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Are You Discrete? Patients' Treatment Preferences and the Discrete Choice Experiment

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ABSTRACT

The discrete choice experiment (DCE) was designed for use in economics and marketing research to study consumer preferences. However, DCE has been increasingly used in health care research as a method to elicit patient preferences for characteristics of different types of treatments. In a DCE, attributes are defined for treatments (for example: frequency of administration, occurrence of side effects, how long treatment effect lasts) and levels of the attributes (for example: taking one pill once a week, once a day, or twice a day). Respondents are presented with pairs of hypothetical treatments with different combinations of each attribute level and are asked to choose their preferred treatment. Analyzing the responses allows evaluation of the relative importance of the attributes and the trade-off respondents are willing to make between the attributes. This talk will explain how to set up the data and discuss the appropriate analysis using the conditional logit model (PROC PHREG and PROC LOGISTIC).

INTRODUCTION

DCE is a powerful tool to estimate the probability of individuals making choices from alternatives. DCE asks respondents to make a choice between sets of hypothetical alternatives. Each alternative is described by several characteristics, known as attributes, and responses are used to infer the value placed on each attribute. The selection of attributes should be based on literature review, expert opinions, key informant interviews, and surveys. Levels of attributes can be ordinal or nominal and are usually 2-6 levels. An equal number of levels for each attribute produces more efficient designs, although this is not required. Levels should be independent and mutually exclusive.

Table 1 illustrates a theoretical example that will be used for this paper. We have six attributes of interest which describe characteristics of medications for a disease.

ATTRIBUTE	LEVEL	DESCRIPTION
Frequency of treatment	1	Once a month
	2	Every 2 weeks
	3	Bi-weekly
	4	Weekly
	5	Daily
	6	Twice daily
Pill taste	1	Chocolate
	2	Berry
	3	Chalk
Pill color	1	Rainbow
	2	Red
	3	Grey
Side effects	1	No side effects
	2	Headache
	3	Coma
Hours wait to eat	1	0
	2	1
	3	2
Co-payment	1	$0
	2	$20
	3	$80

Table 1. Attributes and Levels

Frequency of treatment has 6 levels, while the other attributes have 3 levels each. In this example, the highest level for each attribute is considered the worst and will be the reference value. The analysis will also consider co-payment as a continuous variable.

Figure 1 shows an example of a choice set presented to respondents. Respondents must consider the trade-offs of the different attributes and check the box under the hypothetical treatment (A or B) that they prefer.

	Treatment A	Treatment B
Frequency of treatment	Daily	Bi-weekly
Pill taste	Berry	Chocolate
Pill color	Rainbow	Red
Side effects	No side effect	Coma
Hours wait to eat	0	2
Co-payment	$80	$20
Which treatment would you prefer?	☐	☐

Figure 1. Example of a Choice Set

DATA STRUCTURE

Consider the following set of sample data from this theoretical discrete choice experiment. Respondents would be given 14 sets of choices and asked to choose between pairs of hypothetical treatments. Table 2 shows how the data should be set up for the analysis. For the sake of the example, only the first 5 choice sets are shown for one patient.

RESPONDENT_ID	SETC	TREAT	CHOICE	ATTR1	ATTR2	ATTR3	ATTR4	ATTR5	ATTR6
1001	1	A	0	2	2	3	3	1	3
1001	1	B	1	3	3	1	1	2	1
1001	2	A	1	1	1	2	2	2	1
1001	2	B	0	2	2	3	3	3	2
1001	3	A	1	3	1	2	1	1	3
1001	3	B	0	4	2	3	2	2	1
1001	4	A	1	6	3	1	1	3	2
1001	4	B	0	1	1	2	2	1	3
1001	5	A	1	4	3	1	2	1	3
1001	5	B	0	5	1	2	3	2	1

Table 2. First 10 Observations in Sample Data

Notice we have two records per each choice set for each respondent. The first variable, RESPONDENT_ID is a unique identifier for each respondent and the second variable SETC identifies the choice set within respondent. CHOICE has a value of 1 if respondents chose that set of attributes and 0 if the respondent didn't choose that treatment (i.e., choose between each set of hypothetical treatments A and B). For example, respondent 1001 chose treatment B for choice set 1, and treatment A for choice set 2.

Variables ATTR1 to ATTR6 describe the attribute levels for each treatment included in a choice set. So, for example, treatment B for choice set 5 would be taken daily, taste like chocolate, be red in color, possibly cause coma, need to wait 1 hour before eating, and have a co-payment of $0. For all respondents the attribute descriptions for treatments A and B for each choice set are the same. Therefore, the values of variables ATTR1-ATTR6 will be repeated for each choice set for each respondent. The only variable that might change between respondents is CHOICE, which will depend on which treatment is chosen by each respondent.

ANALYSIS OF DCE WITH PROC PHREG

The PHREG procedure in SAS® is traditionally used to fit the Cox proportional hazards model for survival data. However, we can also use the PHREG procedure to fit conditional logit models. The stratified partial likelihood of PHREG has the same form as the likelihood in the conditional logit model and can also handle tied data.

In our example, we are creating our own dummy variables for each of the ATTR1-ATTR5 variables. For our example, we will use the highest level of each attribute as our reference categories (i.e., we consider these to be the "worst" and hypothesize that patients are more less likely to choose the treatment if this level of the attribute is present). We are going to include the co-payment attribute as a continuous variable in order to estimate the likelihood of treatment selection per $ of co-payment. Please note, however, that the PHREG procedure does support a CLASS statement with several options to specify the design matrix and the reference category (see as an alternative the next example in this paper using PROC LOGISTIC).

We also need to recode our CHOICE variable. To run a conditional logit model with PHREG we need to create artificial "observed times" for each set of choices. We will recode our CHOICE2 variable to have a value of 1 if the treatment is chosen and to have a value of 2 if not chosen, because the "censored time" (i.e., not chosen) *must* be a larger value than the "event time" (i.e., chosen).

The following code shows PROC PHREG to fit the conditional logit model:

```
proc phreg data=temp01 nosummary;
   model choice2*choice2(2) =  attr1_1 attr1_2 attr1_3 attr1_4 attr1_5
                               attr2_1 attr2_2 attr3_1 attr3_2 attr4_1 attr4_2
                               attr5_1 attr5_2 attr6_cont / rl;
  strata respondent_id setc;
run;
```

The NOSUMMARY option suppresses the summary display of the event and censored observation frequencies. CHOICE2 is the artificial time variable and a value of 2 identifies "censored times". RL option produces confidence intervals for hazard ratios. RESPONDENT_ID and SETC are used as stratification variables. STRATA statement specifies that each combination of the variables SETC and RESPONDENT_ID forms a set from which a choice was made.

Output 1 shows the output from PROC PHREG.

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	872.9987	14	<.0001
Score	715.9930	14	<.0001
Wald	471.2869	14	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio	95% Hazard Ratio Confidence Limits	
attr1_1	1	0.02568	0.14217	0.0326	0.8567	1.026	0.776	1.356
attr1_2	1	-0.20426	0.18933	1.1639	0.2807	0.815	0.563	1.182
attr1_3	1	-0.65889	0.20523	10.3073	0.0013	0.517	0.346	0.774
attr1_4	1	-0.82753	0.20924	15.6420	<.0001	0.437	0.290	0.659
attr1_5	1	-0.05586	0.14998	0.1387	0.7096	0.946	0.705	1.269
attr2_1	1	-0.26335	0.08558	9.4702	0.0021	0.768	0.650	0.909
attr2_2	1	0.17575	0.08691	4.0891	0.0432	1.192	1.005	1.414
attr3_1	1	1.83184	0.10186	323.4132	<.0001	6.245	5.115	7.625
attr3_2	1	0.98433	0.09106	116.8528	<.0001	2.676	2.239	3.199
attr4_1	1	0.82766	0.09682	73.0820	<.0001	2.288	1.893	2.766
attr4_2	1	0.54912	0.09317	34.7355	<.0001	1.732	1.443	2.079
attr5_1	1	1.66381	0.10292	261.3426	<.0001	5.279	4.315	6.459
attr5_2	1	1.12793	0.09700	135.2173	<.0001	3.089	2.554	3.736
attr6_cont	1	-0.00318	0.0004714	45.5742	<.0001	0.997	0.996	0.998

Output 1. Output from PROC PHREG

We first get global tests of the null hypothesis. In our example, all three tests are significant. Note in the lower panel you will find the parameter estimates. The "Hazard Ratios" are the exponentiated values of the parameter estimates and for our purposes are actually Odds Ratios. For example, respondents are 6.245 times more likely to choose a rainbow colored pill (ATTR3_1) compared to a grey colored pill (the referenced category for ATTR3). Note the 95%

Confidence Limits are generated by the RL option in the model statement. Also note in the PHREG procedure there is no intercept in the model.

ANALYSIS OF DCE WITH PROC LOGISITIC

PROC LOGISTIC is another way to fit a conditional logit model. The input data is the same as shown in Table 2 and the code would look like the following:

```
proc logistic data = temp01 descending;
  class attr1 attr2 attr3 attr4 attr5 / ref=last;
  model choice = attr1 attr2 attr3 attr4 attr5 attr6_cont;
  strata respondent_id setc;
run;
```

We specified REF=LAST so the highest level will be our reference categories. We are using RESPONDENT_ID and SETC as stratification variables as we did in PHREG. SAS automatically suppresses intercept term when STRATA statement is used.

Output 2 displays the output from PROC LOGISTIC.

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	872.9987	14	<.0001
Score	715.9930	14	<.0001
Wald	471.2869	14	<.0001

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
attr1	1	1	0.3125	0.1119	7.7931	0.0052
attr1	2	1	0.0825	0.1043	0.6262	0.4288
attr1	3	1	-0.3721	0.1082	11.8361	0.0006
attr1	4	1	-0.5407	0.1190	20.6604	<.0001
attr1	5	1	0.2310	0.1304	3.1348	0.0766
attr2	1	1	-0.2341	0.0536	19.0669	<.0001
attr2	2	1	0.2049	0.0543	14.2277	0.0002
attr3	1	1	0.8931	0.0587	231.8369	<.0001
attr3	2	1	0.0456	0.0524	0.7576	0.3841
attr4	1	1	0.3687	0.0535	47.4538	<.0001
attr4	2	1	0.0902	0.0513	3.0877	0.0789
attr5	1	1	0.7332	0.0549	178.4421	<.0001
attr5	2	1	0.1973	0.0512	14.8746	0.0001
attr6_cont		1	-0.00318	0.000471	45.5742	<.0001

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
attr1	1 vs 6	1.026	0.776	1.356
attr1	2 vs 6	0.815	0.563	1.182
attr1	3 vs 6	0.517	0.346	0.774
attr1	4 vs 6	0.437	0.290	0.659
attr1	5 vs 6	0.946	0.705	1.269
attr2	1 vs 3	0.768	0.650	0.909
attr2	2 vs 3	1.192	1.005	1.414
attr3	1 vs 3	6.245	5.115	7.625
attr3	2 vs 3	2.676	2.239	3.199
attr4	1 vs 3	2.288	1.893	2.766
attr4	2 vs 3	1.732	1.443	2.079
attr5	1 vs 3	5.279	4.315	6.459
attr5	2 vs 3	3.089	2.554	3.736
attr6_cont		0.997	0.996	0.998

Output 2. Output from PROC LOGISTIC

PROC LOGISTIC results are the same as the PROC PHREG results. Notice that we get the same values for the model testing the global null hypothesis and the same parameter estimates as the PROC PHREG output. For

example, respondents are again shown to prefer the rainbow colored pill compared to the grey colored pill (OR=6.245).

CONCLUSION

In this paper, we explained what the discrete choice experiment is, how to set up the data for analysis, two methods to perform the analysis using PROC PHREG and PROC LOGISTIC, and how to interpret the results. DCE is a powerful tool for estimating the probability of individuals making a choice between two hypothetical alternatives when the alternatives require trade-offs between their characteristics. Results can be used in predicting real-world choice behaviors and are easy to interpret. We hope this paper provides a better understanding of DCE.

REFERENCES

The following resources were invaluable in putting together this presentation:

Allison PD (1999). *Logistic Regression Using the SAS® System: Theory and Application*, Cary, NC: SAS Institute Inc.

Kuhfeld WF (2000). *Multinomial Logit, Discrete Choice Modeling: An Introduction to Designing Choice Experiments, and Collecting, Processing, and Analyzing Choice Data with the SAS® System*, Cary, NC: SAS Institute Inc.

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