Ordinal Regression 2: Hypothesis Testing & Interpreting Results

This handout borrows heavily (often verbatim) from Long and Freese 2006 chapter 5 and Long 1997.

Basic Hypothesis Testing. Hypothesis testing proceeds pretty much the same as it does in logistic regression. I'll show a couple of different ways to test the hypothesis that the effect of temp is 0. Using the shuttle data,

```
. use http://www.nd.edu/~rwilliam/xsoc73994/statafiles/shuttle2.dta, clear
(First 25 space shuttle flights)

. ologit distress date temp, nolog

Ordered logit estimates                           Number of obs   =         23
                                                  LR chi2(2)      =      12.32
                                                  Prob > chi2     =     0.0021
Log likelihood =  -18.79706                       Pseudo R2       =     0.2468

------------------------------------------------------------------------------
    distress |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        date |    .003286   .0012662     2.60   0.009     .0008043    .0057677
        temp |  -.1733752   .0834473    -2.08   0.038     -.336929   -.0098215
-------------+----------------------------------------------------------------
       _cut1 |   16.42813   9.554813          (Ancillary parameters)
       _cut2 |   18.12227   9.722293
------------------------------------------------------------------------------
```

The default output includes z values, which = coefficient/standard error. This is a Wald test. The `test` command will also do Wald tests:

```
. test temp

 ( 1)  temp = 0

           chi2(  1) =    4.32
         Prob > chi2 =    0.0377

. display r(chi2)^.5
2.0776607
```

As usual, the chi-square statistic is the same as the z-statistic squared. The `test` command can also do more complicated Wald tests:

```
. test temp date

 ( 1)  temp = 0
 ( 2)  date = 0

           chi2(  2) =    7.40
         Prob > chi2 =    0.0247
```

```
. test temp = date

 ( 1) - date + temp = 0

           chi2(  1) =    4.41
         Prob > chi2 =    0.0357
```

Wald tests are convenient in that they only require the estimation of the unconstrained model. Likelihood ratio tests are generally thought to be better but they require the estimation of both the constrained and unconstrained models. We'll show how to do likelihood ratio tests using the `fitstat` and/or `lrtest` commands.

```
. * constrained model; effect of temp = 0
. ologit  distress date, nolog

Ordered logit estimates                           Number of obs   =         23
                                                  LR chi2(1)      =       6.19
                                                  Prob > chi2     =     0.0128
Log likelihood = -21.858866                       Pseudo R2       =     0.1241

------------------------------------------------------------------------------
    distress |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        date |   .0021332   .0009556     2.23   0.026     .0002603    .0040061
-------------+----------------------------------------------------------------
       _cut1 |    18.4606   8.499246          (Ancillary parameters)
       _cut2 |   19.80472   8.648176
------------------------------------------------------------------------------

. fitstat, save

Measures of Fit for ologit of distress

Log-Lik Intercept Only:        -24.955   Log-Lik Full Model:             -21.859
D(20):                          43.718   LR(1):                            6.193
                                         Prob > LR:                        0.013
McFadden's R2:                   0.124   McFadden's Adj R2:                0.004
ML (Cox-Snell) R2:               0.236   Cragg-Uhler(Nagelkerke) R2:       0.266
McKelvey & Zavoina's R2:         0.259
Variance of y*:                  4.441   Variance of error:                3.290
Count R2:                        0.565   Adj Count R2:                     0.286
AIC:                             2.162   AIC*n:                           49.718
BIC:                           -18.992   BIC':                            -3.057
BIC used by Stata:              53.124   AIC used by Stata:               49.718

(Indices saved in matrix fs_0)

. est store m1

. * Unconstrained model
. ologit  distress date temp, nolog
```

```
Ordered logit estimates                           Number of obs   =         23
                                                  LR chi2(2)      =      12.32
                                                  Prob > chi2     =     0.0021
Log likelihood =  -18.79706                       Pseudo R2       =     0.2468

------------------------------------------------------------------------------
    distress |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        date |    .003286   .0012662     2.60   0.009     .0008043    .0057677
        temp |  -.1733752   .0834473    -2.08   0.038     -.336929   -.0098215
-------------+----------------------------------------------------------------
       _cut1 |   16.42813   9.554813          (Ancillary parameters)
       _cut2 |   18.12227   9.722293
------------------------------------------------------------------------------
```

```
. est store m2
. fitstat, diff
```

```
Measures of Fit for ologit of distress

                              Current            Saved        Difference
Model:                         ologit            ologit
N:                                 23                23                 0
Log-Lik Intercept Only        -24.955           -24.955             0.000
Log-Lik Full Model            -18.797           -21.859             3.062
D                              37.594(19)        43.718(20)         6.124(1)
LR                             12.316(2)          6.193(1)          6.124(1)
Prob > LR                       0.002             0.013             0.013
McFadden's R2                   0.247             0.124             0.123
McFadden's Adj R2               0.086             0.004             0.083
ML (Cox-Snell) R2               0.415             0.236             0.179
Cragg-Uhler(Nagelkerke) R2      0.468             0.266             0.202
McKelvey & Zavoina's R2         0.509             0.259             0.250
Variance of y*                  6.698             4.441             2.257
Variance of error               3.290             3.290             0.000
Count R2                        0.609             0.565             0.043
Adj Count R2                    0.357             0.286             0.071
AIC                             1.982             2.162            -0.179
AIC*n                          45.594            49.718            -4.124
BIC                           -21.980           -18.992            -2.988
BIC'                           -6.045            -3.057            -2.988
BIC used by Stata              50.136            53.124            -2.988
AIC used by Stata              45.594            49.718            -4.124

Difference of    2.988 in BIC' provides positive support for current model.

Note: p-value for difference in LR is only valid if models are nested.
```

As we see, the LR chi-square difference between the two models is 6.124 with 1 d.f., which is significant at the .013 level. The BIC and AIC statistics also both favor the unconstrained model, which includes temp. Note that the LR chi-square statistic is bigger than the Wald chi-square in this case. We can also use Stata's built in `lrtest` command (the `est store` commands given earlier saved the necessary information for the test).

```
. lrtest m1 m2, stats
```

```
Likelihood-ratio test                                 LR chi2(1)  =      6.12
(Assumption: m1 nested in m2)                         Prob > chi2 =    0.0133

------------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+----------------------------------------------------------------
          m1 |     23   -24.95526   -21.85887      3     49.71773    53.12421
          m2 |     23   -24.95526   -18.79706      4     45.59412     50.1361
------------------------------------------------------------------------------
```

The `lrdrop1` command (use `findit lrdrop1`) that we used for logistic regression also works after `ologit`.

```
. lrdrop1
Likelihood Ratio Tests: drop 1 term
ologit regression
number of obs = 23
------------------------------------------------------------------------
distress     Df      Chi2      P>Chi2    -2*log ll   Res. Df   AIC
------------------------------------------------------------------------
Original Model                             37.59       19      45.59
   -date      1     10.33      0.0013      47.92       18      53.92
   -temp      1      6.12      0.0133      43.72       18      49.72
------------------------------------------------------------------------
Terms dropped one at a time in turn.
```

The `bicdrop1` command works too.

```
. bicdrop1
BIC Difference Tests: drop 1 term
ologit regression
number of obs = 23
------------------------------------------------------------------------------
distress   df   -2*log ll       AIC      BICprime       BIC     BICdiff  prob
------------------------------------------------------------------------------
Full Model  4       37.59       45.59       -6.05       -21.98
 -date      3       47.92       53.92        1.15       -14.79      7.2  0.027
 -temp      3       43.72       49.72       -3.06       -18.99      3.0  0.183
------------------------------------------------------------------------------
Terms dropped one at a time in turn.
```

Since the BICdiff values are all positive, using a BIC test we would keep both variables in the model.

Finally, the `nestreg` command provides a convenient means for contrasting nested models. (The `sw` prefix also works if you want to do stepwise selection of variables.) The `lr` option says to do a likelihood ratio (rather than Wald) test; `quietly` suppresses the output from the `ologit` command; and `store(m)` causes the results from each model to be stored as m1, m2, etc. Note that you can put parentheses around sets of variables you want entered simultaneously; otherwise variables get entered one at a time.

```
. nestreg, lr quietly store(m): ologit  distress date temp

Block  1: date
Block  2: temp

  +----------------------------------------------------------------+
  | Block |        LL        LR     df  Pr > LR       AIC       BIC |
  |-------+--------------------------------------------------------|
  |     1 | -21.85887     6.19      1   0.0128  49.71773  53.12421 |
  |     2 | -18.79706     6.12      1   0.0133  45.59412   50.1361 |
  +----------------------------------------------------------------+
```

Predicted probabilities. As we've already shown, the `predict` command can give you the predicted probabilities for each case. We'll go back to the "Attitudes toward working mothers" data again.

```
. use http://www.nd.edu/~rwilliam/xsoc73994/long2006/ordwarm2.dta, clear
(77 & 89 General Social Survey)

. ologit  warm yr89 male white age ed prst

Ordered logistic regression                       Number of obs   =       2293
                                                  LR chi2(6)      =     301.72
                                                  Prob > chi2     =     0.0000
Log likelihood = -2844.9123                       Pseudo R2       =     0.0504

------------------------------------------------------------------------------
        warm |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        yr89 |   .5239025   .0798988     6.56   0.000     .3673037    .6805013
        male |  -.7332997   .0784827    -9.34   0.000    -.8871229   -.5794766
       white |  -.3911595   .1183808    -3.30   0.001    -.6231815   -.1591374
         age |  -.0216655   .0024683    -8.78   0.000    -.0265032   -.0168278
          ed |   .0671728    .015975     4.20   0.000     .0358624    .0984831
        prst |   .0060727   .0032929     1.84   0.065    -.0003813    .0125267
-------------+----------------------------------------------------------------
       /cut1 |  -2.465362   .2389126                     -2.933622   -1.997102
       /cut2 |   -.630904   .2333155                     -1.088194    -.173614
       /cut3 |   1.261854   .2340179                      .8031873    1.720521
------------------------------------------------------------------------------

. predict SDlogit Dlogit Alogit SAlogit
(option p assumed; predicted probabilities)

. list  warm yr89 male white age ed prst SDlogit Dlogit Alogit SAlogit in 1/10

     +------------------------------------------------------------------------------------------+
     | warm   yr89    male      white   age   ed   prst    SDlogit     Dlogit     Alogit    SAlogit |
     |------------------------------------------------------------------------------------------|
  1. |   SD   1977   Women   Not Whit    33   10     31   .0980375   .3069408   .4137853   .1812363 |
  2. |   SD   1977     Men   Not Whit    74   16     50   .2467438   .4255115   .2593212   .0684236 |
  3. |   SD   1989     Men   Not Whit    36   12     41   .1052787   .3189487   .4060106    .169762 |
  4. |   SD   1977   Women   Not Whit    73    9     36   .2115191   .4153165   .2908586   .0823058 |
  5. |   SD   1977   Women   Not Whit    59   11     62   .1288297   .3519578   .3792823   .1399302 |
     |------------------------------------------------------------------------------------------|
  6. |   SD   1989     Men   Not Whit    33    4     17   .1792009   .3983401   .3231964   .0992626 |
  7. |   SD   1977   Women   Not Whit    43    7     40   .1352046   .3594842   .3719443   .1333668 |
  8. |   SD   1977   Women   Not Whit    48   12     48   .1060422   .3201599   .4051716   .1686263 |
  9. |   SD   1977     Men   Not Whit    27   17     69   .0897339   .2919445   .4221392   .1961823 |
 10. |   SD   1977     Men   Not Whit    46   12     50    .189387    .404597   .3126505   .0933655 |
     +------------------------------------------------------------------------------------------+
```

The first person in the sample was a nonwhite female, interviewed in 1977, age 33, with 10 years of education and an occupational prestige score of 31 (the scale runs from a low of 12 to a high of 82 with a mean of 39.58; hence this woman is a bit below average). There is only about a 10% chance that such a person will strongly disagree with the statement “A working mother can establish just as warm and secure a relationship with her child as a mother who does not work.” By way of contrast, the nonwhite male who follows her, age 74, with 16 years of education and an occupational prestige score of 50, is predicted to have about a 25% chance of strongly disagreeing.

The `extremes` (use `findit extremes`) command helps you to see who is most likely and least likely to be predicted to strongly disagree:

```
. extremes  SDlogit warm yr89 male white age ed prst

  +------------------------------------------------------------------+
  | obs:    SDlogit   warm   yr89    male   white   age   ed   prst |
  |------------------------------------------------------------------|
  | 1214.   .0153572      A   1989   Women   White    27   20     68 |
  | 2241.   .0196022     SA   1989   Women   White    21   15     61 |
  | 2048.   .0201602     SA   1989   Women   White    26   17     52 |
  | 1980.     .02232     SA   1989   Women   White    26   15     57 |
  |  803.   .0223478      D   1989   Women   White    30   16     60 |
  +------------------------------------------------------------------+

  +--------------------------------------------------------------------+
  | 1449.   .4474411      A   1977     Men   Not Whit    71    4     23 |
  |   87.   .4530791     SD   1977     Men   Not Whit    83    5     51 |
  |  526.   .4607455      D   1977     Men   Not Whit    76    4     32 |
  | 1729.   .4649382      A   1977     Men   Not Whit    81    5     36 |
  |   27.   .4657959     SD   1977     Men   Not Whit    82    5     39 |
  +--------------------------------------------------------------------+
```

Based on the results, we see that fairly young white women in 1989 with high levels of education and occupational prestige were predicted to be the least likely to strongly disagree. Conversely, nonwhite elderly males in 1977 with low levels of education and generally low levels of occupational prestige had almost a 50% predicted probability of strongly disagreeing. Of course, we already knew from the `ologit` coefficients the characteristics of those who tended to support and not support working mothers, but numbers like the above may help make the differences much more tangible and meaningful.

As we have done in the past, we can use the `prvalue` command to see the probabilities for individuals with various sets of characteristics (the `adjust` command will give you E(Y*) but, alas, it doesn't seem to want to give predicted probabilities – so Long and Freese's `prvalue` seems to have a clear edge when doing ordinal regression). (Note: I am modifying the Long and Freese example from pp. 205-207; it looks to me like they used values of education that were 4 higher than they should be so I have changed that, and ergo, my results differ a bit from theirs.)

Working Class Men in 1977 who are near retirement:

```
. prvalue, x(yr89 = 0 male = 1 prst =20 age = 64 ed=12) rest(mean)

ologit: Predictions for warm

Confidence intervals by delta method

                                95% Conf. Interval
     Pr(y=SD|x):       0.2829   [ 0.2378,    0.3280]
     Pr(y=D|x):        0.4289   [ 0.4038,    0.4541]
     Pr(y=A|x):        0.2307   [ 0.1975,    0.2638]
     Pr(y=SA|x):       0.0575   [ 0.0443,    0.0707]

        yr89      male     white       age        ed      prst
x=         0         1  .8765809        64        12        20
```

We see that such individuals are likely to Disagree or Strongly Disagree that a working mother can have just as warm a relationship with her child.

Young, highly educated women in 1989 with prestigious jobs

```
. prvalue, x(yr89=1 male = 0 prst = 80 age = 30 ed = 20) rest(mean)

ologit: Predictions for warm

Confidence intervals by delta method

                                 95% Conf. Interval
     Pr(y=SD|x):      0.0213   [ 0.0149,    0.0278]
     Pr(y=D|x):       0.0988   [ 0.0753,    0.1222]
     Pr(y=A|x):       0.3553   [ 0.3141,    0.3965]
     Pr(y=SA|x):      0.5246   [ 0.4585,    0.5907]

        yr89      male     white       age        ed      prst
x=         1         0  .8765809        30        20        80
```

Such individuals are extremely likely to either agree or strongly agree that working women (i.e. people like themselves) can have just as warm a relationship with their children.

An "average" individual in 1977

```
. prvalue, x(yr89=0) rest(mean)

ologit: Predictions for warm

Confidence intervals by delta method

                                 95% Conf. Interval
     Pr(y=SD|x):      0.1336   [ 0.1176,    0.1496]
     Pr(y=D|x):       0.3577   [ 0.3348,    0.3806]
     Pr(y=A|x):       0.3737   [ 0.3517,    0.3957]
     Pr(y=SA|x):      0.1349   [ 0.1195,    0.1504]

         yr89       male      white        age         ed       prst
x=          0  .46489315   .8765809  44.935456  12.218055  39.585259
```

We see that, in 1977, the "average" person was pretty evenly split between agreeing and disagreeing.

An "average" individual in 1989

```
. prvalue, x(yr89=1) rest(mean)

ologit: Predictions for warm

Confidence intervals by delta method

                                 95% Conf. Interval
     Pr(y=SD|x):      0.0837   [ 0.0711,    0.0963]
     Pr(y=D|x):       0.2802   [ 0.2571,    0.3032]
     Pr(y=A|x):       0.4277   [ 0.4046,    0.4507]
     Pr(y=SA|x):      0.2085   [ 0.1855,    0.2315]

         yr89       male      white        age         ed       prst
x=          1  .46489315   .8765809  44.935456  12.218055  39.585259
```

By 1989, the “average” person was likely to agree or strongly agree that a working mother could have just as warm a relationship with her child.

NOTE: Long and Freese recommend using clear value labels for the DV, so you don’t get confused about each outcome.

The `prtab` command provides another way of coming up with predicted values for various combinations of outcomes. (I’ve rearranged the output a little bit).

```
. prtab yr89 male, novarlbl

ologit: Predicted probabilities for warm
```

```
Predicted probability of outcome 1 (SD)

--------------------------
          |      male
     yr89 |  Women     Men
----------+---------------
     1977 | 0.0989  0.1859
     1989 | 0.0610  0.1191
--------------------------
```

```
Predicted probability of outcome 2 (D)

--------------------------
          |      male
     yr89 |  Women     Men
----------+---------------
     1977 | 0.3083  0.4026
     1989 | 0.2282  0.3394
--------------------------
```

```
Predicted probability of outcome 3 (A)

--------------------------
          |      male
     yr89 |  Women     Men
----------+---------------
     1977 | 0.4129  0.3162
     1989 | 0.4406  0.3904
--------------------------
```

```
Predicted probability of outcome 4 (SA)

--------------------------
          |      male
     yr89 |  Women     Men
----------+---------------
     1977 | 0.1799  0.0953
     1989 | 0.2703  0.1510
--------------------------
```

```
          yr89       male      white        age         ed       prst
x=   .39860445  .46489315   .8765809  44.935456  12.218055  39.585259
```

Throughout, you can see that men are less likely than women to believe that a working mother can have just as warm a relationship. Between 1977 and 1989, both men and women developed more positive attitudes toward working women.

Analyzing Residuals. No methods for detecting influential observations and outliers have been developed specifically for the ORM. Long & Freese therefore suggest that you follow Hosmer and Lemeshow’s advice: Estimate M-1 binary regression models and analyze the residuals produced by them. This is not ideal, because the residuals come from a model other than the one you have fitted; but if the parallel regression assumption is not rejected, you can be more confident in the results of your residual analysis.

Using the attitudes toward working mothers data,

```
. gen warmlt2 = (warm<2) if !missing(warm)
. gen warmlt3 = (warm<3) if !missing(warm)
. gen warmlt4 = (warm<4) if !missing(warm)
. quietly logit  warmlt2 yr89 male white age ed prst
. predict rstd_lt2, rs
```

You can now use the various means we have discussed before for analyzing residuals. For example, here is how you can use the `extremes` command (I have modified the layout to save space).

```
. extremes  rstd_lt2
```

```
  +--------------------+       +-----------------+
  |  obs:     rstd_lt2 |       | 274.   4.777354 |
  |--------------------|       | 286.   4.820951 |
  |  863.   -.9838704  |       | 167.   4.826796 |
  |  982.   -.9596406  |       |  93.   5.418802 |
  | 2089.   -.9596406  |       | 191.   5.418802 |
  |  526.   -.9446225  |       +-----------------+
  | 1729.    -.936599  |
  +--------------------+
```

```
. quietly logit  warmlt3 yr89 male white age ed prst
. predict rstd_lt3, rs
. extremes  rstd_lt3
```

```
  +--------------------+       +------------------+
  |  obs:     rstd_lt3 |       |  414.   2.240629 |
  |--------------------|       |  675.   2.307215 |
  | 1729.   -2.365898  |       | 1001.   2.357419 |
  | 1449.   -2.276901  |       |  563.   2.547484 |
  | 1344.   -2.139651  |       |  803.   2.659929 |
  | 1404.   -2.096862  |       +------------------+
  | 1305.   -2.080196  |
  +--------------------+
```

```
. quietly logit  warmlt4 yr89 male white age ed prst
. predict rstd_lt4, rs
. extremes  rstd_lt4
```

```
  +--------------------+       +------------------+
  |  obs:     rstd_lt4 |       | 1096.   1.185728 |
  |--------------------|       | 1759.   1.185728 |
  | 1963.   -4.961208  |       |  578.   1.208186 |
  | 2138.   -4.918912  |       | 1123.   1.208186 |
  | 2107.   -4.812184  |       | 1232.   1.208186 |
  | 2119.   -4.770702  |       +------------------+
  | 2093.   -4.644297  |
  +--------------------+
```

Long & Freese's `leastlikely` command provides another way of identifying outlier cases. `leastlikely` lists the in-sample observations with the lowest predicted probabilities of observing the outcome value that was actually observed.

```
. use http://www.nd.edu/~rwilliam/xsoc73994/long2006/ordwarm2.dta, clear
(77 & 89 General Social Survey)

. quietly ologit  warm yr89 male white age ed prst

. leastlikely  warm yr89 male white age ed prst
```

Outcome: 1 (SD)

	Prob	warm	yr89	male	white	age	ed	prst
112.	.0464241	SD	1989	Women	White	46	16	57
167.	.0401364	SD	1989	Women	White	37	15	61
222.	.0449925	SD	1989	Women	White	29	12	46
245.	.0467743	SD	1989	Women	White	32	12	50
271.	.0407333	SD	1989	Women	White	20	12	31

Outcome: 2 (D)

	Prob	warm	yr89	male	white	age	ed	prst
474.	.1345096	D	1989	Women	NotWhite	32	14	36
563.	.1072643	D	1989	Women	NotWhite	41	18	69
675.	.1367011	D	1989	Women	White	25	16	50
803.	.1028648	D	1989	Women	NotWhite	30	16	60
1001.	.1307181	D	1989	Women	White	32	18	62

Outcome: 3 (A)

	Prob	warm	yr89	male	white	age	ed	prst
1305.	.159677	A	1977	Men	White	79	8	41
1344.	.1559092	A	1977	Men	White	72	7	22
1408.	.1594647	A	1977	Men	White	74	6	45
1449.	.1358758	A	1977	Men	White	71	4	23
1729.	.1283106	A	1977	Men	White	81	5	36

Outcome: 4 (SA)

	Prob	warm	yr89	male	white	age	ed	prst
1963.	.0387174	SA	1977	Men	White	64	6	26
2093.	.0450309	SA	1977	Men	White	48	4	17
2107.	.0413501	SA	1977	Men	White	69	8	33
2119.	.042078	SA	1977	Men	White	58	4	41
2138.	.0393529	SA	1977	Men	White	57	3	37

Long and Freese also demonstrate graphical means for examining the outliers, and there are several other residual statistics that can be computed as well. Based on these results, you may want to take a closer look on some of the more extreme outliers. Perhaps there are coding errors, or perhaps there are problems with your model specification.

Standardized Coefficients/ Marginal Change in Y*. As was the case in logistic regression, standardized coefficients can be an aid to interpretation.

```
. ologit  warm yr89 male white age ed prst
. listcoef, std help

ologit (N=2293): Unstandardized and Standardized Estimates

 Observed SD: .9282156
   Latent SD: 1.9410634

-------------------------------------------------------------------------------
        warm |      b         z     P>|z|    bStdX    bStdY   bStdXY      SDofX
-------------+-----------------------------------------------------------------
        yr89 |   0.52390    6.557   0.000   0.2566   0.2699   0.1322     0.4897
        male |  -0.73330   -9.343   0.000  -0.3658  -0.3778  -0.1885     0.4989
       white |  -0.39116   -3.304   0.001  -0.1287  -0.2015  -0.0663     0.3290
         age |  -0.02167   -8.778   0.000  -0.3635  -0.0112  -0.1873    16.7790
          ed |   0.06717    4.205   0.000   0.2123   0.0346   0.1094     3.1608
        prst |   0.00607    1.844   0.065   0.0880   0.0031   0.0453    14.4923
-------------------------------------------------------------------------------
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
   bStdX = x-standardized coefficient
   bStdY = y-standardized coefficient
  bStdXY = fully standardized coefficient
   SDofX = standard deviation of X
```

Some interpretations you can draw from the above:

In 1989, support for working mothers was .27 standard deviations higher than it was in 1977, holding all other variables constant. (See the coefficient for yr89 in the column labeled bStdY).

Each standard deviation increase in education increases support for working mothers by .11 standard deviations, holding all other variables constant. (See the coefficient for ed in the column labeled bStdXY).

Marginal and Discrete Changes in Predicted Probabilities. As was the case with logistic regression, you can use the `prchange` and `mfx` commands to compute marginal and discrete changes. Remember that the marginal/discrete effect produced by change in a variable depends on the values of the other variables. So, to compute the effect of changes in age for 1989 females who are "average" on all other variables,

```
. prchange age, x(male=0 yr89=1) rest(mean)

ologit: Changes in Predicted Probabilities for warm

age
           Avg|Chg|          SD           D           A          SA
Min->Max   .16441458   .10941909   .21941006  -.05462247  -.27420671
   -+1/2   .00222661   .00124099   .00321223   -.0001803  -.00427291
  -+sd/2    .0373125    .0208976   .05372739  -.00300205  -.07162295
MargEfct   .00222662   .00124098   .00321226  -.00018032  -.00427292

               SD          D          A         SA
Pr(y|x)  .06099996  .22815652  .44057754  .27026597

          yr89     male    white      age       ed     prst
    x=       1        0  .876581  44.9355  12.2181  39.5853
sd(x)=  .489718  .498875  .328989   16.779  3.16083  14.4923
```

The above results make clear that older women are more likely to strongly disagree or disagree that a working mother can have just as warm a relationship with her child. However, the effect of a 1 year change is relatively small, and it may be useful to consider the effect of a larger period of time, e.g. 10 years. The delta parameter will let us do that.

```
. prchange age, x(male=0 yr89=1) rest(mean) delta(10)

ologit: Changes in Predicted Probabilities for warm

(Note: d = 10)

age
           Avg|Chg|          SD           D           A          SA
Min->Max   .16441458   .10941909   .21941006  -.05462247  -.27420671
   -+d/2   .02225603   .01242571   .03208634  -.00179818  -.04271388
  -+sd/2    .0373125    .0208976   .05372739  -.00300205  -.07162295
MargEfct   .00222662   .00124098   .00321226  -.00018032  -.00427292

               SD          D          A         SA
Pr(y|x)  .06099996  .22815652  .44057754  .27026597

          yr89     male    white      age       ed     prst
    x=       1        0  .876581  44.9355  12.2181  39.5853
sd(x)=  .489718  .498875  .328989   16.779  3.16083  14.4923
```

The row labeled -+d/2 tells us that for an "average" woman in 1989, a 10 year increase in age makes her 1.2% more likely to Strongly Disagree, 3.2% more likely to Disagree, .17% less likely to agree, and 4.3% less likely to Strongly Agree.

You can also use the `mfx` command after `ologit` and `oprobit`, but its use tends to be awkward because you have to give a separate command for each outcome, e.g.

```
. mfx, predict (p outcome(1))

Marginal effects after ologit
      y  = Pr(warm==1) (predict, p outcome(1))
         =  .11125716
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
   yr89*|  -.0499367      .00762   -6.55   0.000  -.064872 -.035002   .398604
   male*|   .0746143       .0086    8.67   0.000   .057749   .09148   .464893
  white*|   .0345242      .00939    3.68   0.000   .016122  .052926   .876581
    age |   .0021423      .00025    8.41   0.000   .001643  .002641   44.9355
     ed |   -.006642       .0016   -4.16   0.000  -.009772 -.003512   12.2181
   prst |  -.0006005      .00033   -1.84   0.066   -.00124  .000039   39.5853
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

Similarly, for the other outcomes you give the commands

```
. mfx, predict (p outcome(2))
. mfx, predict (p outcome(3))
. mfx, predict (p outcome(4))
```

It is much easier to use the user-written `mfx2` command, which automates the above process. `mfx2` supports most of the options `mfx` does, e.g. you can give a command like `mfx2, at(male=0 yr89=1).` See the help for `mfx2` for more details. [Note: the `margeff` routine is sometimes a quicker alternative to `mfx2`, but it doesn't work after as many estimation commands.]

```
. mfx2

[Intermediate output deleted; you should look at this though, to make sure mfx did not
encounter problems, and also to look for info not reported in the final output, e.g. the
mean value of each X]

Original results are now active. mfx results are stored as ologit_mfx.

-------------------------------------------------------------------------------
Model ologit_mfx (Marginal effects after ologit)
-------------------------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
SD           |
        yr89 |  -.0499367     .00762    -6.55   0.000    -.0648717   -.0350018
        male |   .0746143    .008605     8.67   0.000     .0577488    .0914797
       white |   .0345242   .0093889     3.68   0.000     .0161223    .0529262
         age |   .0021423   .0002546     8.41   0.000     .0016432    .0026413
          ed |   -.006642   .0015972    -4.16   0.000    -.0097724   -.0035116
        prst |  -.0006005   .0003264    -1.84   0.066    -.0012401    .0000392
-------------+----------------------------------------------------------------
D            |
        yr89 |  -.0775187   .0121323    -6.39   0.000    -.1012977   -.0537398
        male |    .104621   .0115237     9.08   0.000      .082035    .1272071
       white |    .059359    .018307     3.24   0.001      .023478      .09524
         age |   .0031946   .0003899     8.19   0.000     .0024305    .0039588
          ed |  -.0099047   .0023956    -4.13   0.000    -.0145999   -.0052095
        prst |  -.0008954   .0004869    -1.84   0.066    -.0018497    .0000588
-------------+----------------------------------------------------------------
A            |
        yr89 |   .0539133    .008294     6.50   0.000     .0376573    .0701694
        male |  -.0813708   .0096843    -8.40   0.000    -.1003516     -.06239
       white |  -.0355765   .0085927    -4.14   0.000    -.0524178   -.0187352
         age |  -.0024072   .0003126    -7.70   0.000    -.0030199   -.0017945
```

```
          ed |   .0074635   .0018362     4.06   0.000     .0038645    .0110625
        prst |   .0006747   .0003683     1.83   0.067    -.0000472    .0013967
-------------+----------------------------------------------------------------
SA           |
        yr89 |   .0735421   .0117236     6.27   0.000     .0505643    .0965199
        male |  -.0978645   .0106715    -9.17   0.000    -.1187802   -.0769487
       white |  -.0583067   .0193334    -3.02   0.003    -.0961996   -.0204139
         age |  -.0029296     .00034    -8.62   0.000    -.0035961   -.0022632
          ed |   .0090832   .0021702     4.19   0.000     .0048296    .0133368
        prst |   .0008212   .0004455     1.84   0.065    -.0000519    .0016943
------------------------------------------------------------------------------
```

These results show, for example, that, (according to the ordered logit model) compared to 1977, the "average" person in 1989 was about 5% less likely to strongly disagree, 7.8% less likely to disagree, 5.4% more likely to agree, and 7.4% more likely to strongly agree. The results also show that for an "average" male and "average" female, the male is 7.5% more likely to strongly disagree, 10.5% more likely to disagree, 8.1% less likely to agree, and 9.8% less likely to strongly agree.

An additional advantage of `mfx2` is that it saves the results in a format that can be easily used with table-formatting commands like `outreg2`, `estout` and `esttab` (see the help files for these programs for more details). For example, here is how we could do a side by side comparison of the marginal effects for an `ologit` and `mlogit` analysis of these data.

```
. quietly mlogit  warm yr89 male white age ed prst
. quietly mfx2, nolog
. esttab ologit_mfx mlogit_mfx, mtitles(ologit mlogit)

--------------------------------------------
                      (1)             (2)   
                   ologit          mlogit   
--------------------------------------------
SD                                          
yr89              -0.0499***      -0.0928***
                  (-6.55)         (-7.03)   

male               0.0746***       0.0350** 
                   (8.67)          (2.67)   

white              0.0345***       0.0479** 
                   (3.68)          (2.89)   

age               0.00214***      0.00181***
                   (8.41)          (4.45)   

ed               -0.00664***      -0.0111***
                  (-4.16)         (-4.35)   

prst            -0.000600        0.000140   
                  (-1.84)          (0.24)   

D                                           
yr89              -0.0775***      -0.0443*  
                  (-6.39)         (-2.14)   

male                0.105***        0.133***
                   (9.08)          (6.60)   

white              0.0594**        0.0261   
                   (3.24)          (0.84)   
```

```
age                0.00319***      0.00439***
                    (8.19)          (6.82)

ed                -0.00990***     -0.00171
                   (-4.13)         (-0.41)

prst             -0.000895        -0.00248**
                   (-1.84)         (-2.86)

A
yr89                0.0539***       0.0887***
                    (6.50)          (4.10)

male               -0.0814***      -0.0190
                   (-8.40)         (-0.91)

white              -0.0356***      -0.0117
                   (-4.14)         (-0.36)

age               -0.00241***     -0.00358***
                   (-7.70)         (-5.25)

ed                 0.00746***      0.00515
                    (4.06)          (1.16)

prst              0.000675         0.00145
                    (1.83)          (1.61)

SA
yr89                0.0735***       0.0484**
                    (6.27)          (2.96)

male               -0.0979***       -0.149***
                   (-9.17)         (-9.59)

white              -0.0583**       -0.0623*
                   (-3.02)         (-2.36)

age               -0.00293***     -0.00262***
                   (-8.62)         (-5.08)

ed                 0.00908***      0.00767*
                    (4.19)          (2.18)

prst              0.000821        0.000898
                    (1.84)          (1.33)
--------------------------------------------
N                     2293            2293
--------------------------------------------
t/z-statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001
```

Such side by side comparisons can be useful for assessing the different implications of different models. For example, the `mlogit` model shows a stronger tendency to strongly disagree in 1989 than does the `ologit` model, i.e. `mlogit` suggests that the biggest reason people were more supportive in 1989 is because they moved away from the most negative position toward more moderate positions, rather than becoming strongly supportive.

Long and Freese provide other examples of how to analyze marginal and discrete changes.