Discrete Choice Modeling
Exercise 4
Multinomial Choice

This assignment will consist of some exercises with the multinomial logit models. The data for the exercises is the multinomial choice file

mnc.lpj

This project file contains both the choice data sets discussed in class, the brand choices data and the travel mode data. Altogether, there are 12,800 observations in the brand choices data. The travel mode data appear in the first 840 rows of the data area. These computations will be based only on the shoe brand data.

Preliminaries: The exercises will build on the basic model

\[ U(brand) = \beta_1 Fashion + \beta_2 Quality + \beta_3 Price + \beta_4 Price^2 + \gamma ASC4 + \epsilon_{brand} \]
\[ U(\text{none}) = \gamma + \epsilon_{\text{none}}. \]

The model analyzes 4 choices, brand1, brand2, brand3, and 'none of the brands.' ASC4 is the constant term that appears only in the 'NONE' choice. The central model command will be

\[
\text{NLOGIT} \; ; \; \text{Lhs = choice} \; ; \; \text{Choices = brand1,brand2,brand3,none} \\
\; ; \; \text{Rhs = fash, qual, price, pricesq,asc4 $}\
\]

There are two characteristic variables, gender and age. Gender is coded as MALE = 1 for men, 0 for women. AGE is categorized as AGE25 = 1 if age ≤ 25 and 0 else, AGE39 if 25 < age ≤ 39 and 0 else, and AGE40 if age > 40. For modeling purposes, we will drop AGE40.

Part I. Multinomial Choice

1. Fit the basic model. Is pricesq significant. Use the Wald test based on estimates of the basic model. Fit model without pricesq and use a likelihood ratio test.

2. Do age and sex matter? Add age24, age39 and male to the basic model and use a likelihood ratio test. Note that these variables are choice invariant, so they must be added as

\[
\; ; \; \text{Rh2 = male, age24, age39}\
\]

If you add them to the Rhs list instead, estimation will break down.
3. Is there a more general age difference in utility. To explore this, use a Chow style test. To start,

```
CREATE ; Young = age25 $
```

Then,

```
NLOGIT ; if [young = 1] … $ 
CALC ; lyoung = logl $ 
NLOGIT ; if [young = 0] … $ 
CALC ; lold = logl $ 
NLOGIT ; … $ 
CALC ; list ; lrtest = 2*(lyoung+lold – logl) $
```

Is the statistic larger than the critical value? Note, there is a way to combine all of these in a single operation:

```
NLOGIT ; For[ (test) young = *,0,1] 
; … your model specification (must not include age25) $ 
```

**Part II. Elasticities and Marginal Analysis**

We estimate a marginal effect (of price) in the MNL model. What are the estimates of the own and cross elasticities across the three brands? What is the evidence of the IIA assumption in these results? Try the following:

```
NLOGIT ; Lhs = Choice ; Choices=Brand1,Brand2,Brand3,None 
; Rhs = Fash,Qual,Price,Asc4 
; Effects : Price (*) $ 
```

What are the effects. Note that the squared price is not in the equation. It is unclear how to compute the elasticity directly in the presence of the square. But, there is a way to explore the effects with the simulator. Consider the following:

```
NLOGIT ; Lhs = Choice ; Choices=Brand1,Brand2,Brand3,None 
; Rhs = Fash,Qual,Price,Pricesq,Asc4 $ 
NLOGIT ; Lhs = Choice ; Choices=Brand1,Brand2,Brand3,None 
; Rhs = Fash,Qual,Price,Pricesq,Asc4 
; Simulate = * ; Scenario: 
price (brand*) = [*] 1.1 / 
pricesq(brand*)=[*]1.21 $ 
```

The scenario increases the price by 10% and consequently, the square by 21%. What happens to the market shares under this scenario? Try a larger price increase, say 25% (and 62.5%).

**Part III. Attribute Nonattendance**

One aspect of choice theory that has attracted some attention is the possibility that in a choice study, some individuals in the sample may be ignoring some of the attributes. This is called ‘attribute nonattendance’ in the recent literature. Individuals sometimes appear to be revealing this kind of behavior, but there is no definitive observed indicator. The latent class model provides a way to analyze this possibility. In the example below, we fit a model in which two
attributes, fashion and quality are allowed to be separately or jointly nonattended. Note that the nonzero coefficients are the same in the 4 classes.

\[
\text{NLOGIT} \quad ; \ Lhs = \text{Choice} \ ; \ Choices=\text{Brand1,Brand2,Brand3,None} \\
\quad ; \ Rhs = \text{Fash,Qual,Price,ASC4} \\
\quad ; \ LCM \ ; \ Pds = 8 \ ; \ Pts = 4 \\
\quad ; \ RST = b1,b2,b3,c, \ b1, 0,b3,c, \ 0,b2,b3,c, \ 0, 0,b3,c$
\]

**Part IV. A Random Parameters Model**

We fit different specifications of a random parameters model. The first has a random coefficient on price. We also examine the implied population distribution and the distribution of conditional means.

\[
\text{NLOGIT} \quad ; \ Lhs = \text{Choice} \ ; \ Choices=\text{Brand1,Brand2,Brand3,None} \\
\quad ; \ Rhs = \text{Fash,Qual,Price,ASC4}$
\]

\[
\text{NLOGIT} \quad ; \ Lhs = \text{Choice} \ ; \ Choices=\text{Brand1,Brand2,Brand3,None} \\
\quad ; \ Rhs = \text{Fash,Qual,Price,ASC4} \\
\quad ; \ RPL \ ; \ Fcn= \text{Price(n)} \ ; \ Pds = 8 \ ; \ Pts = 25 \ ; \ halton \ ; \ par$
\]

\[
\text{SAMPLE} \quad ; \ 1-800$
\]

\[
\text{CREATE} \quad ; \ \text{ebprice} = \beta_i$
\]

\[
\text{CREATE} \quad ; \ \text{bprice} = \text{rnn((b(1)),(b(5)))}$
\]

\[
\text{KERNEL} \quad ; \ \text{rhs=bprice,ebprice}$
\]

\[
\text{SAMPLE} \quad ; \ all$
\]

Describe your findings. Repeat the operation with the fashion coefficient. (To do so, you need only change Price(n) to Fash(n) in the estimation command.)

====================================================================

This part of the assignment will use the mode choice, conditional logit data. In what follows, be sure that you are only using the first 840 rows in the combined data set. The command to set this data set is

\[
\text{SAMPLE} \ ; \ 1 – 840$
\]

You can see the number of observations in the current sample at the top of the project window, as shown below.

If this value is not 840 at any time, you can just issue the sample command to reset the sample. Note, it is possible to enforce this “on the fly” in the estimation commands by including ‘If[ _Obsno <= 840]’ at the beginning of the command.

====================================================================
Do the multinomial logit and multinomial probit models give similar results? You can’t tell directly from the coefficient estimates because of scaling and normalization, so you have to rely on other indicators such as marginal effects. Fit a multinomial probit and a multinomial logit model, and compare the results. Note, estimation of the MNP model is extremely slow, so we have set it up with a very small number of replications and stopped the iterations at 5. This particular model would take 30-50 iterations, and an hour or two, to finish. As it is, this will take several minutes.

```
NLOGIT ; Lhs = Mode ; output=ic ; Choices = Air,Train,Bus,Car ; Rhs = TTME,INVC,INVT,GC; Rh2=One,Hinc ; Effects: invc (*) $
NLOGIT ; Lhs = Mode ; MNP ; PTS = 5 ; Maxit = 5 ; Halton ; Choices = Air,Train,Bus,Car ; Rhs = TTME,INVC,INVT,GC; Rh2=One,Hinc ; Effects: invc (*) $
```

The multinomial probit model is distinguished by allowing the correlations across utility functions and to some degree, heteroscedasticity across utilities – though not across individuals. For a four outcome model, the covariance matrix for a multinomial probit model must be of the form

\[
\Sigma = \begin{bmatrix}
\sigma_{11} & \sigma_{12} \\
\sigma_{21} & \sigma_{22} \\
\sigma_{31} & \sigma_{32} & 1 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]

The restrictions on the last two rows are normalizations needed for identification. The built in multinomial probit estimator in Stata actually goes further, and imposes \( \Sigma = I \). You can replicate this model by adding

```
; SDV = 1 ; COR = 0
```

To the multinomial probit command. Fit this model, then compare the reported elasticity matrix to that reported by the initial multinomial logit model. (The difference mostly reflects scale differences in the coefficients – this is the familiar relationship between probit and logit models.)