Cameron and Trivedi 15-2, 15-3, 15-4

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<u>15 - 2</u>

Use a 50% subsample of the fishing mode choice data of Section 15.2.

(a)

Estimate the conditional logit model of Section 15.2.1.

Estimates are reported in Table 1. See attached .do and .log files for more detail.

(b)

Comment on the statistical significance of parameter estimates.

The reported Wald statistic for the joint significance of p, q, and inc is 124, making the regressors highly statistically significant (jointly).

(c)

What is the effect of an increase in price on the various modes of fishing?

Marginal effects are reported in Table 2. See attached .do and .log files for more detail. While, all the changes in probabilities are small they are all significant at the 5% level, and have the expected signs. In all cases, a one dollar price increase in a mode of fishing has a negative effect on the probabilities on those modes, and a positive effect on the other three. This mirrors the results reported in Cameron and Trivedi using the full sample, although they report their results for $100 changes in prices.

<u>15 - 3</u>

Use a 50% subsample of the fishing mode choice data of Section 15.2.

(a)

Estimate the multinomial logit model of Section 15.2.2.

Estimates are reported in Table 1. See attached .do and .log files for more detail.

(b)

Comment on the statistical significance of parameter estimates.

A Wald test of the joint significance yields a test statistic of 14.28, making the coefficient estimates jointly significant at the 5% level.

(c)

What is the effect of an increase in income on the various modes of fishing?

Marginal effects are reported in Table 2. See attached .do and .log files for more detail. For a \$1,000 change in income, only two of the reported coefficients are significant at the 5% level. Those are the decrease in probability for Pier fishing, and the increase in the probability of Private. The direction of these changes is as expected.

Table 1, 15-2 and 15-3 Estimation Results

				Model Type		
Regressor	**Type**	**Coefficient**	**CL (Mixed)**	**P-value**	**MNL**	**P-value**
Price (P)	Specific	β_P	-0.022	(0.000)	-	-
Catch rate (C)	Specific	β_{CR}	0.208	(0.162)	-	-
Intercept	Invariant	α_1 : *Beach*	-	-	-	-
		α_2 : *Pier*	0.859	(0.009)	0.869	(0.008)
		α_3 : *Private*	0.931	(0.003)	1.070	(0.000)
		α_2 : *Charter*	1.953	(0.000)	1.533	(0.000)
Income (I)	Invariant	β_{I1} : *Beach*	-	-	-	-
		β_{I2} : *Pier*	-0.171	(0.022)	-0.177	(0.018)
		β_{I3} : *Private*	-0.003	(0.963)	0.021	(0.707)
		β_{I4} : *Charter*	-0.122	(0.080)	-0.096	(0.097)
Log likelihood			-622		-739	
Pseudo-R^2			-		0.0104	

Table 2, 15-2 and 15-3 Marginal Effects					
	$1 Change in Price of*				$1,000 Change
	Beach	**Pier**	**Private**	**Charter**	**in Income***
Change in Pr[$Beach$]	-0.0013	0.0001	0.0006	0.0006	0.0062
Change in Pr[$Pier$]	0.0001	-0.0015	0.007	0.0007	-0.0173
Change in Pr[$Private$]	0.0006	0.0007	-0.0055	0.0042	0.0272
Change in Pr[$Charter$]	0.0006	0.0007	0.0042	-0.0055	-0.0162

*These results are from the multinomial logit model, the marginal effects for price changes are for the conditional (mixed) logit model.

15 - 4

Use a 50% subsample of the fishing mode choice data of Section 15.2. Suppose we collapse the model to three alternatives and order the alternatives, with $y = 0$ if fishing from a pier or beach, $y = 1$ if fishing from a private boat and $y = 2$ if fishing from a charter boat.

(a)

Estimate an ordered logit model with income as the only regressor.

See attached .do and .log files.

(b)

Provide an interpretation of the estimated coefficient.

The coefficient estimate is positive, indicating that an increase in income is positively correlated with moving up the "scale" of fishing modes. It is not clear to me that the order here is meaningful for the private vs. charter modes. In fact the results from the multinomial logit model indicate that as income increases, the probability of private boat increases (this result is statistically significant). Whereas for charter, the probability decreased as income increased although the result wasn't statistically significant. This would point to the possibility that the suggested ordering here is not correct, and perhaps a model flipping the order of private and charter might be a better fit.

(c)

Compare the fit of this model with that from a three-choice multinomial model with income as the regressor.

See attached .do and .log files for this estimation. The three-choice multinomial model performs better than the ordered logit. The Pseudo-R^2 for the ordered logic was 0.0000, whereas it is 0.0133 for the multinomial logit model. The explanation in part (a), provides some possible intuition behind why this is the case.

```
******** *****************************************************************
******** Spring 2014 **************************************************************
******** Robert Ackerman **********************************************************
**** HW2: Cameron and Trivedi, Microeconometrics: Methods and Applications ****

********* 1. Initial Settings *********
clear
clear matrix
capture cd "/Users/robertackerman/Desktop/Dropbox/
log using "HW2_Ackerman.log", replace

set more off
pause on

******** 2. Load the Entire Sample ********

infile mode price crate dbeach dpier dprivate dcharter pbeach ppier pprivate pcharter qbeach qpier qprivate qcharter income using NLDATA.ASC

******** 3. Generate 50% Subsample ********

** Fix Seed, so  the Same Subsample is Drawn Each Time **
set seed 123456789

** 50% Randomly Generated Subsample **
sample 50
su dbeach
su dpier
su dprivate
su dcharter

******** 4. Data Magagement, Note: This is based heavily on Cameron and Trivedi's mma15p2gev.do file ********

** Re-scale income by 1000 **
gen inc = income/1000

** Data are one entry per individual **
** Reshape to 4 observations per individual; one for each alternative **
** Use reshape to do this **
** Note:  alternatv = 1 if beach, = 2 if pier; = 3 if private boat; = 4 if charter **
```

```
** First generate new variables **
gen id = _n
gen d1 = dbeach
gen p1 = pbeach
gen q1 = qbeach
gen d2 = dpier
gen p2 = ppier
gen q2 = qpier
gen d3 = dprivate
gen p3 = pprivate
gen q3 = qprivate
gen d4 = dcharter
gen p4 = pcharter
gen q4 = qcharter

** Now use the reshape command **
reshape long d p q, i(id) j(alterntv)
** This automatically generates variable alterntv = 1 (beach), 2 (pier), 3 (boat) and 4 (charter) **

******** 5. 15-2 ********

** (a) Estimate the conditional logit model of Section 15.2.1. **
asclogit d p q, case(id) alternatives(alterntv) casevars(inc)

** (c) What is the effect of an increase in price on the various modes of fishing? **
estat mfx, varlist(p)

******** 6. 15-3 ********
clear

** Re-load the data, re-scale income and generate the subsample**
infile mode price crate dbeach dpier dprivate dcharter pbeach ppier pprivate pcharter qbeach qpier qprivate qcharter income using NLDATA.ASC
gen inc = income/1000
set seed 123456789
sample 50

** (a) Estimate the multinomial logit model of Section 15.2.2. **
mlogit mode inc, b(1)

** (b) Comment on the statistical significance of the parameter estimates. **
test inc
```

```
** (c) What is the effect of an increase in income on the various modes of fishing? **
margins, dydx(inc) predict(outcome(1)) atmean
margins, dydx(inc) predict(outcome(2)) atmean
margins, dydx(inc) predict(outcome(3)) atmean
margins, dydx(inc) predict(outcome(4)) atmean


******** 7. 15-4 ********
** Collapse the data into a three alternative model **
replace mode=0 if mode==1 | mode==2
replace mode=1 if mode==3
replace mode=2 if mode==4

** (a) Estimate an ordered logit model with income as the only regressor. **
ologit mode inc

** (b) Provide an interpretation of the estimated coefficient **

** (c) Compare the fit of this model with that from a three-choice multinomial model with income as the regressor **
mlogit mode inc, b(1)

clear

log close
```

```
----------------------------------------------------------------------
-----------------------------------------------
      name:  <unnamed>
       log:  /Users/robertackerman/Desktop/Dropbox/
HW2_Ackerman.log
  log type:  text
 opened on:  24 Jan 2014, 16:17:18

.
. set more off

. pause on

.
. ******** 2. Load the Entire Sample ********
.
. infile mode price crate dbeach dpier dprivate dcharter pbeach ppier
pprivate pcharter qbeach qpier qprivate qcharte
> r income using NLDATA.ASC
(1182 observations read)

.
. ******** 3. Generate 50% Subsample ********
.
. ** Fix Seed, so  the Same Subsample is Drawn Each Time **
. set seed 123456789

.
. ** 50% Randomly Generated Subsample **
. sample 50
(591 observations deleted)

. su dbeach

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
      dbeach |       591    .1167513    .3213957          0          1

. su dpier

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
       dpier |       591     .142132    .3494812          0          1

. su dprivate

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
    dprivate |       591    .3722504    .4838141          0          1
```

```
. su dcharter

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
    dcharter |       591    .3688663    .4829064          0          1

.
. ******** 4. Data Magagement, Note: This is based heavily on Cameron
and Trivedi's mma15p2gev.do file ********
.
. ** Re-scale income by 1000 **
. gen inc = income/1000

.
. ** Data are one entry per individual **
. ** Reshape to 4 observations per individual; one for each
alternative **
. ** Use reshape to do this **
. ** Note:  alternatv = 1 if beach, = 2 if pier; = 3 if private boat;
= 4 if charter **
.
. ** First generate new variables **
. gen id = _n

. gen d1 = dbeach

. gen p1 = pbeach

. gen q1 = qbeach

. gen d2 = dpier

. gen p2 = ppier

. gen q2 = qpier

. gen d3 = dprivate

. gen p3 = pprivate

. gen q3 = qprivate

. gen d4 = dcharter

. gen p4 = pcharter

. gen q4 = qcharter

.
. ** Now use the reshape command **
```

```
. reshape long d p q, i(id) j(alterntv)
(note: j = 1 2 3 4)

Data                               wide   ->   long
----------------------------------------------------------------------
-------
Number of obs.                      591   ->    2364
Number of variables                  30   ->      22
j variable (4 values)                     ->   alterntv
xij variables:
                           d1 d2 ... d4   ->   d
                           p1 p2 ... p4   ->   p
                           q1 q2 ... q4   ->   q
----------------------------------------------------------------------
-------

. ** This automatically generates variable alterntv = 1 (beach), 2
(pier), 3 (boat) and 4 (charter) **
.
. ******** 5. 15-2 ********
.
. ** (a) Estimate the conditional logit model of Section 15.2.1. **
. asclogit d p q, case(id) alternatives(alterntv) casevars(inc)

Iteration 0:   log likelihood = -650.20658
Iteration 1:   log likelihood = -624.53682
Iteration 2:   log likelihood = -622.23988
Iteration 3:   log likelihood =  -622.2215
Iteration 4:   log likelihood =  -622.2215

Alternative-specific conditional logit         Number of obs      =
2364
Case variable: id                              Number of cases    =
591

Alternative variable: alterntv                 Alts per case: min =
4
                                                              avg =
4.0
                                                              max =
4

                                                  Wald chi2(5)    =
123.84
Log likelihood =  -622.2215                       Prob > chi2     =
0.0000

----------------------------------------------------------------------
--------
           d |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
```

```
Interval]
-------------
+----------------------------------------------------------------
alterntv     |
           p |   -.022383   .0021848   -10.24   0.000    -.0266651
-.0181009
           q |   .2083431   .1489423     1.40   0.162    -.
0835784    .5002646
-------------
+----------------------------------------------------------------
1            |  (base alternative)
-------------
+----------------------------------------------------------------
2            |
         inc |  -.1711379   .0746539    -2.29   0.022    -.3174569
-.024819
       _cons |   .8594627   .3266417     2.63   0.009     .2192567
1.499669
-------------
+----------------------------------------------------------------
3            |
         inc |  -.0031477   .0680852    -0.05   0.963    -.
1365923    .1302968
       _cons |   .9310191    .312062     2.98   0.003     .3193888
1.542649
-------------
+----------------------------------------------------------------
4            |
         inc |  -.1215695   .0693994    -1.75   0.080    -.
2575897    .0144508
       _cons |    1.95299   .3195131     6.11   0.000     1.326756
2.579224
---------------------------------------------------------------------
--------


.
. ** (c) What is the effect of an increase in price on the various
modes of fishing? **
. estat mfx, varlist(p)

Pr(choice = 1|1 selected) = .06266738
---------------------------------------------------------------------
---------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]
X
-------------
+-----------------------------------------------------------------
p            |
           1 | -.001315    .00017   -7.72   0.000  -.001649  -.000981
98.279
```

```
           2 |  .000103   .000024    4.38   0.000   .000057   .000149
98.279
           3 |  .000607   .000083    7.34   0.000   .000445   .000769
52.413
           4 |  .000605   .000083    7.32   0.000   .000443   .000767
81.514
----------------------------------------------------------------------
---------

Pr(choice = 2|1 selected) = .07350399
----------------------------------------------------------------------
---------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]
X
-------------
+------------------------------------------------------------------
p            |
           1 |  .000103   .000024    4.38   0.000   .000057   .000149
98.279
           2 | -.001524   .000186   -8.20   0.000  -.001889   -.00116
98.279
           3 |  .000712   .000092    7.73   0.000   .000531   .000892
52.413
           4 |  .000709   .000092    7.70   0.000   .000529    .00089
81.514
----------------------------------------------------------------------
---------

Pr(choice = 3|1 selected) = .43263014
----------------------------------------------------------------------
---------
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]
X
-------------
+------------------------------------------------------------------
p            |
           1 |  .000607   .000083    7.34   0.000   .000445   .000769
98.279
           2 |  .000712   .000092    7.73   0.000   .000531   .000892
98.279
           3 | -.005494   .000559   -9.83   0.000  -.006589  -.004399
52.413
           4 |  .004176   .000545    7.66   0.000   .003107   .005244
81.514
----------------------------------------------------------------------
---------

Pr(choice = 4|1 selected) = .43119849
----------------------------------------------------------------------
---------
```

```
variable     |   dp/dx   Std. Err.    z     P>|z|  [    95% C.I.    ]
X
-------------
+------------------------------------------------------------------
p            |
           1 |  .000605   .000083    7.32   0.000   .000443   .000767
98.279
           2 |  .000709   .000092    7.70   0.000   .000529    .00089
98.279
           3 |  .004176   .000545    7.66   0.000   .003107   .005244
52.413
           4 |  -.00549   .000559   -9.82   0.000  -.006586  -.004394
81.514
----------------------------------------------------------------------
---------

.
. ******** 6. 15-3 ********
. clear

.
. ** Re-load the data, re-scale income and generate the subsample**
. infile mode price crate dbeach dpier dprivate dcharter pbeach ppier
pprivate pcharter qbeach qpier qprivate qcharte
> r income using NLDATA.ASC
(1182 observations read)

. gen inc = income/1000

. set seed 123456789

. sample 50
(591 observations deleted)

.
. ** (a) Estimate the multinomial logit model of Section 15.2.2. **
. mlogit mode inc, b(1)

Iteration 0:   log likelihood = -746.89332
Iteration 1:   log likelihood = -739.23819
Iteration 2:   log likelihood = -739.15294
Iteration 3:   log likelihood = -739.15281
Iteration 4:   log likelihood = -739.15281

Multinomial logistic regression                   Number of obs   =
591
                                                  LR chi2(3)      =
15.48
                                                  Prob > chi2     =
0.0014
```

```
Log likelihood = -739.15281                       Pseudo R2       =
0.0104

----------------------------------------------------------------------
--------
        mode |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------
+----------------------------------------------------------------
1            |  (base outcome)
-------------
+----------------------------------------------------------------
2            |
         inc |  -.1773109   .0749714    -2.37   0.018    -.3242521
-.0303698
       _cons |   .8689192   .3270223     2.66   0.008     .2279672
1.509871
-------------
+----------------------------------------------------------------
3            |
         inc |    .020615   .0548374     0.38   0.707    -.
0868643    .1280943
       _cons |   1.070403   .2726271     3.93   0.000     .5360635
1.604742
-------------
+----------------------------------------------------------------
4            |
         inc |  -.0959633   .0578337    -1.66   0.097    -.
2093152    .0173886
       _cons |   1.532838   .2748424     5.58   0.000     .9941565
2.071519
----------------------------------------------------------------------
--------

.
. ** (b) Comment on the statistical significance of the parameter
estimates. **
. test inc

 ( 1)  [1]o.inc = 0
 ( 2)  [2]inc = 0
 ( 3)  [3]inc = 0
 ( 4)  [4]inc = 0
       Constraint 1 dropped

           chi2(  3) =   14.28
         Prob > chi2 =    0.0025

.
. ** (c) What is the effect of an increase in income on the various
```

```
modes of fishing? **
. margins, dydx(inc) predict(outcome(1)) atmean

Conditional marginal effects                      Number of obs   =
591
Model VCE    : OIM

Expression   : Pr(mode==1), predict(outcome(1))
dy/dx w.r.t. : inc
at           : inc             =    3.993232 (mean)

----------------------------------------------------------------------
--------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------
+---------------------------------------------------------------
         inc |   .0061745   .0053773     1.15   0.251    -.
0043649    .0167138
----------------------------------------------------------------------
--------

. margins, dydx(inc) predict(outcome(2)) atmean

Conditional marginal effects                      Number of obs   =
591
Model VCE    : OIM

Expression   : Pr(mode==2), predict(outcome(2))
dy/dx w.r.t. : inc
at           : inc             =    3.993232 (mean)

----------------------------------------------------------------------
--------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------
+---------------------------------------------------------------
         inc |  -.0172535   .0069147    -2.50   0.013    -.0308062
-.0037009
----------------------------------------------------------------------
--------

. margins, dydx(inc) predict(outcome(3)) atmean

Conditional marginal effects                      Number of obs   =
591
Model VCE    : OIM
```

```
Expression   : Pr(mode==3), predict(outcome(3))
dy/dx w.r.t. : inc
at           : inc             =    3.993232 (mean)

----------------------------------------------------------------------
--------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------
+----------------------------------------------------------------
         inc |   .0272352   .0084595     3.22   0.001     .
0106549    .0438155
----------------------------------------------------------------------
--------

. margins, dydx(inc) predict(outcome(4)) atmean

Conditional marginal effects                      Number of obs   =
591
Model VCE    : OIM

Expression   : Pr(mode==4), predict(outcome(4))
dy/dx w.r.t. : inc
at           : inc             =    3.993232 (mean)

----------------------------------------------------------------------
--------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------
+----------------------------------------------------------------
         inc |  -.0161561   .0089038    -1.81   0.070    -.
0336072     .001295
----------------------------------------------------------------------
--------

.
.
. ******** 7. 15-4 ********
. ** Collapse the data into a three alternative model **
. replace mode=0 if mode==1 | mode==2
(153 real changes made)

. replace mode=1 if mode==3
(220 real changes made)

. replace mode=2 if mode==4
```

```
(218 real changes made)

.
. ** (a) Estimate an ordered logit model with income as the only
regressor. **
. ologit mode inc

Iteration 0:   log likelihood = -641.57828
Iteration 1:   log likelihood = -641.35973
Iteration 2:   log likelihood = -641.35972

Ordered logistic regression                       Number of obs   =
591
                                                  LR chi2(1)      =
0.44
                                                  Prob > chi2     =
0.5085
Log likelihood = -641.35972                       Pseudo R2       =
0.0003

----------------------------------------------------------------------
--------
        mode |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------
+-----------------------------------------------------------------
         inc |  -.0207248   .0313372    -0.66   0.508    -.
0821446     .040695
-------------
+-----------------------------------------------------------------
       /cut1 |  -1.137323    .160189                     -1.451288
-.8233587
       /cut2 |   .4524875   .1536252                      .
1513877    .7535873
----------------------------------------------------------------------
--------


.
. ** (b) Provide an interpretation of the estimated coefficient **
.
. ** (c) Compare the fit of this model with that from a three-choice
multinomial model with income as the regressor *
> *
. mlogit mode inc, b(1)

Iteration 0:   log likelihood = -641.57828
Iteration 1:   log likelihood = -636.71194
Iteration 2:   log likelihood = -636.70685
Iteration 3:   log likelihood = -636.70685
```

```
Multinomial logistic regression                   Number of obs   =
591
                                                  LR chi2(2)      =
9.74
                                                  Prob > chi2     =
0.0077
Log likelihood = -636.70685                       Pseudo R2       =
0.0076

----------------------------------------------------------------------
--------
        mode |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------
+----------------------------------------------------------------
0            |
         inc |  -.1054007   .0454581    -2.32   0.020     -.194497
-.0163044
       _cons |   .0659322   .2100869     0.31   0.754    -.
3458305    .4776949
-------------
+----------------------------------------------------------------
1            |  (base outcome)
-------------
+----------------------------------------------------------------
2            |
         inc |  -.1151731   .0412571    -2.79   0.005    -.1960355
-.0343106
       _cons |   .4567516   .1914001     2.39   0.017     .
0816144    .8318889
----------------------------------------------------------------------
--------

.
. clear

.
. log close
      name:  <unnamed>
       log:  /Users/robertackerman/Desktop/Dropbo:
HW2_Ackerman.log
  log type:  text
 closed on:  24 Jan 2014, 16:17:20
----------------------------------------------------------------------
-----------------------------------------------
```