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RESEARCH PAPER SERIES

Perceptual Choice Experiments: Enhancing CBC to Get from Which to Why

Bryan Orme
Sawtooth Software, Inc.

1457 E 840 N Orem, Utah
+1 801 477 4700
www.sawtoothsoftware.com

Perceptual Choice Experiments:
Enhancing CBC to Get from Which to Why

Bryan Orme, Sawtooth Software, Inc.

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Introduction:

CBC (Choice-Based Conjoint) choice simulators predict share of choice for product concepts within competitive market scenarios, but they provide no insights into perceptions—the *why's* behind the choice. We introduce *Perceptual Choice Experiments* as an extension of CBC questionnaires for integrating diagnostic perceptual dimensions into CBC analysis and simulators. With Perceptual Choice Experiments pick-any agreement questions (on perceptual dimensions) are the dependent variables and traditional conjoint attributes (using standard CBC experimental designs) are the independent variables. The perceptual questions may be added beneath traditional CBC questions, or may be done as separate series of questions.

For years, researchers have investigated perceptual dimensions via additional batteries of brand by attribute questions, such as "How much do you agree or disagree that <Honda> is <A Safe Vehicle to Drive>?" Such sequences often measure two or more brands on several dimensions. The data may be analyzed via tables of means (with means often displayed graphically via line charts or heat maps) or perceptual maps (e.g. correspondence analysis, discriminant analysis, biplot). However, these approaches focus only on brand perceptions. Aspects other than brand make up a product offering. Those additional non-brand attributes certainly affect perceptions, attitudes, influence usage occasions, and resonate with motivations.

Perceptual Choice Experiments add pick-any agreement questions to the CBC questionnaire. Given the data, we estimate weights for the conjoint attribute levels (brands as well as levels of other attributes) to predict for any product concept the likelihood that respondents would agree that it is described by different perceptual/motivational dimensions. Using those weights, the researcher can specify a product concept within a choice simulator (e.g. Honda, hybrid engine, all-wheel drive, 2-doors, $35,000) and predict the likelihood that respondents would agree that this particular Honda specification is *A Safe Vehicle to Drive*, *Good for the Environment*, *A Good Value for the Money*, *A Car I Want to Be Seen in*, etc. A simulator enhanced with such data not only does the standard work of predicting *which* products respondents prefer (share of choice, see Exhibit 1), but also provides insights into *why* they prefer each one (see Exhibit 2)[1]. Given such a tool, the researcher could conduct sensitivity analysis (for a given product concept in the simulator, holding the competitive concepts constant, changing each conjoint attribute level-by-level) to see how each attribute level contributes to perceptions on the diagnostic dimensions.

[1] Fictitious data for illustration only presented in Exhibits 1 & 2.

Exhibit 1: A Standard Market Simulator Interface and Output

Product Specifications:

	Brand:	Engine:	Drive:	Doors:	Price:
Product 1:	Honda	Hybrid	All-Wheel	2-door	$35,000
Product 2:	Ford	Standard	Front-Wheel	4-door	$30,000
Product 3:	Toyota	Hybrid	Front-Wheel	4-door	$28,000

Resulting Shares of Preference:

Product 1:	25%
Product 2:	20%
Product 3	55%

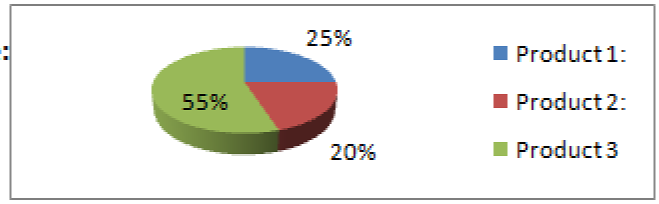
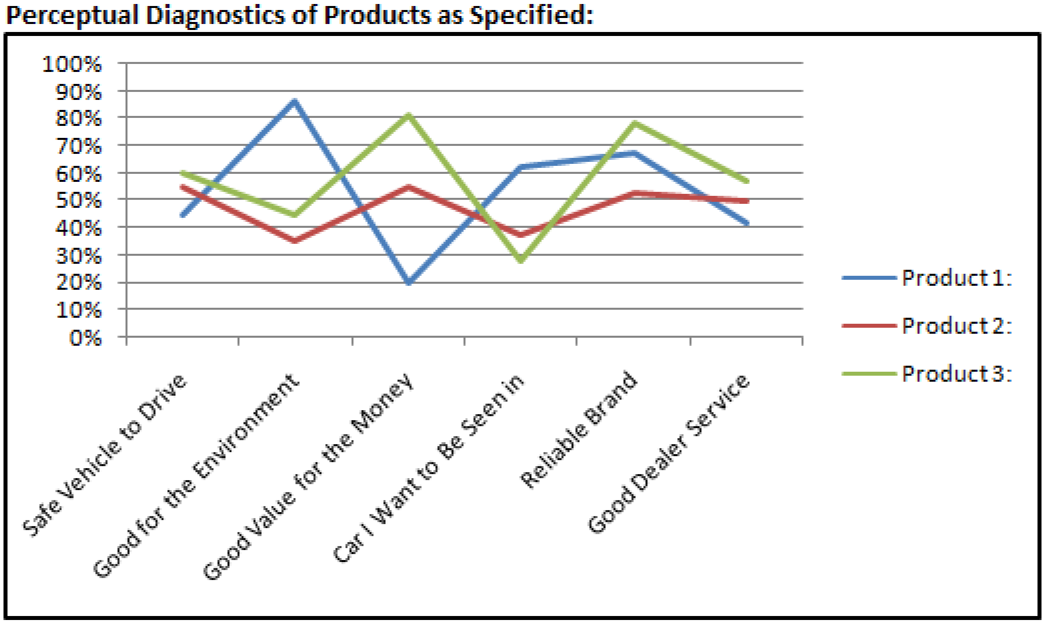


Exhibit 2: Additional Perceptual Diagnostic Output

Product Specifications:

	Brand:	Engine:	Drive:	Doors:	Price:
Product 1:	Honda	Hybrid	All-Wheel	2-door	$35,000
Product 2:	Ford	Standard	Front-Wheel	4-door	$30,000
Product 3:	Toyota	Hybrid	Front-Wheel	4-door	$28,000

Perceptual Diagnostics of Products as Specified:



Questionnaire Appearance:

To extend CBC for Perceptual Choice Experiments, we recommend asking additional follow-up perceptual questions beneath Best-Worst (BW) CBC questions (Exhibit 3).

Exhibit 3: Questionnaire Appearance

	Which of the following would you be most and least likely to purchase?		
	Product A:	Product B:	Product C:
	Brand C Red Package Style 1 Performance Level 3 Price Level 2	Brand A Green Package Style 3 Performance Level 1 Price Level 3	Brand B Yellow Package Style 2 Performance Level 2 Price Level 1
Most Likely to Buy:	○	○	○
Least Likely to Buy:	○	○	○

Which of the following descriptions describe or apply to these products above?

	Product A:	Product B:	Product C:
Statement 8:	❑	❑	❑
Statement 2:	❑	❑	❑
Statement 5:	❑	❑	❑
	❑ None describe Package A	❑ None describe Package B	❑ None describe Package C

The perceptual items shown at the bottom left of Exhibit 3 are randomized and a subset (for example, three items) are shown in each task. To facilitate this, one could use SSI Web's randomized lists capability—or better yet, an experimental plan generated by Sawtooth Software's MaxDiff designer. Showing a subset of the items avoids the burden of too many statements to consider each time (which could bias the selection rate of associations downward). It also makes it possible (with very large sample sizes) to include a long list of perceptual statements without overwhelming any one respondent.

The perceptual statements could be claims, occasions, motivations, perceptual adjectives, etc. developed based on the researcher's expertise as well as upfront qualitative research. Examples:

- A good value
- A product I'd use on the weekends
- Something my mother would buy
- A product I'd tell my friends I was using
- Modern

Analysis of Perceptions:

The perceptual choice experiment as displayed in Exhibit 3 leverages the attribute list and experimental design of a standard CBC and involves a pick-any association task for a list of perceptual items. For the CBC portion of the task, we may estimate part-worth utilities via HB, leading to the usual market simulator that predicts choice probabilities for product concepts in competitive scenarios.

For the perceptual pick-any questions, the data are typically too sparse at the individual level to use HB. Thus, we suggest employing aggregate logit analysis for each of the perceptual items (a separate binary logit model per item). The conjoint attributes serve as independent variables (effects- or dummy-coded), plus an additional constant to capture the utility of the "not selected" alternative (equivalent to the "None" in CBC). For each perceptual item, the dependent variable is the choice of the item or not (binary logit setup, with two alternatives per choice task). With large enough sample size, interaction effects could be specified. As an example of an interaction effect, a vacation package might be viewed as *a good value* only if it had a low cost per person together with a longer duration in terms of number of nights.

The market simulator may be built in Excel, with shares of choice estimated as usual using the CBC part-worths and the additive, logit rule (or other variants such as RFC). For each product concept in the simulator, we may also use the logit rule (with the part-worth perceptions estimated from a series of independent binary logit models predicting the choice of diagnostic perceptual statements) to predict the percent of respondents who would check the box for each perceptual item about that specific product. Those results could be shown as a Line Chart (Exhibit 4) or as a Heat Map (Exhibit 5).

Exhibit 4: Line Chart for Diagnostics/Perceptions

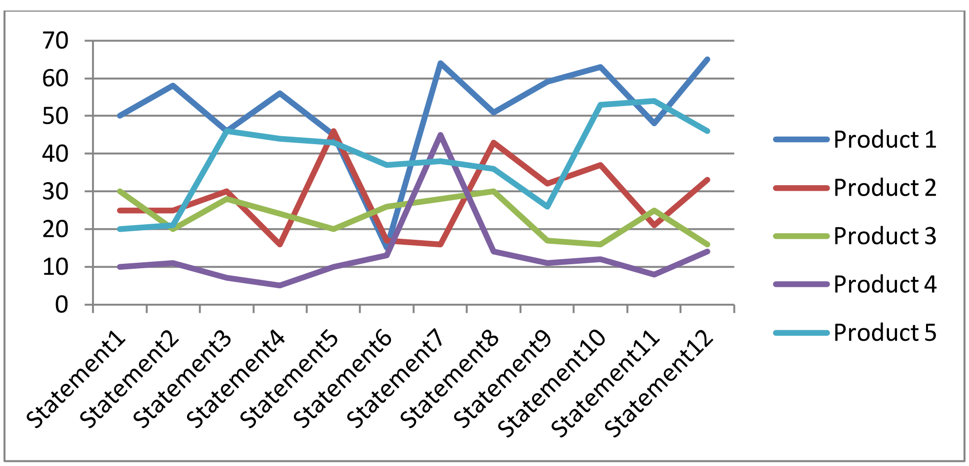
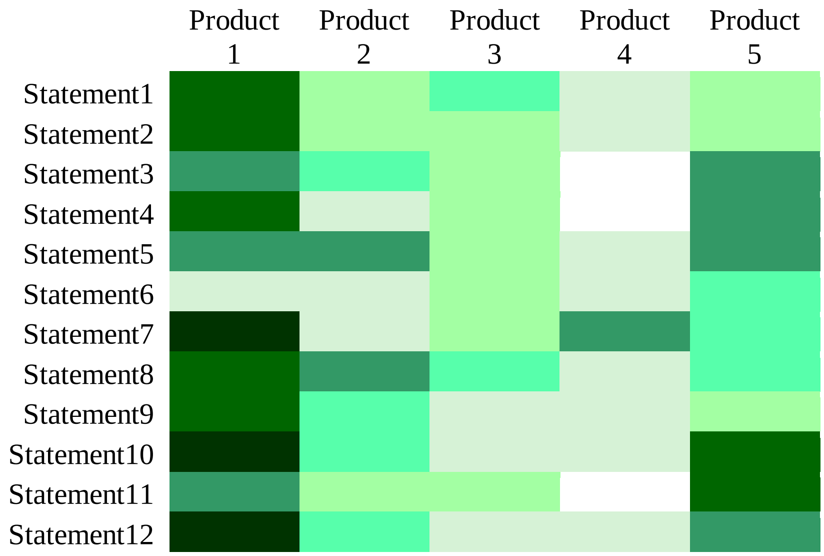


Exhibit 5: Heat Map for Diagnostics/Perceptions



Some perceptual statements may have low correlation with product choice (see explanation in the next section). These could be dropped from the charts. The significant statements can be sorted from most impact to least impact for presentation. For better visualization with the heat map, we could emphasize the importance of each statement by making its row (or column) height proportional to importance.

Aggregate analysis cannot reveal the different perceptions of heterogeneous groups, so researchers may decide to conduct the analysis by segments.

Sample Size Considerations

One may wonder about sample size requirements to stabilize models where conjoint attributes predict choice of perceptual statements. Following Rich Johnson's logic and recommendations for aggregate CBC models (Johnson and Orme, 2003) we might recommend that each level of each attribute appear with each perceptual item at minimum 500 times and preferably 1000 times across all respondents x choice tasks. Some algebra allows us to solve for the suggested sample size according to this simple rule-of-thumb:

C = Largest number of levels for any one conjoint attribute
D = Number of perceptual diagnostic items
A = Number of alternatives per CBC task
T = Number of CBC tasks
F = Number of perceptual items shown per CBC task

$$\text{Minimum } N = 500CD / ATF$$
$$\text{Preferred } N = 1000CD / ATF$$

Consider a study with the largest number of levels for any one conjoint attribute being 5 (C), 12 perceptual diagnostic items (D), 3 alternatives per CBC task (A), 8 CBC tasks (T), and 3 perceptual items shown per CBC task (F). Solving for N, Johnson's rule-of-thumb suggests a minimum sample size of 417 respondents and a preferred sample size of 833.

Determinance Scores for Perceptual Items

Exhibits 4 and 5 show predicted perceptual item scores (percent of respondents that agree) for products specified in the choice simulator, but they don't tell us which items are positively associated[2] with product choice. Alpert (1971) referred to these as *determinant attributes*. Determinant attributes are those that the buyer perceives as differing among product offerings and that positively influence preference. For example, *A safe airline to fly* is certainly important to respondents; but if buyers don't perceive any difference among airlines on safety, then it cannot be a determinant attribute since it alone will not influence choice among airlines.

One could perform a simple counting analysis to compute determinance scores for each perceptual statement (reflecting positive association with product choice). Recall that the respondent clicks which statements she associates with each product concept. Sometimes the checked perceptual statements are associated with concepts chosen as *best* and other times with concepts indicated as *worst* (from the B/W CBC task directly above the perceptual grid)[3]. If we find that *best* product choices are often associated with a certain perceptual statement but *worst* choices are rarely associated with the same statement, then we might conclude that this perceptual statement is somehow related to choice. For each perceptual item, we can compute a summary determinance score by taking the %Best - %Worst; or, alternatively, %Best / %Worst, where the two scores are computed as follows:

Only considering the association data for <u>Best</u> concepts for item i:
$\%Best_i = \#Times\_Picked_i / \#Times\_Available\_to\_be\_Picked_i$

Only considering the association data for <u>Worst</u> concepts for item i:
$\%Worst_i = \#Times\_Picked_i / \#Times\_Available\_to\_be\_Picked_i$

Rather than using counting, a straightforward logit modeling approach[4] for computing determinance scores yields standard errors for performing t-tests of significance and computing confidence intervals. Aggregate logit, latent class, or disaggregate HB logit analysis could be used. The model follows the best/worst pattern suggested first by Louviere and also used within Sawtooth Software's popular MaxDiff

[2] We stop short of referring to these as "drivers of choice" since this would imply causality.

[3] Although our example uses B/W CBC questions, determinance analysis (by either counting or soon-to-be-described logit) can be conducted with standard best-only CBC.

[4] Many readers will recognize that the determinance modeling approach we present here is just a best/worst, univariate (single variable at a time) variation of the kind of derived importance regressions that have been used already for decades in market research. Researchers have commonly used ratings (or choices) of brands on perceptual statements to predict past brand choice, future intentions, or other brand preference ratings. A weakness of most of these approaches (including the determinance score estimation we present here) is the tendency to achieve significant parameters due to the halo effect.

analysis, as shown in Exhibit 6. For each concept x perceptual statement seen by the respondent, the task is coded for a binary logit model (in Exhibit 6, *IV* refers to an Independent Variable, *DV* refers to a Dependent Variable).

Exhibit 6: Coding for Estimating Attribute Determinance

	IV	DV	
Task1	1	1	(Perceptual item was selected for a "Best" concept)
	0	0	
Task2	1	0	(Perceptual item was not selected for a "Best" concept)
	0	1	
Task3	-1	1	(Perceptual item was selected for a "Worst" concept)
	0	0	
Task4	-1	0	(Perceptual item was not selected for a "Worst" concept)
	0	1	

For ease of interpretation, we may convert the estimated logit utility scores to a scale reflecting the difference between the likelihood of association with best choices less worst choices using the transform: $\text{Exp}(U_i)/[\text{Exp}(U_i)+1] - \text{Exp}(-U_i)/[\text{Exp}(-U_i)+1]$. Alternatively, one could covert to an odds ratio scale: $\text{Exp}(U_i)/[\text{Exp}(U_i)+1]\ /\ \text{Exp}(-U_i)/[\text{Exp}(-U_i)+1]$.

Notes:

1. We assume that choices of "Best" or "Worst" concepts are influenced by the same latent dimension of attribute determinance.
2. This measure of determinance has the desirable quality of being a derived versus an overtly stated measure, meaning that it should mitigate common problems with stated measures such as social desirability and acquiescence bias.
3. If a perceptual item has at most a relatively low association with all product concepts (i.e. at most 10% agree that the product alternative is associated with a perceptual attribute, irrespective of the product composition), the researcher might decide to drop the item from the perceptual choice simulator, even if the determinance coefficient is statistically significant.

Past Research Integrating Perceptions and Conjoint Data

At the 1989 Sawtooth Software Conference, Harla Hutchinson delivered a paper entitled, "Gaining a Competitive Advantage by Combining Perceptual Mapping and Conjoint Analysis." Within, she described efforts to leverage both part-worth utilities on hard conjoint attributes (for automobiles) with how respondent's perceived that the different automobile makes were positioned on softer attributes. Some of the softer attributes, while described using discrete levels of conjoint attributes, still involved a perceptual aspect, such as amount of *backseat legroom* in cars. The effort involved assigning part-worth utilities to product concepts within a choice simulator based on the conjoint attribute levels and also by assigning part-worth utilities based on perceived (rather than actual) attribute levels by respondents (even if those perceptions differed with reality, on such attributes such as *backseat legroom*, for instance).

Regarding this effort, the author of this paper (Orme) wrote in 2003:

> "Combining perceptual information and preference part worths is not new. My colleagues Rich Johnson and Chris King developed choice simulators that used part worths mapped to each respondent's perceptions of brand performance quite a bit when at John Morton Company in the late 70s and early 80s. One of their colleagues, Harla Hutchinson, delivered a paper on this topic in the 1989 Sawtooth Software Conference entitled 'Gaining a Competitive Advantage by Combining Perceptual Mapping and Conjoint Analysis.'"
>
> "Based on conversations with Rich and Chris, combining perceptual information and preference part worths was not without problems. The perceptual information often seemed to dominate the overall sensitivity of the simulator. And, working with a model in which attributes did not necessarily have specific objective meaning, but that were mapped to subjective perceptions for each individual, made it difficult to assess how concrete changes to product specifications might affect demand." (Orme, 2003)

At the 2003 Sawtooth Software Conference, Larry Gibson described a related approach of Eric Marder Associates called the SUMM method. Like the effort described in Hutchinson 1989, their method leveraged respondents' subjective perceptions of the alternatives on the various attributes. Preferences (a self-explicated method using an unbounded scale) were then combined with the respondents' idiosyncratic perceptions of alternatives on the various features to produce an integrated choice simulator.

At the 1997 Sawtooth Software Conference, Tom Pilon demonstrated how to create MDS perceptual maps based on perceived similarities among brands or SKUs for FMCG categories, such as beverages. Pilon's proxy for similarity was price cross-elasticity coefficients from CBC experiments involving brands and prices. A drawback of the approach was that the perceptual maps only had brand positions—no attribute information was shown. Thus, the researcher was left to interpret what the dimensions meant on the map (i.e. the y-axis might separate the beverages that are fruity from the colas; the x-axis might separate premium brands from the store brands).

At the 1999 Sawtooth Software Conference, Rich Johnson presented an extension of perceptual mapping called Composite Product Mapping (Johnson 1999). The technique combined the standard brand x attribute perceptual ratings with preference information on the brands (from either chip-allocation or conjoint part-worths on the brands). The perceptual space was developed to emphasize attributes that not only discriminated on brand perceptions, but also on brand preferences. Johnson overlaid contours of preference on the perceptual map, showing how areas of the map were associated with higher relative preference.

Ray Poynter presented a paper at the 1999 Sawtooth Software Conference that inspired the title of this current work. Ray described a qualitative approach for playing back on the computer screen the conjoint survey that a respondent had just completed while having an in-person human interviewer ask respondents open-ended questions to probe why they chose the concepts they did.

At the 2003 Sawtooth Software Conference, Marco Vriens and Curtis Frazier modeled the brand part-worth as a function of perceptual dimensions. Their choice simulator allowed managers not only to specify products within scenarios on the hard conjoint attributes and predict shares of preference, but to see how changes to perceptions of the brand name could also affect product choice. Frazier and co-authors updated the approach in a follow-up paper (Frazier *et al*. 2006).

Yet another effort by Glerum *et al*. (2014) employed semi open-end questions, where respondents were asked to supply several adjectives to describe, for example, transportation modes. These open-end responses were coded by human researchers (evaluators) into a manageable number of pre-coded categories and then used as explanatory variables of revealed choice (the modes of transportation actually used by respondents). Specifically, the authors examined the impact of *perception of comfort of public transportation* on choice. A major challenge to overcome was reconciling how different evaluators related the adjectives to the latent construct.

To summarize the reviewed works, the Pilon, Vriens & Frazier, Johnson, and Glerum *et al*. approaches created associations between soft attribute perceptions and brand, SKU, or transportation mode preference. The Hutchinson and Gibson efforts elicited respondents' perceptions for brands (or vehicle makes) on each of multiple hard or soft attributes. However, what distinguishes our approach is the following, 1) we do not employ self-explicated ratings of brands on the product attributes individually; we use pick-any association data related to experimentally designed full-profile product concepts, 2) our approach predicts how respondents would perceive a given full-profile product concept given its brand and other conjoint attribute levels, not how people's product choices would be influenced based on changes to their perceptions of characteristics associated with the products. Of all the works cited here, the Poynter effort seems most similar to ours in spirit; though our implementation is quite different, since we perform a quantitative analysis on a pre-specified list of perceptual attributes to uncover the why's behind product choice as opposed to the open-end qualitative approach he did.

Pilot and Empirical Tests: Vacation Package Choices

We initially conducted a pilot test in June, 2014 among a convenience sample of n=51 using *single-concept presentation* (described in Appendix A). While it appeared to work and the data had good face validity, we quickly thought of yet another approach that we call the *grid-style presentation* (Exhibit 7). In September, 2014 we conducted a rigorous split-sample methodological test to compare these approaches using 627 respondents from SSI's online panel (many thanks to Survey Sampling International for supporting this research!). We report details of that experiment in Appendix A, the conclusion being that the grid-style approach worked better.

Exhibit 7: The Grid-Style Approach for Perceptual Choice Experiments

If these were your only choices for vacation packages, which would be the Best and Worst options?

* (Price shown is per person based on double occupancy and includes airfare, breakfast each day, & hotel taxes.)

(1 of 8)

	Package A	Package B	Package C
Destination:	San Francisco, CA	Washington, DC	Las Vegas, NV
Number of Nights:	5 nights	3 nights	7 nights
Accommodation:	Luxury (5 star hotel)	Upscale (3 star hotel)	Deluxe (4 star hotel)
Hotel Type:	Boutique (with distinct style/character)	Resort (usually with spa, golf, etc.)	Resort (usually with spa, golf, etc.)
Car Rental:	Full-Size/SUV car rental	None included	Compact car rental
*** Price (per person):**	$1,380	$810	$1,500
Best:			
Worst:			

Which of the following descriptions describe or apply to these vacation packages?
(For each vacation package, select all that apply)

	Package A	Package B	Package C
Will create memories to last a lifetime			
Too expensive			
Good weather			
	None describe Package A	None describe Package B	None describe Package C

Our September 2014 methodological experiment involved the following conjoint attribute characteristics of different vacation packages for domestic travel within the United States (Exhibit 8).

Exhibit 8: Conjoint Attribute List for Vacation Package Choice

1) Destination:
   Las Vegas, NV
   Orlando, FL
   Anaheim, CA
   San Francisco, CA
   Chicago, IL
   New York, NY
   Washington, DC

2) Number of Nights:
   3 nights
   5 nights
   7 nights

3) Accommodation:
   Moderate (2 star hotel)
   Upscale (3 star hotel)
   Deluxe (4 star hotel)
   Luxury (5 star hotel)

4) Hotel Type:
   Business (with meeting/business services)
   Resort (usually with spa, golf, etc.)
   Boutique (with distinct style/character)

5) Car Rental:
   None included
   Compact car rental
   Full-Size/SUV car rental

6) Price (per person):
   $650 to $1,800 depending on number of nights.

	Low Price	Medium Price	High Price
3 nights	$650	$810	$970
5 nights	$920	$1,150	$1,380
7 nights	$1,190	$1,500	$1,800

For the perceptual choice experiment design, we used the following list of perceptual diagnostic statements (Exhibit 9).

Exhibit 9: Perceptual Items:

A trip I'd like to take kids on
A great summer vacation
A great winter vacation
I'd feel very safe in this city
Good weather
Too expensive
Fun
I'd feel pampered
Will create memories to last a lifetime
Relaxing time
Educates and expands horizons
A romantic vacation

We analyzed the upper (CBC) portion of the choice task (see Exhibit 7) using the standard CBC/HB approach as supported by Sawtooth Software's SSI Web software system. In addition, we estimated determinance coefficients for each of the 12 perceptual statements as described earlier (Exhibit 6) using 12 separate univariate, binary aggregate logit models[5].

Exhibit 10 displays the raw determinance coefficients for the statements (sorted in terms of absolute magnitude) for the third of the sample (n=218) that completed the grid-style version of the perceptual choice experiment questionnaire.

Exhibit 10: Determinance Coefficients

	Beta	Std Err.	T-Ratio
Fun	0.82	0.075	10.9
Creates memories	0.73	0.073	9.9
Great summer vacation	0.69	0.073	9.4
Relaxing	0.62	0.072	8.6
I'd feel pampered	0.53	0.071	7.5
Too expensive	-0.49	0.071	-7.0
Good weather	0.47	0.071	6.7
Educates	0.40	0.070	5.8
Romantic	0.40	0.070	5.8
Take kids on	0.36	0.070	5.1
Feel safe	0.34	0.070	4.9
Great winter vacation	0.26	0.069	3.8

The perceptual dimension *Fun* is the most determinant item, meaning that it was most highly related to product choice. Using the formula we earlier introduced, we can compute the difference in choice likelihood between product concepts that respondents perceived as *Fun* versus those not perceived as *Fun*:

$$\text{Exp}(0.82)/[\text{Exp}(0.82)+1] - \text{Exp}(-0.82)/[\text{Exp}(-0.82)+1] = 0.3885$$

When a concept was viewed as *Fun*, its choice probability for the sample was 38.85% higher (in absolute magnitude) than a concept not viewed as *Fun*. Expressed as an odds ratio…

$$\text{Exp}(0.82)/[\text{Exp}(0.82)+1] \,/\, \text{Exp}(-0.82)/[\text{Exp}(-0.82)+1] = 2.2705$$

…concepts associated with *Fun* are 2.27 times more likely to be chosen than those not viewed as *Fun*.

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[5] It should be noted that the separate models could be formulated as a single multivariate logit model. This could be a useful approach if using latent class analysis to develop market segments of respondents who share similar motivations and perceptions as related to choice. Extending this idea, the CBC data could also be integrated within this same choice model for an integrated latent class model of choice involving conjoint utilities and diagnostic betas (but not without the problems of mixing two choice contexts with different response error rates). An alternative that avoid this problem is to use the segment membership assignments from separate latent class runs on determinance scores and CBC utilities within Cluster Ensemble analysis (e.g. CCEA software)

The least determinant item was *Great Winter Vacation*. Following the same formulas, respondents chose concepts marked as a *Great Winter Vacation* with a 12.93% higher absolute probability (or as an odds ratio, selected 1.30 times as often) as those not perceived as a *Great Winter Vacation*.

Perceptual Choice Experiment Modeling

The key trick with perceptual choice experiments is building aggregate logit models[6] relating the conjoint attribute levels to choice of the perceptual items (one binary logit model per perceptual item). In Exhibit 11, we show results for just three of the perceptual statements (with significant attributes bolded). These models are in reality each discrete choice conjoint experiments, except that the dependent variable is perceptual association rather than product choice. As with standard conjoint output, the part-worths may only be compared *within* attributes.

In terms of the item, *A Romantic Vacation*, Orlando, Anaheim, and Chicago score relatively lower than Las Vegas, San Francisco or New York. Respondents find a resort-style or boutique hotel more romantic than a business style hotel. Regarding the statement *I'd Feel Pampered,* spending either 5 or 7 nights at a 3-star or higher quality hotel—especially a resort type hotel—is more associated with that perception. However, longer trips (5 and 7 nights) are also positively associated with the perception of *Too Expensive*. But (holding price constant) the perception of being too expensive can be lowered by the vacation package including an upscale hotel or a Full-Size/SUV car rental.

Exhibit 11: Logit Coefficients as Predictors of Perceptions (3 of 12 statements, for illustration)
(First Level of Each Attribute Constrained to Zero via Dummy Coding)

	Romantic	Pampered	Too Expensive
Las Vegas, NV	**0.00**	**0.00**	0.00
Orlando, FL	**-0.71**	**-0.12**	0.09
Anaheim, CA	**-0.85**	**-0.54**	0.04
San Francisco, CA	**0.41**	**-0.14**	-0.14
Chicago, IL	**-0.81**	**-0.14**	0.22
New York, NY	**0.20**	**-0.23**	-0.15
Washington, DC	**-0.56**	**-0.22**	-0.33
3 nights	0.00	**0.00**	**0.00**
5 nights	-0.26	**0.46**	**0.98**
7 nights	-0.23	**0.41**	**1.68**
Moderate (2 star hotel)	0.00	**0.00**	**0.00**
Upscale (3 star hotel)	0.30	**0.55**	**-0.41**

[6] Each model potentially could use all conjoint attribute levels as predictors of perceptual item choice. With certain perceptual items, however, some conjoint attributes made no logical sense as predictors, so we excluded them from the model. For example, regarding association with *Safe City*, conjoint attributes such as Hotel Type, Car Rental, and Vacation package Price are excluded from the model.

Deluxe (4 star hotel)	0.21	**0.89**	**-0.48**
Luxury (5 star hotel)	0.32	**1.13**	**-0.62**
Business (with meeting/business	**0.00**	**0.00**	0.00
Resort (usually with spa, golf, etc.)	**0.53**	**1.03**	-0.17
Boutique (with distinct style/character)	**0.30**	**0.52**	-0.24
None included	0.00	0.00	**0.00**
Compact car rental	0.08	0.05	**-0.15**
Full-Size/SUV car rental	-0.16	0.14	**-0.32**
Low Price	0.00	0.00	**0.00**
Med Price	0.07	0.30	**0.73**
High Price	0.02	-0.22	**1.16**
Alternative Specific Constant:	-1.02	-2.29	-1.81

Given these utility scores, we can predict the percent of agreement that any vacation package (described using one attribute level from each attribute) would be associated with each of the perceptual statements. Consider the *Romantic* perceptual statement. Referring to the utilities in Exhibit 11, the percent of respondents that would agree that [Orlando, 3 nights, Luxury (5 star hotel), Resort (usually with spa, golf, etc.), Compact car rental, Med Price] was a romantic vacation package is:

Orlando	-0.71
3 nights	0.00
Luxury (5 star hotel)	0.32
Resort (usually with spa…)	0.53
Compact car rental	0.08
Med Price	0.07
Alternative Specific Constant	-1.02
Sum:	-0.73

[7]Probability agree this package is "Romantic" = Exp(-0.73) / [Exp(-0.73) + Exp(0)] = 32.5%

Though not shown in Exhibit 11, the standard errors associated with conjoint attribute levels predicting the perceptual statements range from about 0.14 (for 3-level attributes) to 0.28 (for the 7-level attribute). If we had used 800 respondents instead of 200, the standard errors would be halved (doubling the precision) with standard errors ranging from 0.07 to 0.14. For aggregate logit scores involving choice data, standard errors of this magnitude are higher than what we typically are accustomed to for CBC data (where we typically see standard errors of 0.05 or less). Considering the precision of the results from the analysis of determinance (Exhibit 10) and the analysis to compute weights that predict perceptual statements (Exhibit 11), we see that the latter analysis is much more demanding on sample size. For

[7] In our binary logit formulation, the "not chosen" constant alternative was constrained as the zero-utility alternative (a vector of zeros in the design matrix), leading to the Exp(0) term in the denominator of this equation.

obtaining relatively precise results for this latter analysis, which is the core focus of perceptual choice experiments (Exhibit 11), perhaps n=800 to 1000 would be worth the cost and effort.

Earlier, we referred to Johnson's rule-of-thumb for suggested sample size. For this conjoint attribute list and particulars of our questionnaire design involving 12 perceptual items and a conjoint attribute involving at most 7 levels, that formula suggests sample size between n=583 (minimum) and n=1167 (preferred). Perceptual choice experiments can be quite demanding on sample size!

Choice Simulations with "Why" Insights

Next, we built a market simulator to predict choice likelihood for different vacation packages (the standard CBC simulator based on HB scores) as well as to use the conjoint attributes to predict the degree of agreement on the perceptual dimensions we included in the questionnaire. We decided to report perceptual results only for the most determinant dimensions via a heat map[8], where the width of the column is proportional to determinance (Exhibit 12).

For our base case scenario, the 3-night San Francisco vacation package at a boutique-style 5-star hotel, with full-size car rental for $810 per person is the most preferred package. The perceptual choice experiment simulation gives some insight into why. This San Francisco travel package is perceived to be essentially the most *Fun* (59% agreement) and *Relaxing* (52%) vacation package of the seven. It scores high as well on other dimensions and relatively low on the *Too Expensive* dimension.

Washington D.C., on the other hand, only captures 3.4% share of choice (the lowest share). Although it is perceived by the sample of respondents to be the vacation package that is most likely to *Educate and Expand Horizons*, that attribute has relatively lower determinance (as we computed earlier using aggregate logit). The Washington D.C. vacation packages scores lowest of the seven on the *Fun* dimension, which is the most determinant attribute.

[8] Excel's ***Conditional Formatting + Highlight Cells Rules*** makes it relatively easy to create these heat maps.

Exhibit 12: Choice Simulator with Predicted Agreement on Perceptual Items

Destination:	Number of Nights:	Star Hotel:	Hotel Type:	Car Rental:	Price: (per Person)	Share of Preference	Fun	Lifetime Memories	Great Summer Vacation	Relaxing	I'd Feel Pampered	Too Expensive	Good Weather	Educates	Romantic
Las Vegas	3 nights	4 star	Business	None	$650	18.2%	60%	30%	23%	33%	22%	8%	43%	11%	23%
Orlando	5 nights	3 star	Business	Full Size	$920	23.0%	59%	53%	39%	31%	23%	15%	56%	14%	13%
Anaheim	7 nights	4 star	Boutique	Compact	$1,500	9.8%	55%	32%	52%	46%	24%	38%	58%	12%	23%
San Francisco	3 nights	5 star	Boutique	Full Size	$810	26.7%	59%	51%	44%	52%	41%	10%	44%	25%	41%
Chicago	7 nights	5 star	Resort	Compact	$1,500	11.1%	37%	37%	29%	39%	48%	52%	10%	28%	22%
New York	5 nights	5 star	Boutique	None	$1,380	7.7%	43%	43%	32%	27%	39%	32%	16%	30%	33%
Washington D.C.	3 nights	2 star	Business	Full Size	$650	3.4%	33%	38%	26%	17%	7%	8%	14%	53%	12%

Change Product Specifications Here…

Results Are Displayed Here…

If we change the vacation package for Orlando, 5 nights from the business-style hotel to a resort/spa style hotel and rerun the market simulation, its share of preference increases from 23.0% to 32.7%. With that change in hotel type, perceptions (that are significantly influenced by hotel type) for the Orlando, 5 night package shift as follows:

Exhibit 13: Shifts in Perceptions Due to Changing Orlando, 5 Night Package from Business to Spa/Resort Hotel

Fun:	59%	⇨	66%
Lifetime Memories:	53%	⇨	57%
Great Summer Vacation:	39%	⇨	48%
Relaxing:	31%	⇨	43%
I'd Feel Pampered:	23%	⇨	40%
Romantic:	13%	⇨	19%

A market simulator built in Excel displays these changes to share of preference and perceptions instantaneously with updates to the heat map colors and values on the grid.

Summary and Conclusion:

We have introduced an extension to CBC called *Perceptual Choice Experiments* that provides insights into *why* respondents make choices. The approach involves placing perceptual items and pick-any association tasks directly beneath standard CBC questions. We demonstrated how the insights could be visualized for managers via a heat map integrated within a what-if choice simulator. We also demonstrated how to estimate determinance weights for the perceptual items, allowing the researcher to prioritize the items and ignore any not related to choice.

Unfortunately, very few things in life come for free. Our Perceptual Choice Experiment slightly more than doubles the time for respondents to complete the eight-question CBC survey (see details in Appendix A). Rather than a median time of 20 seconds per CBC task, the CBC + perceptual choice experiment took respondents a total of 44 seconds per task (a total of nearly six minutes for an 8-question CBC). Also, perceptual choice experiments require large sample sizes (perhaps n=600 to 1200, for a typical experimental design) to obtain reasonably precise predictions of perceptual agreement for product concepts.

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Appendix A

Comparison of Two Questionnaire Formats
for Conducting Perceptual Choice Experiments

In September 2014, we conducted a split-sample experiment (with thanks to Survey Sampling International for providing the sample) to test which of two different questionnaire formats was better for conducting perceptual choice experiments. Respondents with HH income > $34,000 and who intended to travel out-of-state for a vacation in the next 12 months were invited to complete one of three different (randomly selected) questionnaires. The subject matter was vacation packages. The conjoint attribute list had six attributes: Destination (7 cities), #Nights (3 levels), #Stars for Hotel (4 levels), Type of Hotel (3 levels), Car Rental (3 levels), and Price (3 levels).

The perceptual choice experiment involved 12 statements, such as *A great summer vacation*, *Fun*, and *A romantic vacation.*

These three cells (different versions of the questionnaire) were as follows:

Cell 1: CBC + Single-Card Perceptual Choice Experiment (n=199)
Cell 2: CBC + Grid-Based Perceptual Choice Experiment (n=218)
Cell 3: CBC with no perceptual choice experiment (n=210)

The two perceptual choice formats were *Single-Concept Format* or *Grid Format* as shown below in Exhibits A1 and A2. Cell 3 was a control group that only completed a standard CBC exercise for comparison. The perceptual choice questions were asked beneath each of 8 choice tasks in the surveys for Cells 1 and 2.

Exhibit A1: Single-Concept Format[9]

If these were your only choices of vacation packages, which would be the Best and Worst options?

* (Price shown is per person based on double occupancy and includes airfare, breakfast each day, & hotel taxes.)

(1 of 8)

	Package A	Package B	Package C
Destination:	San Francisco, CA	Washington, DC	New York, NY
Number of Nights:	7 nights	5 nights	3 nights
Accommodation:	Luxury (5 star hotel)	Deluxe (4 star hotel)	Moderate (2 star hotel)
Hotel Type:	Resort (usually with spa, golf, etc.)	Business (with meeting/business services)	Boutique (with distinct style/character)
Car Rental:	Compact car rental	Full-Size/SUV car rental	Full-Size/SUV car rental
*** Price (per person):**	$1,800	$1,150	$650
Best:	☐	☐	☐
Worst:	☐	☐	☐

You may or may not have picked Package A above, but we'd like to know what you think about it. We've randomly picked among a series of descriptions and shown them below to the right of Package A. These descriptions may or may not describe Package A very well. We'd like to know your opinion.

Which of these descriptions describe or apply to Package A?

Package A (reminder from above):		(Check all that apply or "None of these"):
Destination:	San Francisco, CA	☐ A great summer vacation
Number of Nights:	7 nights	☐ Relaxing time
Accommodation:	Luxury (5 star hotel)	☐ A romantic vacation
Hotel Type:	Resort (usually with spa, golf, etc.)	☐ Fun
Car Rental:	Compact car rental	☐ Educates and expands horizons
Price (per person):	$1,800	☐ Too expensive
		☐ *None of these*

[9] A random task is selected to ensure a level-balanced and orthogonal design for efficient binary logit modeling of perceptual choices. If only the respondent's selected concept from the CBC question was used in the perceptual follow-up, then the perceptual choice experimental design would be strongly biased in favor of preferred levels.

Exhibit A2: Grid Format

If these were your only choices for vacation packages, which would be the Best and Worst options?

* (Price shown is per person based on double occupancy and includes airfare, breakfast each day, & hotel taxes.)

(1 of 8)

	Package A	Package B	Package C
Destination:	San Francisco, CA	Washington, DC	Las Vegas, NV
Number of Nights:	5 nights	3 nights	7 nights
Accommodation:	Luxury (5 star hotel)	Upscale (3 star hotel)	Deluxe (4 star hotel)
Hotel Type:	Boutique (with distinct style/character)	Resort (usually with spa, golf, etc.)	Resort (usually with spa, golf, etc.)
Car Rental:	Full-Size/SUV car rental	None included	Compact car rental
*** Price (per person):**	$1,380	$810	$1,500
Best:	☐	☐	☐
Worst:	☐	☐	☐

Which of the following descriptions describe or apply to these vacation packages?
(For each vacation package, select all that apply)

	Package A	Package B	Package C
Will create memories to last a lifetime	☐	☐	☐
Too expensive	☐	☐	☐
Good weather	☐	☐	☐
	☐ None describe Package A	☐ None describe Package B	☐ None describe Package C

Anecdotal Pre-Test Evidence

Prior to fielding the split-sample study, we conducted an informal poll among employees at Sawtooth Software. About 2/3 preferred the grid-style (Cell 2) approach to the single-concept (Cell 1) approach. Those who preferred the grid-style approach commented that it seemed strange that the single-concept (Cell 1) approach randomly selected one of the concepts for evaluation on the perceptual items. The randomly selected single concept approach made them feel more at the mercy of an arbitrary process rather than empowered and in control of providing their opinions regarding concepts they both liked and didn't like from the CBC portion of the task. Although this is purely anecdotal evidence from a small and certainly biased sample of market researchers and software developers, it is interesting feedback.

Time to Complete Choice Screens

Median time per choice screen (task) for the three questionnaires is shown in Exhibit A3.

Exhibit A3: Median Seconds per Task

	Task1	Task2	Task3	Task4	Task5	Task6	Task7	Task8	Average
Cell1	61.5	41.5	37	32	31	27.5	28.5	27	35.75
Cell2	71	50	44	41	37	36	36	34	43.63
Cell3	34	23	18	18	18	18	15	15	19.88

Adding the perceptual questions to the CBC experiment doubles the time to complete the choice screens. The grid-style approach (Cell 2) is a bit longer to complete than the single-concept approach, but with 50% more information collected (given our questionnaire design): with the single-concept layout, we showed 6 items per task x 8 tasks = 48 perceptual agreement check-boxes; the grid-style approach featured 3 items per task x 3 concepts per task x 8 tasks = 72 perceptual agreement check-boxes.

Qualitative Assessment of the Questionnaires

At the end of the survey, we asked respondents to evaluate their experience using a 5-point scale (1=Strongly Disagree, 2=Somewhat Disagree, 3=Neither Agree Nor Disagree, 4=Somewhat Agree, 5=Strongly Agree).

Exhibit A4: Qualitative Assessment of Questionnaire Experience

	Cell 1 CBC + Single-Concept Perceptions	Cell2 CBC + Grid Perceptions	Cell3 CBC Only (No Perceptual Questions)
This survey sometimes was confusing	2.13 (0.082) 18% agree	2.13 (0.084) 19% agree	1.90 (0.078) 14% agree
This survey was enjoyable	4.07 (0.062) 77% agree	3.99 (0.067) 76% agree	4.19 (0.059) 80% agree
This survey was too repetitive	2.64 (0.089) 32% agree	2.64 (0.084) 27% agree	2.29 (0.086) 23% agree
I found myself starting to lose concentration at least once	2.30 (0.088) 25% agree	2.43 (0.083) 22% agree	2.07 (0.079) 14% agree
This survey was too long	2.11 (0.079) 13% agree	2.27 (0.081) 16% agree	1.78 (0.073) 8% agree
The questions about which descriptions applied to different vacation packages were easy to answer	4.02 (0.067) 78% agree	3.91 (0.072) 75% agree	NA

(No statistically significant differences between first 2 columns. Standard errors shown in parenthesis.)

The data suggest that respondents saw no difference between the single-concept and grid-style approaches on these qualitative dimensions.

Number of Perceptual Boxes Checked

If respondents clicked very few perceptual check-boxes (indicating agreement that the product concepts were described well by perceptual statements), we'd have little to go by to model how conjoint attribute levels led to agreement with the perceptual statements. We use binary logit to build the models, so maximal efficiency occurs if the item is selected 50% of the time. As the probability of agreeing with perceptual items tends toward either 0% or 100%, the binary logit models have very little information by which to estimate part-worth perceptual parameters (other than the constant).

The single-concept approach (Cell 1) led to 28% of the perceptual boxes checked. The grid-style approach (Cell 2) led to 35%.

Assembling the information reported to this point:

- Regarding time to complete, Cell 2 was 35.75 seconds / 43.63 seconds = 0.82 as efficient.
- Regarding amount of data collected, Cell 2 was 1.5 as efficient (9 checks vs. 6 checks per task).
- Regarding percent of agreement boxes checked, Cell2 collected 35%/28% = 1.25x more information.

Net, Cell 2 was: 0.82 x 1.5 x 1.25 = 1.54 as efficient as Cell 1 per time-equalized respondent effort.

Do Follow-Up Perceptual Questions Affect CBC Responses?

An important question is whether the presence of the perceptual follow-up questions leads to higher or lower quality responses to the standard CBC tasks at the top of the choice screen. Perhaps when respondents know that they will be asked to delve deeper by evaluating the perceptual aspects of each of the product concepts, they provide better CBC choices. To investigate this, prior to the CBC questions we asked respondents a series of self-explicated questions about four of the attributes (destination, hotel stars, hotel type, and car rental options). Respondents chose their preferred level for each of the attributes as well as whether each of the attributes mattered to them on a 3-point scale (Yes, it's very important; Yes, but not very important; No). For each respondent, we then compared the most preferred levels for the HB utilities estimated from the CBC tasks to the self-explicated preferred levels (but ignoring any attributes that were rated as not very or not at all important). The two groups of respondents who completed perceptual choice questions beneath each CBC task had hit rate matches between self-explicated and CBC/HB utilities 9% and 6% higher (for cells 1 and 2, respectively) than the control respondents who only completed the standard CBC tasks (Cell 3). Though these hit rates are directionally higher for perceptual choice experiment respondents, the differences were not statistically significant. The data suggest, but do not confirm, that respondents provide better quality answers to the CBC questions when they are asked follow-up perceptual diagnostic questions about the product concepts.

Summary

Our experiment suggests that the grid-based method (Cell 2) of data collection for perceptual choice experiments is better than the single-card approach (Cell 1):

- Factoring in the time to complete the questions and the amount of data collected, the grid-style approach is 1.54 more times efficient than the single-concept approach. In other words, for every second of respondent effort, it is 54% more efficient, while being no less tiring or confusing.
- The grid-based approach is more compact to present on the survey page.
- Individual-level analysis suggests that when respondents are asked to complete additional perceptual association questions, the quality of their answers to the standard CBC tasks on the same page may be slightly improved.
- Our qualitative assessment is that the grid-style approach seems more logical than to ask respondents perceptual questions about a randomly selected concept.

Appendix B

Data Preparation for Sawtooth Software's MBC (Menu-Based Choice) Software

Any software that can perform MNL or binary logit analysis may be used to estimate the perceptual choice models described in this paper. Among the Sawtooth Software tools, MBC (Menu-Based Choice) software is rather handy for performing the modeling.

The data should be prepared in a comma-separated values file (.csv file) as shown below:

Exhibit B1: Data Preparation for MBC Software

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE
CaseID	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
1001	1	3	4	2	2	3	2	2	2	2	1	2	1	1	2	2	2	2	2	2	2	2	2	2	1	2	2	2	2	2
1001	2	3	3	2	3	1	2	2	2	2	1	2	1	1	2	2	2	2	2	2	2	2	1	2	1	1	2	2	2	2
1001	3	1	4	3	1	2	2	2	2	2	1	2	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
1001	1	2	1	1	3	1	1	1	2	2	2	2	2	2	2	1	2	2	2	1	2	2	2	2	2	2	2	2	2	2
1001	2	1	4	2	1	3	1	1	2	2	2	2	2	2	2	1	2	2	2	2	2	2	2	2	2	2	2	1	2	2
1001	6	2	4	1	2	2	1	1	2	2	2	2	2	2	2	1	2	2	1	2	2	2	2	2	2	2	2	1	2	2
1001	2	3	2	1	1	2	2	2	2	1	2	1	2	2	1	2	2	2	2	2	2	2	2	1	2	2	2	2	2	2
1001	3	1	2	2	3	2	2	2	2	1	2	1	2	2	1	2	2	2	2	2	2	1	2	2	2	2	1	2	2	2
1001	7	2	3	3	2	1	2	2	2	1	2	1	2	2	1	2	2	2	2	2	2	2	2	2	2	2	1	2	2	2
1001	2	3	4	2	2	2	2	2	1	2	2	2	2	2	2	2	1	1	2	2	2	2	2	2	2	2	2	2	1	1
1001	5	1	3	1	1	3	2	2	1	2	2	2	2	2	2	2	1	1	2	2	2	2	2	2	2	2	2	2	2	2
1001	7	2	1	3	3	1	2	2	1	2	2	2	2	2	2	2	1	1	2	2	1	2	2	2	2	2	2	2	2	2
1001	4	3	4	3	3	3	2	2	1	1	2	2	2	1	2	2	2	2	2	2	1	1	2	2	2	1	2	2	2	2
1001	1	2	2	2	1	1	2	2	1	1	2	2	2	1	2	2	2	2	2	2	2	1	2	2	2	2	2	2	2	2
1001	3	2	1	1	2	1	2	2	1	1	2	2	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
1001	6	3	2	1	3	2	2	1	2	2	1	2	2	2	2	1	2	2	2	1	2	2	2	2	2	2	2	2	2	2
1001	4	1	1	1	1	2	2	1	2	2	1	2	2	2	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2
1001	5	1	3	3	3	3	2	1	2	2	1	2	2	2	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2
1001	2	3	3	2	1	1	1	2	2	2	2	2	1	2	1	2	2	2	1	2	2	2	2	2	1	2	1	2	2	2
1001	7	1	4	2	3	3	1	2	2	2	2	2	1	2	1	2	2	2	1	2	2	2	2	2	1	2	1	2	2	2
1001	6	2	3	3	2	3	1	2	2	2	2	2	1	2	1	2	2	2	1	2	2	2	2	2	1	2	1	2	2	2
1001	5	2	4	1	2	3	2	2	2	2	2	1	2	2	2	2	1	1	2	2	2	2	2	1	2	2	2	2	2	2
1001	3	3	1	3	2	1	2	2	2	2	2	1	2	2	2	2	1	1	2	2	2	2	2	2	2	2	2	2	1	2
1001	4	1	3	2	2	2	2	2	2	2	2	1	2	2	2	2	1	1	2	2	2	2	2	2	2	2	2	2	1	2

For our questionnaire layout as described in Appendix A, each respondent's data are coded in 24 rows (8 choice screens x 3 vacation concepts per screen).

The data layout is:

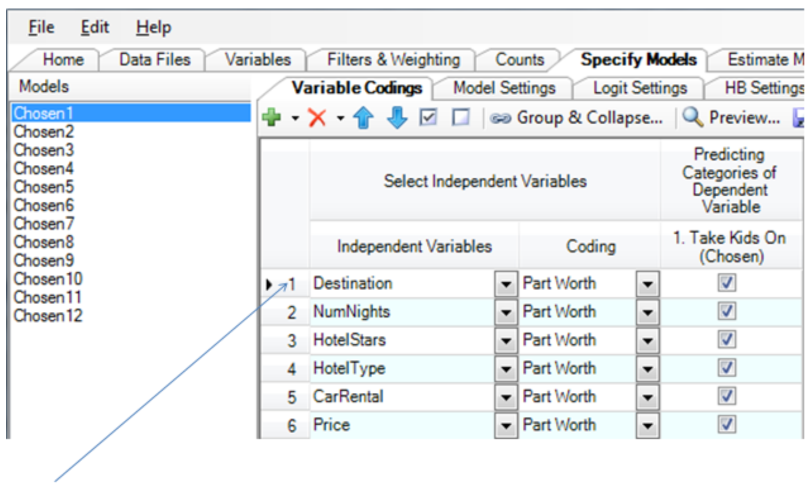
Fields	**Description**
CaseID:	Respondent number
A1 – A6:	Conjoint design, attribute level indices for attributes 1 through 6
B1-B12:	Availability flags for perceptual items 1-12, 1=available, 2=not available.
C1-C12:	Whether each of perceptual items 1-12 was selected, 1=Yes, 2=No.

For example, in choice task #1, respondent #1001 evaluated the conjoint concept: "1, 3, 4, 2, 2, 3" which means "Las Vegas, NV; 7 nights; Luxury (5 star hotel); Resort (usually with spa, golf, etc.); Compact car rental; $1,800"…with respect to perceptual statements 5, 7, and 8 (Good weather, Fun, and I'd feel pampered). The respondent clicked boxes indicating that only item 7 (Fun) described the conjoint concept.

To analyze the data using MBC, classify variables A1-A6 and B1-B12 as independent variables. Specify C1-C12 as dependent variables (where "2" is the off-state). Specify that Variable C1 is conditional upon B1 equal to "1" (is available); variable C2 is conditional upon B2 = 1, etc. for all twelve dependent variables.

The *Specify Models* dialog looks like the following, for each of 12 aggregate logit model specifications (modeling the dependent variable *Take Kids On* is shown below):

Exhibit B2: Variable Codings Dialog



Note: only include independent variables that make logical sense as predictors of the perceptual evaluations! For example, Car Rental would not be a logical predictor of "Good Weather"

The MBC software automatically dummy-codes the independent variables, with the first level of each independent variable selected as reference (0-utility) levels. The aggregate logit output from MBC software is shown in Exhibit B3.

Exhibit B3: MBC Logit Output

```
Run includes 211 respondents (211.00 weighted).

1266 tasks are included in this model, for a weighted average of 6.0 tasks per respondent.

Total number of choices in each response category:
Category  Frequency  Percent
-----------------------------------------------------
       1      409.0   32.31%
       2      857.0   67.69%


Iteration    1  Log-likelihood = -744.16509  Chi Sq = 266.71847  RLH = 0.55554
Iteration    2  Log-likelihood = -741.40437  Chi Sq = 272.23993  RLH = 0.55676
Iteration    3  Log-likelihood = -741.37576  Chi Sq = 272.29715  RLH = 0.55677
Iteration    4  Log-likelihood = -741.37575  Chi Sq = 272.29717  RLH = 0.55677
*Converged after 0.16 seconds.

Log-likelihood for this model =       -741.37575
Log-likelihood for null model =       -877.52433
                                     ------------
                  Difference =        136.14858

Percent Certainty                 =     15.51508
Consistent Akaike Info Criterion  =   1629.33661
Chi-Square                        =    272.29717
Relative Chi-Square               =     15.12762


         Effect        Std Err       t Ratio      Variable
  1     -2.24876       0.29872      -7.52793     ASC (1. Take Kids On (Chosen))
  2      2.12857       0.26948       7.89883     Destination_2 [Part Worth]
  3      1.53610       0.26802       5.73127     Destination_3 [Part Worth]
  4      1.09733       0.26986       4.06625     Destination_4 [Part Worth]
  5      0.42718       0.29629       1.44178     Destination_5 [Part Worth]
  6      0.84712       0.27678       3.06064     Destination_6 [Part Worth]
  7      1.29795       0.26998       4.80755     Destination_7 [Part Worth]
  8      0.15467       0.15400       1.00429     NumNights_2 [Part Worth]
  9      0.14704       0.15802       0.93053     NumNights_3 [Part Worth]
 10      0.08739       0.20502       0.42626     HotelStars_2 [Part Worth]
 11      0.10945       0.20079       0.54510     HotelStars_3 [Part Worth]
 12      0.00865       0.22360       0.03868     HotelStars_4 [Part Worth]
 13      0.08365       0.16983       0.49253     HotelType_2 [Part Worth]
 14      0.33321       0.15321       2.17488     HotelType_3 [Part Worth]
 15      0.04971       0.15586       0.31893     CarRental_2 [Part Worth]
 16      0.10914       0.15408       0.70833     CarRental_3 [Part Worth]
 17      0.03357       0.16401       0.20469     Price_2 [Part Worth]
 18      0.06858       0.17953       0.38197     Price_3 [Part Worth]
```

Since MBC software employs dummy-coding, the first levels of each categorical attribute are constrained to have utility = 0 (and are not shown in the report). For example, Destination #1 “Las Vegas” with a zero utility (the reference level) has a lower likelihood of predicting choice of being a good vacation package to *Take Kids On* than Destination # 2 (Orlando, FL) with a logit utility (Effect) of 2.12857.