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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. 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 with varying levels are defined for treatments. Respondents are presented with pairs of hypothetical treatments that have different combinations of attribute levels and are asked to choose their preferred treatment. Analyzing the responses allows evaluation of the relative importance of the attributes and the trade-offs that respondents are willing to make between the attributes. This paper explains how to set up the data and discusses how to use the PHREG and LOGISTIC procedures to appropriately analyze the conditional logit model.

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

By default, SAS uses effect coding for the parameter estimates. However, SAS always uses reference cell coding when reporting odds ratios. With reference cell coding, each parameter represents the difference between the given level and the 'reference level' whereas with effect coding each parameter represents the difference between the given level and the 'average response'. We can tell SAS to use reference cell coding by specifying the PARAM=REF option on the CLASS statement. For example, ATTR1 (REF='1') / PARAM=REF tells SAS that for the variable ATTR1 the desired reference category is 1 and then tells SAS that we want to use reference coding in parameter estimates.

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.

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;
  class attr1 (ref='6') attr2 (ref='3') attr3 (ref='3') attr4 (ref='3')
        attr5 (ref='3') / param=ref;
  model choice2*choice2(2) =   attr1 - attr5 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


                    Type 3 Tests

                                Wald
Effect          DF    Chi-Square    Pr > ChiSq

attr1            5       24.0272        0.0002
attr2            2       21.0019        <.0001
attr3            2      327.2283        <.0001
attr4            2       74.7431        <.0001
attr5            2      265.7118        <.0001
attr6_cont       1       45.5742        <.0001
```

Output 1. Output from PROC PHREG

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, continued

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 (ref='6') attr2 (ref='3') attr3 (ref='3') attr4 (ref='3')
        attr5 (ref='3') / param=ref;
  model choice = attr1 attr2 attr3 attr4 attr5 attr6_cont;
  strata respondent_id setc;
run;
```

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

Type 3 Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
attr1	5	24.0272	0.0002
attr2	2	21.0019	<.0001
attr3	2	327.2283	<.0001
attr4	2	74.7431	<.0001
attr5	2	265.7118	<.0001
attr6_cont	1	45.5742	<.0001

Output 2. Output from PROC LOGISTIC

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
attr1	1	1	0.0257	0.1422	0.0326	0.8567
attr1	2	1	-0.2043	0.1893	1.1639	0.2807
attr1	3	1	-0.6589	0.2052	10.3073	0.0013
attr1	4	1	-0.8275	0.2092	15.6420	<.0001
attr1	5	1	-0.0559	0.1500	0.1387	0.7096
attr2	1	1	-0.2633	0.0856	9.4702	0.0021
attr2	2	1	0.1758	0.0869	4.0891	0.0432
attr3	1	1	1.8318	0.1019	323.4132	<.0001
attr3	2	1	0.9843	0.0911	116.8528	<.0001
attr4	1	1	0.8277	0.0968	73.0820	<.0001
attr4	2	1	0.5491	0.0932	34.7355	<.0001
attr5	1	1	1.6638	0.1029	261.3426	<.0001
attr5	2	1	1.1279	0.0970	135.2173	<.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, continued

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 (ATTR3 1 vs 3, 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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