estimation, orthogonal designs often are not possible in the case of prohibitions. In practice, using optimized search routines is usually the more feasible approach.

We see from this table that the best design efficiency (Complete Enumeration) is only 64.50% as efficient as the design without prohibitions. Prohibitions in this example have lead to a 35.5% decrease in efficiency.

We caution about drawing detailed conclusions from this example, as the pattern and severity of the prohibitions chosen will dramatically alter the results. However, the main points to be made are:

- Prohibitions can have a negative effect upon design efficiency. (In some cases, severe prohibitions can result in inability to measure even main effects.)
- Some design strategies in CBC are better able to handle particular patterns of prohibitions than others. (We suggest testing each strategy through design simulations.)
- Computer search routines can accommodate prohibitions. Orthogonal plans are much more difficult to manage for prohibitions.

Now that we have provided what at the surface may seem to be a convincing argument that prohibitions are damaging, we'll demonstrate that they are not always detrimental. In fact, prohibitions in some situations can actually *improve* design efficiency. The prior example assumed no particular pattern of utilities. Under that assumption, prohibitions are by definition harmful to design efficiency. But in real-world examples, respondents have preferences.

At this point, we should mention another factor that impacts design efficiency: utility balance. Utility balance characterizes the degree to which alternatives in a choice set are similar in preference. Severe imbalance leads to obvious choices that are less valuable for refining utility estimates. Huber and Zwerina (1996) showed that by customizing the designs for each respondent to eliminate choice tasks that had a high degree of imbalance, they were able to generate designs that were about 10-50% more efficient than an unconstrained approach.

Let's again consider the previous example with Processor Speed and RAM. Lets assume that respondents have the following part worth utilities for these levels:

200 MHZ	-1.0	32 Meg RAM	-1.0
400 MHZ	0.0	64 Meg RAM	0.0
500 MHZ	1.0	128 Meg RAM	1.0

The combinations of levels most likely to lead to utility imbalance are 200 MHZ with 32 Meg RAM (-1.0 + -1.0 = -2.0) and 500 MHZ with 128 Meg RAM (1.0 + 1.0 = 2.0). If we prohibit those combinations, the frequency grid (with utilities in parentheses) would look like:

	32 Meg RAM (-1.0)	64 Meg RAM (0.0)	128 Meg RAM (+1.0)
200 MHZ (-1.0)	**X** (-2.0)	(-1.0)	(0.0)
300 MHZ (0.0)	(-1.0)	(0.0)	(1.0)
400 MHZ (+1.0)	(0.0)	(1.0)	**X** (2.0)

If we assume no pattern of preferences (part worths of zero for all levels), such a prohibition would lead to a 13% decrease in design efficiency with respect to main-effects estimation, relative to the orthogonal design with no prohibitions. But, if we assume part worth utilities of 1, 0, -1, the pattern of prohibitions above leads to a 22% *gain* in efficiency relative to the orthogonal design with no prohibitions. Note that this strategy (prohibiting certain combinations for all respondents) works well if the attributes have a rational *a priori* preference order, such as is the case for Processor Speed and RAM. Otherwise, a more complex, customized design strategy might be developed for each respondent, as illustrated by Huber and Zwerina.

Often, prohibitions are dictated by the client. With respect to Processor Speed and RAM, it is more likely that the client would state that it is highly unlikely that a 200 MHZ processor would be offered with 128 Meg RAM, or that a 400 MHZ processor would be offered with 32 Meg RAM. Let's examine those prohibitions:

	32 Meg RAM (-1.0)	64 Meg RAM (0.0)	128 Meg RAM (+1.0)
200 MHZ (-1.0)	(-2.0)	(-1.0)	**X** (0.0)
300 MHZ (0.0)	(-1.0)	(0.0)	(1.0)
400 MHZ (+1.0)	**X** (0.0)	(1.0)	(2.0)

Note that these prohibitions have discarded the combinations with the best utility balance and retained those combinations leading to the least utility balance. The net loss in design efficiency for this combination of prohibitions relative to the orthogonal design with no prohibitions is –34%.

The main points to be made are:

- For attributes with *a priori* preference order, prohibitions that lead to utility balance can enhance the efficiency of main-effect estimation.
- The prohibitions that clients often suggest (to make product alternatives more realistic) can be very detrimental to design efficiency.

We should note that the utility-balancing strategies above for prohibitions probably should not be implemented for price attributes. A conditional pricing strategy can lead to improved utility balance without specifying any prohibitions. The equivalent of having alternative-specific prices, conditional pricing, in CBC involves the use of a "look-up" table. Price levels are defined in terms of percentage deviations from an average price. If a premium product alternative is displayed in a task, the look-up function references a correspondingly higher price range relative to average or discount product alternatives. We won't take time in this paper to elaborate on this technique, as the details are available in Sawtooth Software's CBC manual.

Conclusion

There are several different approaches to designing choice-based conjoint experiments and several kinds of effects one might want to model and quantify in such experiments. The approaches differ in terms of which effects they can capture and in how efficiently they do so. No one design approach is clearly superior in all circumstances, but the capabilities comparison and the efficiency comparisons give the practitioner a good idea of when to use which type of design.

Researchers with good data processing skills and access to software such as CBC and SPSS can simulate respondent data and compute design efficiency prior to actual data collection. We recommend that reasonable *a priori* utilities be used when simulating respondent answers, and that a variety of design strategies be tested. The simulation results we report here can serve as a guide for choosing candidate design strategies.

Appendix

Computing D-Efficiency using CBC and SPSS™ Software

1) Compute a set of logit utilities using CBC software. Under the advanced settings, make sure to specify that you want the report to include the covariance matrix.

2) Use SPSS software to compute the relative precision of the design. An example of SPSS matrix command language to do this follows, for a small covariance matrix for 4 estimated parameters. Paste the covariance matrix from the logit report into the syntax between the brackets, and add the appropriate commas and semicolons.

```
MATRIX.
COMPUTE covm={
  0.000246914 , -0.000123457 , -0.000000000 , -0.000000000 ;
 -0.000123457 ,  0.000246914 , -0.000000000 , -0.000000000 ;
 -0.000000000 , -0.000000000 ,  0.000246914 , -0.000123457 ;
 -0.000000000 , -0.000000000 , -0.000123457 ,  0.000246914
}.
COMPUTE fpeff=DET(covm).
COMPUTE deffic=fpeff**(-1/4).
PRINT deffic.
END MATRIX.
```

Note that this procedure reads the covariance matrix into a matrix variable called "covm". The determinant of that matrix is saved to a variable called "fpeff." The precision of the design is computed as fpeff raised to the -1/4 power (the negative of the reciprocal of the number of rows in the covariance matrix). In another example with 24 estimated parameters, the inverse of the covariance matrix should be raised to the -1/24 power. The precision is printed.

The resulting output is as follows:

```
Run MATRIX procedure:

DEFFIC
   4676.529230

----- END MATRIX -----
```

This needs to be done for two designs, a test design and a reference design. The ratio of the precision of the test design to that of the reference design is the relative D-efficiency of the test design (Bunch *et al.* 1994).

References

Addelman, Sidney (1962) "Orthogonal Main Effects Plans for Asymmetrical Factorial Experiments," *Technometrics* **4,** 21-46.

Anderson, Donald A. and James B. Wiley (1992) "Efficient Choice Set Designs for Estimating Availability Cross-Effect Designs," *Marketing Letters* **3**, 357-70.

Bunch, David S., Jordan J. Louviere and Don Anderson (1994) "A Comparison of Experimental Design Strategies for Multinomial Logit Models: The Case of Generic Attributes." Working paper UCD-GSM-WP# 01-94. Graduate School of Management, University of California, Davis.

Chrzan, Keith and Terry Elrod (1995) "Partial Profile Choice Experiments: A Choice-Based Approach for Handling Large Numbers of Attributes," *1995 Advanced Research Techniques Conference Proceedings*. Chicago: American Marketing Association (in press).

Chrzan, Keith (1998) "Design Efficiency of Partial Profile Choice Experiments," paper presented at the INFORMS Marketing Science Conference, Paris.

Chrzan Keith and Michael Patterson (1999) "Full Versus Partial Profile Choice Experiments: Aggregate and Disaggregate Comparisons," *Sawtooth Software Conference Proceedings*, 235-48.

Huber, Joel and Klaus B. Zwerina (1996) "The Importance of Utility Balance in Efficient Choice Designs," *Journal of Marketing Research* **33** (August), 307-17.

Kuhfeld, Warren F. (2000) *Marketing Research Methods in the SAS System, Version 8 Edition*, SAS Institute.

Kuhfeld, Warren, Randal D. Tobias and Mark Garratt (1995) "Efficient Experimental Designs with Marketing Research Applications," *Journal of Marketing Research* **31** (November), 545-57.

Kuhfeld, Warren, (1997) "Efficient Experimental Designs Using Computerized Searches," *Sawtooth Software Conference Proceedings*, 71-86.

Lazari, Andreas G. and Donald A. Anderson (1994) "Designs of Discrete Choice Set Experiments for Estimating Both Attribute and Availability Cross Effects," *Journal of Marketing Research* **31**, 375-83.

Louviere, Jordan J. (1988) "Analyzing Decision Making: Metric Conjoint Analysis" Sage University Paper Series on Quantitative Applications in the Social Sciences, 07-

67. Beverly Hills: Sage.

Louviere, Jordan J. and George Woodworth (1983) "Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data," *Journal of Marketing Research,* **20** (November) pp. 350-67.

Mulhern, Mike (1999) "Assessing the Relative Efficiency of Fixed and Randomized Experimental Designs," *Sawtooth Software Conference Proceedings*, 225-32.

Sawtooth Software, Inc. (1999), *CBC User Manual*, Sequim: Sawtooth Software.

Sawtooth Software, Inc. (1999), *The CBC/HB Module*, Sequim: Sawtooth Software.

SPSS (1997) *Trial Run*. Chicago: SPSS.

Steinberg, Dan and Phillip Colla (1998) *LOGIT: A Supplementary Module by Salford Systems*, San Diego: Salford Systems.