DUAL RESPONSE "NONE" APPROACHES: THEORY AND PRACTICE

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INTRODUCTION

Over the past several years a variant of choice-based conjoint referred to as *Dual Response "None"* has been the subject of increasing interest and use. With Dual Response "None," two responses are elicited for each task: a choice among available product alternatives, and then a choice between the "None" concept and the previous alternative(s). Even though this approach has been growing in use, its documentation has been sparse to date (Uldry, *et al.* 2002; Brazell, *et al.* 2006, Sawtooth Software 2005). This paper will introduce and explain Dual Response "None" and provide guidance on how to put it into practice.

DESCRIBING DUAL RESPONSE "NONE" (DR)

As the name implies, Dual Response "None" or DR, differs from standard CBC in that with each choice task respondents are asked two choice questions ("dual response") instead of only one choice question ("single response"). The first choice question (a forced choice task) elicits a choice among the described alternatives, not including the "None/Other" option. The second choice question has respondents choose whether, given what they know about the current marketplace, they would really buy the product they just selected. Essentially, it is a choice between the most preferred alternative and "None/Other." If respondents would actually buy the product, then they would not prefer "None/Other" but if they would not buy the product, then they would prefer "None/Other" over the given product.

There are actually several variations of DR tasks. One is as just described, where a respondent is asked in the second choice to choose between the most preferred alternative and "None/Other." We will call this DR-2Max, because it is a choice between two alternatives: the preferred and "None/Other." Alternatively, the second task could be more global in nature, asking whether the respondent would buy any of the given alternatives. We will call this the DR-AnyMax task because it is a choice between none and any of the given alternatives. Example 1 shows a DR-2Max task and Example 2 shows a sample DR-AnyMax task.

Scenario A7	Compaq	Rio	Philips
Memory	16 MB	32 MB	64 MB
Form and Size	Deck of Cards	Like a Credit Card, Thin	Like a Credit Card, Thin
Ruggedness	Very Rugged	Very Rugged	Very Rugged
Color and Material	Face Plate	Face Plate	Face Plate
Rechargeable battery	Yes	Yes	No
FM	No	No	Yes
Voice recorder	No	No	No
LCD screen size	1 line	4 lines	4 lines
Sound enhancement	4 mode	4 mode	4 mode
Battery life	About 8 hours	About 4 hours	About 8 hours
Price	$125	$185	$245
Memory type	No internal Memory, comes with card	Internal, non-expandable	Internal, non-expandable
If you had to buy one, and these were the only available Flashplayer, which would you buy?	○ **Compaq**	○ **Rio**	○ **Philips**
Given your knowledge of the market, would you actually buy the option you selected in the previous question?		○ **Yes**	○**No**

(Example 1)

Scenario A7	Compaq	Rio	Philips
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Price	$125	$185	$245
Memory type	No internal Memory, comes with card	Internal, non-expandable	Internal, non-expandable
If you had to buy one, and these were the only available Flashplayer, which would you buy?	○ **Compaq**	○ **Rio**	○ **Philips**
Given your knowledge of the market, would you actually buy any of the MP3 players listed above?		○ **Yes**	○**No**

(Example 2)

In these two examples, the "None/Other" option is not explicitly included in the grid describing the alternatives, as is the case with more traditional CBC tasks.

In practice, the DR-2Max task is preferred to the DR-AnyMax task. Though perhaps obvious, the DR-2Max task has the advantage of providing greater respondent focus and simplicity. The DR-AnyMax task may seem awkward and harder to understand.

DR may be implemented with another task variation where the question order is reversed as compared to DR-AnyMax. The first question becomes a traditional CBC question and the second one a forced choice. The respondent is first asked to choose among all of the alternatives, including "None/Other," and the second task is a forced task among only the given, described alternatives.

Other than these differences in the task, few other differences remain between DR and standard CBC. DR requires the same experimental design considerations and the same reporting requirements of CBC. The only differences, other than the task layout, between DR and CBC involve the estimation data setup (construction of the estimation design) and choice of estimation algorithm.

Now that we have described DR, we will review why you might want to use DR in the first place. Following this description, the remainder of the paper will detail the data setup and estimation requirements (focusing on the DR-2Alt and DR-AnyMax task formats) to guide the practitioner in successful DR application.

BENEFITS OF USING DUAL RESPONSE

On the face, it appears that DR would take both more respondent time (two questions instead of one) and analyst effort (because the data layout is more complex than standard CBC). If this is the case, why would a researcher use DR?

DR provides greater efficiency and power than CBC. In contrast to standard CBC, with DR, we still obtain information about non-"None" alternatives when a respondent selects "None/Other" as the preferred alternative. The model can therefore capture and use more information about the relative value of the attributes and levels, in addition to the information that the "None/Other" alternative is more appealing than any of the given alternatives.

As the incidence of "None/Other" choices rises, the benefit of DR becomes greater. With 12% "None/Other" responses, using DR creates a 25% decrease in model error This is equivalent to the difference between using 180 respondents in CBC and only needing 130 respondents using DR to get the same level of model error. Likewise, with 33% "None/Other" response, DR provides a 55% decrease in error requiring only 130 respondents where 290 would be required with standard CBC (Uldry, *et al.* 2002).

The good news is that DR has not been found to significantly alter the underlying model estimates—with the exception of the coefficient for the "None/Other" alternative. Accounting for scale differences, using real-world and simulated data sets, aggregate parameter estimates do not differ significantly between DR and standard CBC. (Uldry *et al.* 2002).

Finally, researchers will also find that using DR provides higher resolution on preferences at the individual level. Because of less "missing" information when respondents select "None/Other" as the preferred alternative, more information is available for individual-level modeling.

The benefits of using DR should lead many researchers to consider applying it in a broader range of projects. As mentioned earlier, DR differs from CBC, not only in the task, but in the data setup and estimation requirements. Because data setup depends on the estimation approach, we will first examine the estimation requirements.

Estimation Algorithm Differences between DR and CBC

DR captures two responses instead of just one. Therefore, a different estimation algorithm is needed. Information from two responses must be combined to estimate one coherent model.

Typical CBC estimation uses the standard Multinomial Logit (MNL) theory. This is expressed below in Equation 1.

$$P(i \mid FC \,\&\, FC_0) = \frac{e^{\beta'_{FC} x_i}}{\left(\sum_j e^{\beta'_{FC} x_j} + e^{\beta_{FC0}}\right)}$$

Equation 1 – Typical MNL.

The MNL represents the probability that alternative i will be chosen from the alternatives in the combined set of FC and FC_0. FC (representing "forced choice") are the given alternatives in the choice set and FC_0 is the "None/Other alternative).

In DR, and specifically DR-2Max, the probability of choice can be expressed as a joint probability between choosing the most preferred given alternative and the choice that the most preferred alternative is chosen over "None/Other." The probability of choosing alternative i from the set of given alternatives, FC, can be expressed as Equation 2:

$$P(i \mid FC) = \frac{e^{\beta'_{FC} x_i}}{\left(\sum_j e^{\beta'_{FC} x_j}\right)}$$

Equation 2 – Forced Choice.

And the probability of choosing i over FC_0 is then represented by Equation 3.

$$P(i \mid 2nd) = \frac{e^{\beta'_{FC} x_i}}{\left(e^{\beta'_{FC} x_i} + e^{\beta_{2nd0}}\right)}$$

Equation 3.

If we assume that these probabilities are independent, they can be multiplied to form a joint-probability. The joint expression, the DR-2Max likelihood function, is denoted as Equation 4:

$$P(i \mid DR) = \frac{e^{\beta'_{FC}x_i}}{\left(\sum_j e^{\beta'_{FC}x_j}\right)} \times \frac{e^{\beta'_{FC}x_i}}{\left(e^{\beta'_{FC}x_i} + e^{\beta_{2nd0}}\right)}$$

Equation 4 – DR-2Max likelihood function.

Alternatively, the DR-AnyMax model can be expressed as the joint likelihood between the forced choice and the choice of "None/Other" over any of the given alternatives. Again, the forced choice can be represented as Equation 2 above.

The second choice can be represented as Equation 6:

$$P(FC \mid 2nd) = \frac{\left(\sum_j e^{\beta'_{FC}x_j}\right)}{\left(\sum_j e^{\beta'_{FC}x_j} + e^{\beta_{2nd0}}\right)}$$

Equation 6.

These likelihoods can then be multiplied to become Equation 7:

$$P(i \mid DR_2) = \frac{e^{\beta'_{FC}x_i}}{\left(\sum_j e^{\beta'_{FC}x_j}\right)} \times \frac{\left(\sum_j e^{\beta'_{FC}x_j}\right)}{\left(\sum_j e^{\beta'_{FC}x_j} + e^{\beta_{2nd0}}\right)}$$

Equation 7.

Which then reduces to Equation 8, and is the DR-AnyMax likelihood function.

$$P(i \mid DR_2) = \frac{e^{\beta'_{FC}x_i}}{\left(\sum_j e^{\beta'_{FC}x_j} + e^{\beta_{2nd0}}\right)}$$

Equation 8 – DR-AnyMax likelihood.

This expression can then be converted to a log-likelihood expression and embedded within either a traditional maximum likelihood estimation routine or into a hierarchical Bayes approach. Working in this manner would require building a custom estimation routine.

However, standard MNL routines may be used. Because the joint likelihood is multiplicative in nature, the log-likelihood is additive. As an additive function, the DR model does not need to be estimated simultaneously with both responses included in a joint likelihood function during estimation. Instead, the responses can be included sequentially (as two choice tasks) and summed. In this way, a typical MNL estimation algorithm can be used to estimate a DR model. The dual responses can be fed one at a time into the estimation algorithm. To do this, the estimation algorithm must be able to accept tasks with different numbers of alternatives within the same respondent.

An alternative to building a custom routine and to using a standard MNL is to use the DR capability in Sawtooth Software's CBC/HB v4 (Sawtooth Software 2005).

Using a standard CBC estimation routine would require a different or unique data setup, which is the focus of the next section.

DATA SETUP FOR TYPICAL CBC ESTIMATION

A standard CBC estimation algorithm can be used to estimate a DR model. The only requirement is that the routine allow for differing numbers of alternatives within each respondent.

The dual responses must first be split into two separate choice tasks and these tasks must be "stacked" together for each respondent in the estimation design data. Essentially, each response is treated as a separate choice task. The first response is set up as its own forced choice task. The second response is either set up as a choice between the chosen alternative and "None/Other" (DR-2Max) or as a choice among all alternatives, including "None/Other" (DR-AnyMax). We will illustrate the data setup using a DR-AnyMax estimation.

ID	Scen	Alt	Choice	ASC1	ASC2	ASC3	A1L1	A1L2	A2L1	A2L2
30001	1	1	**0**	1	0	0	1	0	1	0
30001	1	2	**1**	0	1	1	0	0	0	1
30001	1	3	**0**	0	0	0	0	0	0	0
30001	2	1	**0**	1	0	0	0	1	1	0
30001	2	2	**0**	0	1	1	0	0	0	1
30001	2	3	**1**	0	0	0	1	0	0	0
…	…	…	…	…	…	…	…	…	…	…
30001	1	1	**0**	1	0	0	1	0	1	0
30001	1	2	**1**	0	1	1	0	0	0	1
30001	1	3	**0**	0	0	0	0	0	0	0
30001	1	4	**0**	0	0	0	0	0	0	0
30001	2	1	**0**	1	0	0	0	1	1	0
30001	2	2	**0**	0	1	1	0	0	0	1
30001	2	3	**0**	0	0	0	1	0	0	0
30001	2	4	**1**	0	0	0	0	0	0	0
…	…	…	…	…	…	…	…	…	…	…

These first three rows are redundant and should be removed

Table 1.

Table 1 above illustrates the data setup. The call-out box and circled task show an additional requirement in the data setup: redundant tasks should be eliminated from the estimation design.

In other words, if someone chooses one of the given alternatives, then the information in the second task (where the "None" alternative is included) fully captures the information. Sawtooth Software's CBC/HB v4 software employs this stacked data strategy, automatically stacking the data for the researcher and eliminating any redundant tasks prior to the estimation process.

While in theory, the simultaneous likelihood should provide the same results as the stacked-data / standard CBC estimation, we wanted to confirm this and explore the potential impact of differences in data setup. To this end, several empirical studies and one simulated dataset were employed to compare the difference between simultaneous and sequential estimation and the differences among several methods of stacking the data for sequential estimation.

TESTING OF DIFFERENCES AMONG DATA SETUP OPTIONS AND ESTIMATION APPROACHES

We tested several data setup options in the context of different potential estimation approaches to illustrate consistencies and provide direction for those who wish to employ DR. We conducted these tests on several data sets from actual projects and one simulated data set. The combinations of data setup and estimation approach are as follows:

- "Sawtooth Software"
    - Sawtooth Software's CBC/HB v4
    - Need to reformat .CHO file to include information regarding the Dual None response. Specifications for this are provided in the manual.
- "DR-Custom"
    - Custom function based upon DR-AnyMax likelihood function with simultaneous LL usage of first and second choice
    - Data setup tailored to the specific algorithm needs
- "MNL-AnyMax"
    - Typical MNL
    - Using stacked data, where the second choice is from all alternatives, including None/Other
    - This data setup, when used with a typical MNL estimation, replicates the DR-AnyMax likelihood function.
- "MNL-2Max"
    - Typical MNL with stacked data, where second choice is between the previously chosen alternative in the forced choice and the none
    - This data setup, when used with a typical MNL estimation, replicates the DR-2Max likelihood function.

As a practical note, while the DR-2Max task (from a respondent's perspective) is generally preferred over the DR-AnyMax task, the MNL-AnyMax estimation routine is preferred. The data from a DR-2Max task may be used in the MNL-AnyMax estimation. We will discuss this preference at greater length after describing the results of the tests. All of the comparisons in this paper have been completed using data generated using DR-2Max tasks.

The four conditions above will be compared using hold-out predictions (ability to predict individuals' choices) and MAE (Mean Absolute Error of predictions versus actual choices for the population).

The four conditions were tested using one simulated data set and data from two actual studies. The results are found below in Table 2.

		Sawtooth Software	DR-Custom	MNL-AnyMax	MNL-2Max
Simulated	Hit Rate(%)	63	63	62	62
	MAE	1.41	1.41	1.53	3.29
DataSet1	Hit Rate(%)	63	60	59	57
	MAE	3.21	3.59	3.00	6.09
DataSet2	Hit Rate(%)	65	65	62	65
	MAE	2.83	2.75	2.66	3.40

Table 2.

Our results show that DR-2Max performed more poorly in terms of MAE. However, in all other respects the different approaches performed similarly. The main finding for the purposes of this paper is that the researcher has a variety of estimation options for DR that all perform similarly well. Researchers can use their own custom functions, can stack the data and use the typical MNL or can use the DR feature in Sawtooth Software's CBC/HB v4.

Further Exploration and Explanation

To further explore the reason MNL-2Max performed more poorly, we plotted all of the model estimates together from each data set. We would expect that in a scatterplot, if each of the estimation approaches produced exactly the same estimates, the estimates would align creating a diagonal line at a 45% angle to the horizontal axis. If the different estimation techniques produced models that differed in scale, then the points would create a line that crossed through the origin but differed as to the angle against the horizontal axis. If any points deviated from the line, they would represent potentially significant bias in the model estimates between models.

We found, across datasets, that the MNL-2Max approach consistently produced a downward bias in the estimation of the effect for "None/Other." The plot for the simulated data is shown in Chart 1:

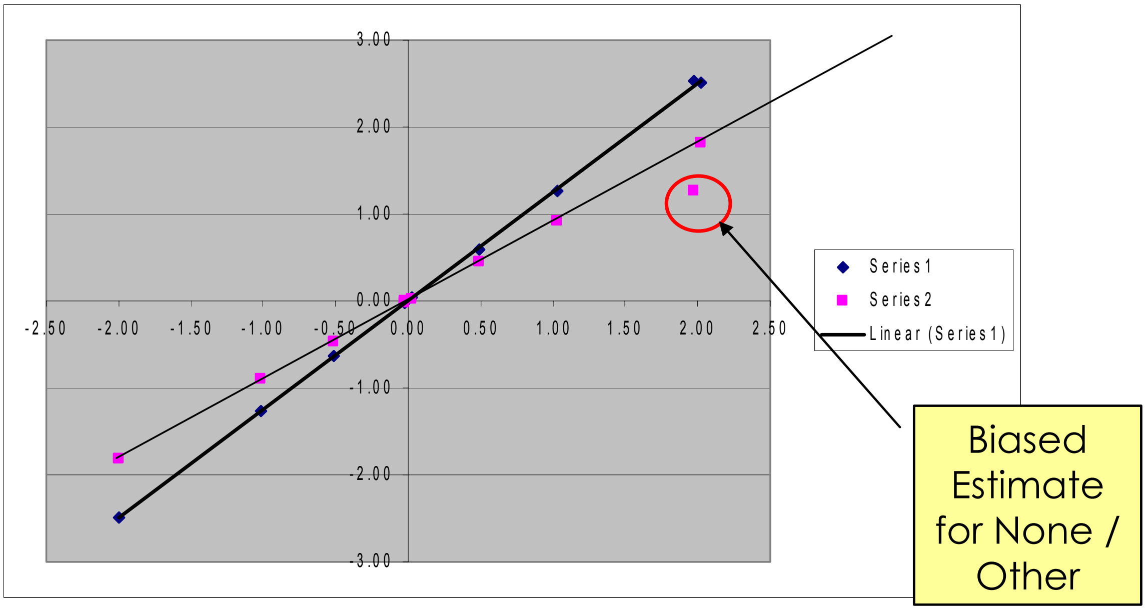

Chart 1.

As the other estimation & data setup conditions utilized the DR-AnyMax likelihood function, the bias can be identified as a difference between using DR-AnyMax and DR-2Max. DR-2Max will consistently produce a lower estimate of "None-Other" than DR-AnyMax. But which is right?

We turned to the simulated dataset (and others that we created) to understand what the absolute bias may be. We found that the direction of this bias depends on the process of generating the data. If we create our simulated dataset using DR-AnyMax assumptions, it appears that DR-2Max underestimates the effect for None/Other. On the other hand if we use DR-2Max assumptions in generating simulated data, we find that DR-AnyMax estimation produces inflated estimates of None/Other.

The reason that DR-AnyMax estimates of None/Other are higher than DR-2Max comes from the second stage of the estimation—the one difference between the two approaches. With DR-AnyMax, for None to be consistently chosen at the same proportion as in the DR-2Max approach, it must have a higher utility because it is "competing" against more than just one other alternative. Each of the alternatives has its own random variation, and so, on average, the estimate for "None/Other" must be greater if it is competing against more alternatives and their independent variation.

The question then turns to whether the 2Max or AnyMax process more closely resembles the decision structure in the real world. In other words, for the given product category, do people ultimately make a buy/no-buy choice when looking only at the preferred alternative? Or, do consumers consider a set of alternatives? We believe it may be an empirical question. In either case, the only bias between the approaches appears to be in the "None/Other" estimate, which is already frequently the subject of post-model adjustment (or even ignored).

As an additional note, we performed many tests with regard to the specific coding of the alternative-specific constants (including that of "None/Other") in the data setup. We could not determine any differences between conditions with regard to model estimates and model accuracy. We tested the specific inclusion of a parameter for "None/Other." We tested the inclusion of a variable picking up the difference between the first and second response. We tested dummy codes versus effects coding. With these and several other tests we found no tangible differences in model estimates or accuracy.

Consistency between Task and Estimation Approach

Our experience suggests the appropriate use of the 2Max task with the AnyMax estimation, even though there appears to be a conceptual inconsistency. Practically speaking, the 2Max task is easier for the respondent and, we believe, should provide better information. From a rational viewpoint, the information respondents provide in the AnyMax task should be the same as that obtained in the 2Max task. However, this research effort did not specifically test the difference between using the two task formats. Additionally, irrespective of the way the data were collected, we perceive that the AnyMax estimation approach more accurately reflects the reality that None/Other is considered in the context of more than one alternative. Our experience and exploration here does suggest that there are no adverse effects of using the 2Max task to generate data for the AnyMax estimation approach or likelihood function.

Summary and Conclusion

The DR approach is now available to practitioners able to perform additional data processing for standard MNL software or within the Sawtooth Software .CHO file. Sawtooth Software plans to implement dual-response None as an automatic option within the next version of CBC/Web (version 6), in which case most any researcher will have access to DR. This paper sets forth the rationale and theory behind DR. Additionally, the research described in this paper shows that DR can be estimated using available software and standard algorithms and that differences between algorithms and data setup are largely inconsequential, meaning the approach is robust to variations in specific items of data setup or to whether you are using a simultaneous or sequential (data-stacking with typical MNL) approach.

To briefly review, past research has shown that DR offers several significant benefits. DR provides more efficient use of data, resulting in smaller design requirements, better prediction at a given sample size and greater statistical significance of parameter estimates. DR also provides potentially more realistic prediction of "None/Other," thus requiring less calibration. It has been shown that when using Dual Response, respondents choose "None/Other" much more often, reducing the need to scale "None/Other" when calibrating to actual market shares.

However, there are trade-offs to using DR and enjoying these benefits. These include a greater time requirement per scenario because there are two tasks instead of just one and the potential for annoying respondents by requiring a forced choice (this potential has not been empirically tested).

That it is a new approach and not well documented in the published literature is probably the largest obstacle and risk in using DR. Being a relatively new approach, Dual Response may raise more questions and may shift the burden of proof on your proposal in an area that should be an advantage.

In short, we have found many empirical benefits and a few drawbacks of the approach.

You, as a researcher, should consider using DR when:

- You expect to have a None/Other option in your choice sets and when you are doing a task that lends itself to a choice instead of some other behavior, like allocation
- You can spare a little more time for the tasks
    - However, if by using DR you can take advantage of the greater power, you can reduce the number of tasks and offset the extra time required to answer two tasks
- Sample size is an issue or you just want more robust estimates
- You are likely to have high number of "None/Other"
- You want to have less calibration of "None/Other."

REFERENCES

Brazell, Jeff D.; Chris Diener, Ekaterina Karniouchina, William L. Moore, Valerie Severin, Pierre Francois Uldry, "The No Choice Option and Dual Response Choice Designs (March 2006), Accepted for publication with Marketing Letters.

Uldry, Pierre; Valerie Severin and Chris Diener. "Using A Dual Response Framework in Choice Modelling," 2002 AMA Advanced Research Techniques Forum, Vail, Colorado.

Sawtooth Software (2005), "CBC/HB v4 Manual," Sequim, Washington, USA.