Interpreting Models for Categorical and Count Outcomes

Rose Medeiros
StataCorp LLC

Stata Webinar
March 21, 2019

Contents

1 Introduction ................................................................. 1
  1.1 Goals ....................................................................... 1

2 Estimation ....................................................................... 1
  2.1 Factor Variables ....................................................... 1

3 Postestimation .................................................................. 7
  3.1 Tests of Coefficients ................................................... 7
  3.2 Predictions .................................................................. 10
  3.3 Marginal Effects ........................................................ 25
  3.4 Other Models ............................................................ 29

4 Conclusion ...................................................................... 36
  4.1 Conclusion ............................................................... 36

1 Introduction

1.1 Goals

Goals

- Learn how to fit models that include categorical variables and/or interactions using factor variable syntax
- Get an overview of tools available for investigating models
- Learn a bit about how Stata partitions model fitting and model testing tasks

2 Estimation

2.1 Factor Variables

A Logistic Regression Model

- We’ll use data from the National Health and Nutrition Examination Survey (NHANES) for our examples
  . webuse nhanes2
- We’ll start with a model for high blood pressure (highbp) using age, body mass index (bmi) and sex (female)
- Before we fit the model, let’s investigate the variables
. codebook highbp age bmi female

<table>
<thead>
<tr>
<th>Codebook Details</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>highbp</strong></td>
</tr>
<tr>
<td>Type: numeric (byte)</td>
</tr>
<tr>
<td>Range: [0,1]</td>
</tr>
<tr>
<td>Units: 1</td>
</tr>
<tr>
<td>Unique values: 2</td>
</tr>
<tr>
<td>Missing: 0/10,351</td>
</tr>
<tr>
<td>Tabulation: Freq. Value</td>
</tr>
<tr>
<td>5,975 0</td>
</tr>
<tr>
<td>4,376 1</td>
</tr>
<tr>
<td><strong>age</strong></td>
</tr>
<tr>
<td>Type: numeric (byte)</td>
</tr>
<tr>
<td>Range: [20,74]</td>
</tr>
<tr>
<td>Units: 1</td>
</tr>
<tr>
<td>Unique values: 55</td>
</tr>
<tr>
<td>Missing: 0/10,351</td>
</tr>
<tr>
<td>Mean: 47.5797</td>
</tr>
<tr>
<td>Std. Dev: 17.2148</td>
</tr>
<tr>
<td>Percentiles: 10% 25% 50% 75% 90%</td>
</tr>
<tr>
<td>24 31 49 63 69</td>
</tr>
<tr>
<td><strong>bmi</strong></td>
</tr>
<tr>
<td>Type: numeric (float)</td>
</tr>
<tr>
<td>Range: [12.385596, 61.129696]</td>
</tr>
<tr>
<td>Units: 1.000e-07</td>
</tr>
<tr>
<td>Unique values: 9,941</td>
</tr>
<tr>
<td>Missing: 0/10,351</td>
</tr>
<tr>
<td>Mean: 25.5376</td>
</tr>
<tr>
<td>Std. Dev: 4.91497</td>
</tr>
<tr>
<td>Percentiles: 10% 25% 50% 75% 90%</td>
</tr>
<tr>
<td>20.1037 22.142 24.8181 28.0267 31.7259</td>
</tr>
<tr>
<td><strong>female</strong></td>
</tr>
<tr>
<td>Type: numeric (byte)</td>
</tr>
<tr>
<td>Range: [0,1]</td>
</tr>
<tr>
<td>Units: 1</td>
</tr>
<tr>
<td>Unique values: 2</td>
</tr>
<tr>
<td>Missing: 0/10,351</td>
</tr>
<tr>
<td>Tabulation: Freq. Value</td>
</tr>
<tr>
<td>4,915 0</td>
</tr>
<tr>
<td>5,436 1</td>
</tr>
</tbody>
</table>

- Now we can fit the model

. logit highbp age bmi female
Working with Categorical Variables

- Now we would like to include `region` in the model, let's take a look at this variable

  `. codebook region`

<table>
<thead>
<tr>
<th>region</th>
<th>1=NE, 2=MW, 3=S, 4=W</th>
</tr>
</thead>
<tbody>
<tr>
<td>type:</td>
<td>numeric (byte)</td>
</tr>
<tr>
<td>label:</td>
<td>region</td>
</tr>
<tr>
<td>range:</td>
<td>[1,4]</td>
</tr>
<tr>
<td>units:</td>
<td>1</td>
</tr>
<tr>
<td>unique values:</td>
<td>4</td>
</tr>
<tr>
<td>missing .:</td>
<td>0/10,351</td>
</tr>
</tbody>
</table>

- region cannot simply be added to the list of covariates because it has 4 categories

- To include a categorical variable, put an `i.` in front of its name—this declares the variable to be a categorical variable, or in Stataese, a `factor variable`

- For example

  `. logit highbp age bmi i.female i.region`

  Iteration 0: log likelihood = -7050.7655
  Iteration 1: log likelihood = -5857.277
  Iteration 2: log likelihood = -5843.2102
  Iteration 3: log likelihood = -5843.169
  Iteration 4: log likelihood = -5843.169

  Logistic regression Number of obs = 10,351
  LR chi2(6) = 2415.19
  Prob > chi2 = 0.0000
Niceities

- Starting in Stata 13, value labels associated with factor variables are displayed in the regression table.
- We can tell Stata to show the base categories for our factor variables with 
  ```stata
  . set showbaselevels on
  ```
  - This means the base category will always be clearly documented in the output.

Factor Notation as Operators

- The `i.` operator can be applied to many variables at once:
  ```stata
  . logit highbp age bmi i.(female region)
  ```

Interpreting Models for Categorical and Count Outcomes © StataCorp LLC Page 4 of 37
In other words, it understands the distributive property

- This is useful when using variable ranges, for example

- For the curious, factor variable notation works with wildcards

- If there were many variables starting with `u`, then `i.u*` would include them all as factor variables

---

### Using Different Base Categories

- By default, the smallest-valued category is the base category

- This can be overridden within commands

  - `b#` specifies the value `#` as the base
  - `b(#)` specifies the `#`th largest value as the base
  - `b(first)` specifies the smallest value as the base
  - `b(last)` specifies the largest value as the base
  - `b(freq)` specifies the most prevalent value as the base
  - `bn` specifies there should be no base

- The base can also be permanently changed using `fvset`; see `help fvset` for more information

---

### Playing with the Base

- We can use `region=3` as the base class on the fly:
  
  ```
  . logit highbp age bmi i.female b3.region
  ```

- We can use the most prevalent category as the base
  
  ```
  . logit highbp age bmi i.female b(freq).region
  ```

- Factor variables can be distributed across many variables
  
  ```
  . logit highbp age bmi b(freq).(female region)
  ```

- The base category can be omitted (with some care here)
  
  ```
  . logit highbp age bmi i.female bn.region, noconstant
  ```

- We can also include a term for `region=4` only
  
  ```
  . logit highbp age bmi i.female 4.region
  ```
### Specifying Interactions

- Factor variables are also used for specifying interactions
  - This is where they really shine
- To include both main effects and interaction terms in a model, put `##` between the variables
- To include only the interaction terms, put `#` between the terms
- Variables involved in interactions are treated as categorical by default
  - Prefix a variable with `c.` to specify that a variable is continuous

- Here is our model with an interaction between `age` and `female`

  ```
  . logit highbp bmi c.age##female i.region
  ```

  Iteration 0:  log likelihood = -7050.7655
  Iteration 1:  log likelihood = -5824.3249
  Iteration 2:  log likelihood = -5795.4621
  Iteration 3:  log likelihood = -5795.4025
  Iteration 4:  log likelihood = -5795.4025

  Logistic regression                      Number of obs = 10,351
  LR chi2(7) = 2510.73
  Prob > chi2 = 0.0000
  Log likelihood = -5795.4025
  Pseudo R2 = 0.1780

  -----------------------------
  highbp  |  Coef.  Std. Err.  z  P>|z|   [95% Conf. Interval]
  -------------+-----------------------------------------------
    bmi      |  .1378163  .005139  26.82  0.000   .1277441   .1478886
    age      |  .0334439  .0018514  18.06  0.000   .0298151   .0370727
  female    |                                    
    0       | (base)                                    
    1       |  -1.883645  .1530275  -12.31  0.000  -2.183574  -1.583717
  female#c.age |                                  
    1      |   .0276653  .0028606   9.67  0.000   .0220585   .033272
  region    |                                    
    NE      | (base)                                    
    MW      |  -.1359488  .0664206   -2.05  0.041  -.2661308  -.0057668
    S       |  -.0902012  .0659821   -1.38  0.169  -.2187713  .0383689
    W       |  -.0379412  .0669444   -0.57  0.571  -.1691490  .0932666
  _cons     |  -5.176679  1.687139  -30.68  0.000  -5.507352  -4.846006
  -----------------------------

### Some Factor Variable Notes

- If you plan to look at marginal effects of any kind, it is best to
  - Explicitly mark all categorical variables with `i`.
  - Specify all interactions using `#` or `##`
  - Specify powers of a variable as interactions of the variable with itself
• There can be up to 8 categorical and 8 continuous interactions in one expression
  ○ Have fun with the interpretation

3 Postestimation

3.1 Tests of Coefficients

Introduction to Postestimation

• In Stata jargon, postestimation commands are commands that can be run after a model is fit, for example
  ○ Predictions
  ○ Additional hypothesis tests
  ○ Checks of assumptions

• We’ll explore postestimation tools that can be used to help interpret model results
  ○ The main example here is after logit models, but these tools can be used with most estimation commands

• The usefulness of specific tools will depend on the types of hypotheses you wish to examine

Finding the Coefficient Names

• Some postestimation commands require that you know the names used to store the coefficients

• To see these names we can replay the model showing the coefficient legend

  . logit, coeflegend

  Logistic regression
  Number of obs = 10,351
  LR chi2(7) = 2510.73
  Prob > chi2 = 0.0000
  Log likelihood = -5795.4025  Pseudo R2 = 0.1780
  ------------------------------------------------------------------------------
  highbp | Coef. Legend
  ---------+------------------------------------------------------------------
   bmi | .1378163  _b[bmi]
   age | .0334439  _b[age]
  female | 0 | 0  _b[0b.female]
      1 | -1.883645  _b[1.female]
 female#c.age | 1 | .0276653  _b[1.female#c.age]
  region | NE | 0  _b[1b.region]
        MW | -.1359488  _b[2.region]
          S | -.0902012  _b[3.region]
          W | -.0379412  _b[4.region]
     _cons | -5.176679  _b[_cons]
  ------------------------------------------------------------------------------
• From here, we can see the full specification of the factor levels:
  ◦ \_b[2.region] corresponds to region=2 which is “MW” or midwest
  ◦ \_b[3.region] corresponds to region=3 which is “S” or south

• The coefficient for the female by age interaction is stored as \_b[1.female#c.age]

---

### Joint Tests

• The `test` command performs a Wald test of the specified null hypothesis
  ◦ The default test is that the listed terms are equal to 0

• `test` takes a list of terms, which may be variable names, but can also be terms associated with factor variables

• To specify a joint test of the null hypothesis that the coefficients for the levels of `region` are all equal to 0
  . test 2.region 3.region 4.region

  ( 1) [highbp]2.region = 0
  ( 2) [highbp]3.region = 0
  ( 3) [highbp]4.region = 0

  chi2( 3) = 4.96
  Prob > chi2 = 0.1744

---

### Testing Sets of Coefficients

• If you are testing a large number of terms, typing them all out can be laborious

• `testparm` also performs Wald tests, but it accepts lists of variables, rather than coefficients in the model

• For example, to test all coefficients associated with `i.region`
  . testparm i.region

  ( 1) [highbp]2.region = 0
  ( 2) [highbp]3.region = 0
  ( 3) [highbp]4.region = 0

  chi2( 3) = 4.96
  Prob > chi2 = 0.1744

---

### Likelihood Ratio Tests

• Likelihood ratio tests provide an alternative method of testing sets of coefficients

• To test the coefficients associated with `region` we need to store our model results. The name is arbitrary, we’ll call them `m1`
  . estimates store m1

• Now we can rerun our model without `region`
  . logit highbp bmi c.age##female if e(sample)
Iteration 0:  log likelihood = -7050.7655
Iteration 1:  log likelihood = -5826.855
Iteration 2:  log likelihood = -5797.9206
Iteration 3:  log likelihood = -5797.8856
Iteration 4:  log likelihood = -5797.8856

Logistic regression
Number of obs = 10,351
LR chi2(4) = 2505.76
Prob > chi2 = 0.0000
Log likelihood = -5797.8856 Pseudo R2 = 0.1777

------------------------------------------------------------------------------
highbp | Coef.  Std. Err.   z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
bmi |  .1376855   .0051366  26.80   0.000     .127618     .147753
age |  .0335286   .0018501  18.12   0.000     .0299025    .0371548

female | 0 (base)
1 | -1.882479   .1530115  -12.30   0.000    -2.182376    -1.582582
female#c.age | 1 |  .027615   .0028601   9.66   0.000     .0220092    .0332207
_cons | -5.247536   .1628488  -32.22   0.000    -5.566713    -4.928358
------------------------------------------------------------------------------

• Adding if e(sample) makes sure the same sample, what Stata calls the estimation sample, is used for both models

Likelihood Ratio Tests (Continued)

• Now we store the second set of estimates
  . estimates store m2

• And use the lrtest command to perform the likelihood ratio test
  . lrtest m1 m2

Likelihood-ratio test                  LR chi2(3)  =  4.97
(Assumption: m2 nested in m1)     Prob > chi2 = 0.1743

• We’ll restore the results from m1 which includes region even though the terms are not collectively significant
  . estimates restore m1
  (results m1 are active now)

• Now it’s as though we just ran the model stored as m1

Tests of Differences

• test can also be used to the equality of coefficients
  . test 3.region = 4.region

( 1)  [highbp]3.region - [highbp]4.region = 0

    ch2(  1) =    0.71
    Prob > ch2 =   0.3978
• A likelihood ratio test can also be used; see help constraint for information on setting the necessary constraints

• The lincom command calculates linear combinations of coefficients, along with standard errors, hypothesis tests, and confidence intervals

• For example, to obtain the difference in coefficients

  . lincom 3.region - 4.region

  ( 1) [highbp]3.region - [highbp]4.region = 0

  -----------------------------------------------------------
  highbp | Coef. Std. Err. z P>|z| [95% Conf. Interval]
  --------+--------------------------------------------------
  (1) | -.05226 .0618078 -0.85 0.398 -.1734012 .0688811
  -----------------------------------------------------------

3.2 Predictions

What are margins?

• Stata defines margins as “statistics calculated from predictions of a previously fit model at fixed values of some covariates and averaging or otherwise integrating over the remaining covariates.”
  ◦ Also known as counterfactuals, or when we fix a categorical variable, potential outcomes

• What sorts of predictions does margins work with?
  ◦ Predicted means, probabilities, and counts
  ◦ Derivatives
  ◦ Elasticities

• We’ll also see contrasts and pairwise comparisons of the above

Average Predictions

• Let’s start with margins in its most basic form

  . margins

  Predictive margins Number of obs = 10,351
  Model VCE : OIM
  Expression : Pr(highbp), predict()

  -----------------------------------------------------------
  | Delta-method
  | Margin Std. Err. z P>|z| [95% Conf. Interval]
  --------+--------------------------------------------------
  _cons | .4227611 .0042898 98.55 0.000 .4143533 .4311689
  -----------------------------------------------------------

• What happened here?
  1. The predicted probability of highbp=1 was calculated for each case, using each case’s observed values of bmi, age, female, and region
  2. The average of those predictions was calculated and displayed

• Unless we tell it to do otherwise, margins works with the estimation sample
Predictions at the Average

- An alternative is to calculate the predicted probability fixing all the covariates at some value, often the mean.

  \[ \text{margins, atmeans} \]

  Adjusted predictions
  Number of obs = 10,351

  Model VCE : OIM

  Expression : Pr(highbp), predict()
  at
  : bmi = 25.5376 (mean)
  age = 47.57965 (mean)
  0.female = .4748333 (mean)
  1.female = .5251667 (mean)
  1.region = .2024925 (mean)
  2.region = .2679934 (mean)
  3.region = .2756255 (mean)
  4.region = .2538885 (mean)

  | Delta-method
  | Margin Std. Err. z P>|z| [95% Conf. Interval]
  |---------------|------------------|------|--------|------------------|
  _cons | .3929783 .0056167 69.97 0.000 .3819697 .4039869

  What happened here?

  1. The mean of each independent variable was calculated
  2. The predicted probability of highbp=1 was calculated using the means from step 1

Predictions at Each Level of a Factor Variable

- Adding a factor variable specifies that the predictions be repeated at each level of the variable, for example.

  \[ \text{margins region} \]

  Predictive margins
  Number of obs = 10,351

  Model VCE : OIM

  Expression : Pr(highbp), predict()

  | Delta-method
  | Margin Std. Err. z P>|z| [95% Conf. Interval]
  |---------------|------------------|------|--------|------------------|
  region |---------------|------------------|------|--------|------------------|
  NE | .4362592 .0095422 45.72 0.000 .4175568 .4549616
  MW | .4103455 .0083278 49.27 0.000 .3940234 .4266677
  S | .4190352 .0081188 51.61 0.000 .4031226 .4349477
  W | .4290013 .0085434 50.21 0.000 .4122565 .4457461

  What happened here?

  1. The predicted probability is calculated treating all cases as if region=1 and using each case's observed values of bmi, age, and female
  2. The mean of the predictions from step 1 is calculated
  3. Repeat steps 1 and 2 for each value of region
Multiple Factor Variables

- We can obtain margins for multiple variables

  . margins region female

<table>
<thead>
<tr>
<th>Predictive margins</th>
<th>Number of obs = 10,351</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model VCE : OIM</td>
<td></td>
</tr>
<tr>
<td>Expression : Pr(highbp), predict()</td>
<td></td>
</tr>
</tbody>
</table>

| Delta-method | Margin | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|--------------|--------|-----------|------|-------|----------------------|
| region       |        |           |      |       |                      |
| NE           | .4362592 | .0095422  | 45.72| 0.000 | .4175568 .4549616  |
| MW           | .4103455 | .0083278  | 49.27| 0.000 | .3940234 .4266777 |
| S            | .4190352 | .0081188  | 51.61| 0.000 | .4031226 .4349477 |
| W            | .4290013 | .0085434  | 50.21| 0.000 | .4122656 .4457461 |
| female       |        |           |      |       |                      |
| 0            | .4692315 | .006393   | 73.40| 0.000 | .4567014 .4817616  |
| 1            | .3766361 | .0057397  | 65.62| 0.000 | .3653866 .3878857  |

- Or combinations of values, for example each combination of region and female

  . margins region#female

<table>
<thead>
<tr>
<th>Predictive margins</th>
<th>Number of obs = 10,351</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model VCE : OIM</td>
<td></td>
</tr>
<tr>
<td>Expression : Pr(highbp), predict()</td>
<td></td>
</tr>
</tbody>
</table>

| Delta-method | Margin | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|--------------|--------|-----------|------|-------|----------------------|
| region#female|        |           |      |       |                      |
| NE#0         | .4839466 | .0112276  | 43.10| 0.000 | .461941 .5059522  |
| NE#1         | .3889131 | .0097392  | 39.93| 0.000 | .3698246 .4080015 |
| MW#0         | .4556986 | .0100844  | 45.19| 0.000 | .4359337 .4754636 |
| MW#1         | .3652888 | .0086372  | 42.29| 0.000 | .3483602 .3822173 |
| S#0          | .4651826 | .0099214  | 46.89| 0.000 | .4457369 .4846282 |
| S#1          | .3731942 | .0084524  | 44.15| 0.000 | .3566278 .3897605 |
| W#0          | .4760455 | .0102535  | 46.43| 0.000 | .455949 .496142  |
| W#1          | .3822812 | .0088891  | 43.01| 0.000 | .3648589 .3997034 |

- We can graph the resulting predictions using the marginsplot command

Graphing Predicted Probabilities

- For example to graph the last set of margins

  . marginsplot
Predictions at Specified Values of Covariates

- The at() option is used to specify values at which margins should be calculated.
- To obtain the average predicted probability setting age=40 specify
  
  . margins, at(age=40)

  Predictive margins Number of obs = 10,351
  Model VCE : OIM
  Expression : Pr(highbp), predict()
  at : age = 40

<table>
<thead>
<tr>
<th>Delta-method</th>
<th>Margin Std. Err. z    P&gt;</th>
<th>z</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>_cons</td>
<td>.3287856 .0053346 61.63 0.000 .31833 .3392413</td>
<td></td>
</tr>
</tbody>
</table>

- at() accepts number lists, so we can obtain predictions setting age to 20, 30, ..., 70

  . margins, at(age=(20(10)70)) vsquish

  Predictive margins Number of obs = 10,351
  Model VCE : OIM
  Expression : Pr(highbp), predict()
  1._at : age = 20
  2._at : age = 30
  3._at : age = 40
  4._at : age = 50
  5._at : age = 60
  6._at : age = 70
Delta-method
Margin Std. Err. z P>|z| [95% Conf. Interval]
-------------+----------------------------------------------------------------
_at | 1 | .1826464 .006436 28.38 0.000 .170032 .1952608
     | 2 | .247219 .0060245 41.04 0.000 .2354113 .2590268
     | 3 | .3287856 .0053346 61.63 0.000 .31833 .3392413
     | 4 | .425936 .0050064 85.08 0.000 .4161236 .4357485
     | 5 | .5326646 .0059775 89.11 0.000 .5209488 .5443804
     | 6 | .6387994 .0076524 83.48 0.000 .6238009 .6537979
-------------+----------------------------------------------------------------

- The `vsquish` option reduces the amount of vertical space the header for margins takes up

Graphing Across Values of Continuous Variables

```
marginsplot
```

![Predictive Margins with 95% CIs](image)

Specifying Values of Multiple Variables

- We can specify values of multiple variables using `at()`
- If we set values of all the independent variables in our model, we can ask very specific questions
- For example, what is the predicted probability of high blood pressure for an male who is age 40, with a bmi of 25 and living in the midwest (`region=2`)? What is the predicted probability if the person is female?

```
margins female, at(age=40 bmi=25 region=2)
```

```
Adjusted predictions                       Number of obs = 10,351
Model VCE : OIM
Expression : Pr(highbp), predict()
at : bmi = 25
     age = 40
```
| Delta-method | Margin Std. Err. z P>|z| [95% Conf. Interval] |
|-------------|-----------------|----------------|---------|-----------------|
| female | 0 | .3706418 | .0118974 | 31.15 | 0.000 | .3473232 | .3939603 |
| 1 | .2130731 | .0096757 | 22.02 | 0.000 | .194109 | .2320372 |

- We can use the contrast operator `r.` to compare the predicted probabilities for males and females

  . margins r.female, at(age=40 bmi=25 region=2)

Contrasts of adjusted predictions
Model VCE : OIM
Expression : Pr(highbp), predict()
at : bmi = 25
    age = 40
    region = 2

| df  | chi2 | P>|chi2|
|-----|------|-------|
| female | 1 | 200.44 | 0.0000 |

| Delta-method | Contrast Std. Err. [95% Conf. Interval] |
|-------------|-----------------------------------|-------------------|
| female | (1 vs 0) | -.1575687 | .0111296 | -.1793822 | -.1357551 |

- We'll see more on contrasts below

### Specifying Ranges of Multiple Variables

- We can also specify ranges of values for multiple variables, for example multiple values of `age` and `bmi`

  . margins, at(age=(20(10)70) bmi=(20(10)40))

- We can also combine the use of factor and continuous variables, for example

  . margins female, at(age=(20(10)70)) vsquish

Predictive margins Number of obs = 10,351
Model VCE : OIM
Expression : Pr(highbp), predict()
1._at : age = 20
2._at : age = 30
3._at : age = 40
4._at : age = 50
5._at : age = 60
6._at : age = 70
Delta-method
Margin Std. Err. z P>|z| [95% Conf. Interval]
-------------+----------------------------------------------------------------
_at#female    
1 0 | 0.2728133 0.0110381 24.72 0.000 0.2511789 0.2944477
1 1 | 0.0997683 0.0065837 15.15 0.000 0.0868644 0.1126722
2 0 | 0.3369363 0.0093499 36.04 0.000 0.3186108 0.3552617
2 1 | 0.1629921 0.0074737 21.81 0.000 0.148344 0.1776402
3 0 | 0.4076871 0.0075866 53.74 0.000 0.3928176 0.4225566
3 1 | 0.2537634 0.0074437 34.09 0.000 0.2391741 0.2683527
4 0 | 0.4826887 0.0070403 68.56 0.000 0.46889 0.4964874
4 1 | 0.3718821 0.0071293 52.16 0.000 0.357909 0.3858552
5 0 | 0.5588757 0.0084532 65.87 0.000 0.5422451 0.5755063
5 1 | 0.5079403 0.0083728 60.51 0.000 0.4914886 0.5243919
6 0 | 0.6329264 0.0108508 58.33 0.000 0.6116592 0.6541935
6 1 | 0.6442392 0.0106744 60.35 0.000 0.6233177 0.6651607

More Plots

. marginsplot, legend(order(3 "Males" 4 "Females"))

. The standard errors are drawn before the lines for the predictions, so we want the legend to show the third and fourth plots

More Predictions

- We can use at() with the generate() suboption to answer different sorts of questions
- For example, what would the averaged predicted probability be if everyone aged 5 years, while their values female and region remained the same?
- The generate(age+5) requests margins calculated at each observations value of age plus 5
Predictive margins Number of obs = 10,351
Model VCE : OIM
Expression : Pr(highbp), predict()
at : age = age+5

| Delta-method | Margin     | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|--------------|------------|-----------|------|------|----------------------|
| _cons        | .4672688   | .004476   | 104.39 | 0.000 | .458496 - .4760416 |

We can specify at() multiple times, to obtain predictions under different scenarios

. margins, at(age=generate(age)) ///
at(age=generate(age+5)) at(age=generate(age+10))

Predictive margins Number of obs = 10,351
Model VCE : OIM
Expression : Pr(highbp), predict()

| Delta-method | Margin     | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|--------------|------------|-----------|------|------|----------------------|
| _at          |            |           |      |      |                      |
| 1            | .4227611   | .0042898  | 98.55 | 0.000 | .414353 - .4311689  |
| 2            | .4672688   | .004476   | 104.39 | 0.000 | .458496 - .4760416 |
| 3            | .512185    | .0048335  | 105.97 | 0.000 | .5027115 - .5216585 |

Predictions Over Groups

The over() option produces predictions averaging within groups defined by the factor variable, for example, female

. margins, over(female)

Predictive margins Number of obs = 10,351
Model VCE : OIM
Expression : Pr(highbp), predict()
over : female

| Delta-method | Margin     | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|--------------|------------|-----------|------|------|----------------------|
| female       |            |           |      |      |                      |
| 0            | .4687691   | .0066113  | 70.90 | 0.000 | .4558112 - .4817269 |
| 1            | .3811626   | .005567   | 68.47 | 0.000 | .3702816 - .3920737 |

Interpreting Models for Categorical and Count Outcomes © StataCorp LLC
• What happened here?

1. The predicted probability for each case is calculated, using the case’s observed values on all variables
2. The average predicted probability is calculated using only cases where female=0
3. Repeat step 2 using only cases where female=1

---

**Pairwise Comparisons of Predictions**

• Earlier we obtained average predicted probabilities at each level of region using

  . margins region

• For pairwise comparisons of these margins we can add the pwcompare option

  . margins region, pwcompare

Pairwise comparisons of predictive margins
Model VCE : OIM
Expression : Pr(highbp), predict()

<table>
<thead>
<tr>
<th></th>
<th>Delta-method Unadjusted</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Contrast Std. Err. [95% Conf. Interval]</td>
<td></td>
</tr>
<tr>
<td>region</td>
<td>---------</td>
<td>--------------</td>
</tr>
<tr>
<td>MW vs NE</td>
<td>-.0259137</td>
<td>.0126665</td>
</tr>
<tr>
<td>S vs NE</td>
<td>-.017224</td>
<td>.0125288</td>
</tr>
<tr>
<td>W vs NE</td>
<td>-.0072579</td>
<td>.0128075</td>
</tr>
<tr>
<td>S vs MW</td>
<td>.0086896</td>
<td>.0116321</td>
</tr>
<tr>
<td>W vs MW</td>
<td>.0186558</td>
<td>.0119339</td>
</tr>
<tr>
<td>W vs S</td>
<td>.0099661</td>
<td>.0117862</td>
</tr>
</tbody>
</table>

• Adding the groups option will allow us to see which levels are statistically distinguishable

  . margins region, pwcompare(groups)

Pairwise comparisons of predictive margins
Model VCE : OIM
Expression : Pr(highbp), predict()

<table>
<thead>
<tr>
<th></th>
<th>Delta-method Unadjusted</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Margin Std. Err. Groups</td>
<td></td>
</tr>
<tr>
<td>region</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NE</td>
<td>.4362592</td>
<td>.0095422</td>
</tr>
<tr>
<td>MW</td>
<td>.4103455</td>
<td>.0083278</td>
</tr>
<tr>
<td>S</td>
<td>.4190352</td>
<td>.0081188</td>
</tr>
<tr>
<td>W</td>
<td>.4290013</td>
<td>.0085434</td>
</tr>
</tbody>
</table>

Note: Margins sharing a letter in the group label are not significantly different at the 5% level.

• The pwcompare() option can be used to specify other suboptions; see help margins pwcompare for more information
Contrasts of Predictions

- The `margins` command allows contrast operators which are used to request comparisons of the margins
  
  - In this case the margins are predicted probabilities

- For example, to compare average predicted probabilities setting `female=0` versus `female=1` add the `r.` prefix
  `margins r.female`

Contrasts of predictive margins
Model VCE : OIM
Expression : `Pr(highbp), predict()`

<table>
<thead>
<tr>
<th></th>
<th>df</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>female</td>
<td>1</td>
<td>116.16</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Delta-method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Contrast</td>
</tr>
<tr>
<td>female</td>
<td></td>
</tr>
<tr>
<td>(1 vs 0)</td>
<td>-.0925953</td>
</tr>
</tbody>
</table>

- We can use the `@` operator to contrast `female` at each level of `region`
  `margins r.female@region`

Contrasts of predictive margins
Model VCE : OIM
Expression : `Pr(highbp), predict()`

<table>
<thead>
<tr>
<th></th>
<th>df</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>female@region</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1 vs 0) NE</td>
<td>1</td>
<td>117.89</td>
<td>0.0000</td>
</tr>
<tr>
<td>(1 vs 0) MW</td>
<td>1</td>
<td>109.28</td>
<td>0.0000</td>
</tr>
<tr>
<td>(1 vs 0) S</td>
<td>1</td>
<td>112.04</td>
<td>0.0000</td>
</tr>
<tr>
<td>(1 vs 0) W</td>
<td>1</td>
<td>115.96</td>
<td>0.0000</td>
</tr>
<tr>
<td>Joint</td>
<td>4</td>
<td>119.65</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Delta-method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Contrast</td>
</tr>
<tr>
<td>female@region</td>
<td></td>
</tr>
<tr>
<td>(1 vs 0) NE</td>
<td>-.0950335</td>
</tr>
<tr>
<td>(1 vs 0) MW</td>
<td>-.0904099</td>
</tr>
<tr>
<td>(1 vs 0) S</td>
<td>-.0919884</td>
</tr>
<tr>
<td>(1 vs 0) W</td>
<td>-.0937643</td>
</tr>
</tbody>
</table>

- This reports the differences in predicted probabilities when `female=1` versus `female=0` at each level of `region`
Contrasts of Predictions (Continued)

- To perform contrasts at different values of a continuous variable use the `at()` option

  . margins r.female, at(age=(20(10)70)) vsquish

  Contrasts of predictive margins
  Model VCE : OIM
  Expression : Pr(highbp), predict()

  1._at : age = 20
  2._at : age = 30
  3._at : age = 40
  4._at : age = 50
  5._at : age = 60
  6._at : age = 70

  +--------------------------------------------------+
  |       df  chi2    P>chi2 |
  +--------------------------+
  | female@_at |                |
  | (1 vs 0) 1 | 1  182.15  0.0000 |
  | (1 vs 0) 2 | 1  211.82  0.0000 |
  | (1 vs 0) 3 | 1  209.80  0.0000 |
  | (1 vs 0) 4 | 1  122.51  0.0000 |
  | (1 vs 0) 5 | 1   18.36  0.0000 |
  | (1 vs 0) 6 | 1    0.56  0.4552 |
  | Joint | 6 123716.83  0.0000 |
  +--------------------------------------------------+

  |       df  chi2    P>chi2 |
  +--------------------------+
  | female@_at |                |
  | (1 vs 0) 1 | -0.173045 0.0128218 -0.1981752 -0.1479147 |
  | (1 vs 0) 2 | -0.1739442 0.0119516 -0.1973689 -0.1505195 |
  | (1 vs 0) 3 | -0.1539237 0.0106268 -0.1747518 -0.1330956 |
  | (1 vs 0) 4 | -0.1108066 0.0100111 -0.1304280 -.0911851 |
  | (1 vs 0) 5 | -0.0509354 0.0118889 -0.0742372 -0.0276335 |
  | (1 vs 0) 6 | 0.0113128 0.0151483 -.0183773 0.041003 |
  +--------------------------------------------------+

- The output gives tests of the differences in predicted probabilities for `female=1` versus `female=0` at each of the specified values of `age`
  - The joint test is statistically significant
  - The differences get smaller in absolute value as `age` increases

Plotting Contrasts

  . marginsplot, yline(0)
Contrast Operators

- A few common contrast operators are
  - r. differences from the base (a.k.a. reference) level
  - a. differences from the next (adjacent) level
  - ar. differences from the previous level (reverse adjacent)
  - g. differences from the balanced grand mean
  - gw. differences from the observation-weighted grand mean
  - There are also operators for Helmert contrasts and contrasts using orthogonal polynomials for balanced and unbalanced cases

contrast suboptions

- So far we’ve obtained contrasts using contrast operators, but margins also allows a contrast() option
- The contrast() option is particularly useful for specifying options to contrast
- For example, to obtain contrasts for continuous variables the atcontrast() suboption is used
  - The effects suboption requests a table showing the contrasts along with confidence intervals and p-values
  - In atcontrast(a) the a contrast operator requests comparisons of adjacent categories

```
.margins, at(age=(20(10)70)) contrast(atcontrast(a) effects) vsquish
```

Contrasts of predictive margins

Model VCE : OIM

Expression : Pr(highbp), predict()

1._at : age = 20
2._at : age = 30
3._at : age = 40
4._at : age = 50
Contrasts with `generate()`

- Earlier we used the `generate()` suboption to obtain predicted probabilities modifying the observed values.
- Specifically, we obtained predicted probabilities using each case’s observed value of `age` and each case’s observed value +5 years.
  
  ```stata
  . margins, at(age=generate(age)) at(age=generate(age+5))
  ```

Predictive margins
Number of obs = 10,351
Model VCE : OIM
Expression : Pr(highbp), predict()

1. _at : age = age
2. _at : age = age+5

- Using the contrast option, we can compare the two
  
  ```stata
  . margins, at(age=generate(age)) ///
     at(age=generate(age+5)) contrast(atcontrast(r))
  ```
Contrasts of predictive margins
Model VCE : OIM
Expression : Pr(highbp), predict()

1._at : age = age
2._at : age = age+5

<table>
<thead>
<tr>
<th>df</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1728.47</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>_at</th>
<th>df</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>1728.47</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Delta-method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contrast</td>
</tr>
<tr>
<td>-------------</td>
</tr>
<tr>
<td>_at</td>
</tr>
<tr>
<td>(2 vs 1)</td>
</tr>
</tbody>
</table>

Contrasts of Differences
- We can also request contrasts of contrasts by combining contrast operators
- For example, to compare the differences between males and females across levels of region use

```
  . margins r.female#r.region
```

Contrasts of predictive margins
Model VCE : OIM
Expression : Pr(highbp), predict()

<table>
<thead>
<tr>
<th>female#region</th>
<th>df</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1 vs 0) (MW vs NE)</td>
<td>1</td>
<td>4.11</td>
<td>0.0426</td>
</tr>
<tr>
<td>(1 vs 0) (S vs NE)</td>
<td>1</td>
<td>1.88</td>
<td>0.1703</td>
</tr>
<tr>
<td>(1 vs 0) (W vs NE)</td>
<td>1</td>
<td>0.32</td>
<td>0.5709</td>
</tr>
<tr>
<td>Joint</td>
<td>3</td>
<td>4.83</td>
<td>0.1851</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Delta-method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contrast</td>
</tr>
<tr>
<td>-------------</td>
</tr>
<tr>
<td>female#region</td>
</tr>
<tr>
<td>(1 vs 0) (MW vs NE)</td>
</tr>
<tr>
<td>(1 vs 0) (S vs NE)</td>
</tr>
<tr>
<td>(1 vs 0) (W vs NE)</td>
</tr>
</tbody>
</table>
Adjusting for Multiple Comparisons

- Use of contrast and pwcompare can result in a large number of hypothesis tests
- The mcompare() option can be used to adjust p-values and confidence intervals for multiple comparisons within factor variable terms
- The available methods are
  - noadjust
  - bonferroni
  - sidak
  - scheffe

Using mcompare()

- To apply Bonferroni’s adjustment to an earlier contrast

  . margins r.female@region, mcompare(bonferroni)

Contrasts of predictive margins
Model VCE : OIM
Expression : Pr(highbp), predict()

<table>
<thead>
<tr>
<th></th>
<th>df</th>
<th>chi2</th>
<th>P&gt;chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>female@region</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1 vs 0) NE</td>
<td>1</td>
<td>117.89</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>(1 vs 0) MW</td>
<td>1</td>
<td>109.28</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>(1 vs 0) S</td>
<td>1</td>
<td>112.04</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>(1 vs 0) W</td>
<td>1</td>
<td>115.96</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Joint</td>
<td>4</td>
<td>119.65</td>
<td>0.0000</td>
<td></td>
</tr>
</tbody>
</table>

Note: Bonferroni-adjusted p-values are reported for tests on individual contrasts only.

<table>
<thead>
<tr>
<th></th>
<th>Number of</th>
</tr>
</thead>
<tbody>
<tr>
<td>female@region</td>
<td>4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Delta-method</th>
<th>Bonferroni</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Contrast</td>
<td>Std. Err.</td>
</tr>
<tr>
<td>--------------</td>
<td>----------</td>
<td>-----------</td>
</tr>
<tr>
<td>female@region</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1 vs 0) NE</td>
<td>-.0950335</td>
<td>.0087525</td>
</tr>
<tr>
<td>(1 vs 0) MW</td>
<td>-.0904099</td>
<td>.0086485</td>
</tr>
<tr>
<td>(1 vs 0) S</td>
<td>-.0919884</td>
<td>.0086906</td>
</tr>
<tr>
<td>(1 vs 0) W</td>
<td>-.0937643</td>
<td>.0087074</td>
</tr>
</tbody>
</table>

- Specifying adjusted p-values with the pwcompare option
Pairwise comparisons of predictive margins

Model VCE : OIM

Expression : Pr(highbp), predict()

---------------------------
| Number of |
| Comparisons |
| region | 6 |
|-----------------------------|
| Delta-method Sidak |
| Contrast Std. Err. [95% Conf. Interval] |

region
MW vs NE | -.0259137 .0126665 -.0592398 .0074124
S vs NE | -.017224 .0125288 -.0501878 .0157398
W vs NE | -.0072579 .0128075 -.0409548 .026439
S vs MW | .0086896 .0116321 -.021915 .0392943
W vs MW | .0186558 .0119339 -.0127429 .0500544
W vs S | .0099661 .0117862 -.0210439 .0409762

3.3 Marginal Effects

Marginal Effects

- In a straightforward linear model, the marginal effect of a variable is the coefficient \( b \)

\[
y = b_0 + b_1 x_1 + b_2 x_2 + e
\]

- In more complex models, this is no longer true
  - models with interactions
  - models with polynomial terms
  - generalized linear models when the margin is not on the linear scale
- For example, in a logistic regression model, the marginal effect of covariates is not constant on the probability scale
- `margins` can be used to estimate the margins of the derivative of a response

A Closer Look at Slopes

- Here is a graph of predicted probabilities across values of `bmi`

```stata
. margins, at(bmi=(12(5)62))
. marginsplot
```
Average Marginal Effects

- The slope of bmi is not constant, but we might want to know what it is on average.
- We can obtain the average marginal effect of bmi

```
. margins, dydx(bmi)
```

Average marginal effects
Number of obs = 10,351
Model VCE : OIM
Expression : Pr(highbp), predict()
dy/dx w.r.t. : bmi

|         | Delta-method | dy/dx  | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|---------|--------------|--------|-----------|------|------|----------------------|
| bmi     | .0262514     | .000852| 30.81     | 0.00 | 2    | .0245816 .0279212 |
```

- What happened here?
  1. Calculate the derivative of the predicted probability with respect to bmi for each observation.
  2. Calculate the average of derivatives from step 1.

- We can do the same for all variables in our model

```
. margins, dydx(*)
```

Average marginal effects
Number of obs = 10,351
Model VCE : OIM
Expression : Pr(highbp), predict()
dy/dx w.r.t. : bmi age 1.female 2.region 3.region 4.region

__________________________________________________________________________
Marginal Effects Over the Response Surface

- It can also be informative to estimate the marginal effect of \( x \) at different values of \( x \)

- For example, we can obtain the derivative with respect to age at age = 20, 30, ..., 70

  \[
  \text{. margins, dydx(age) at(age=(20(10)70)) vsquish}
  \]

  Average marginal effects Number of obs = 10,351
  Model VCE : OIM
  Expression : Pr(highbp), predict()
  dy/dx w.r.t. : age
  1._at : age = 20
  2._at : age = 30
  3._at : age = 40
  4._at : age = 50
  5._at : age = 60
  6._at : age = 70

  | Delta-method |
  | dy/dx | Std. Err. | z  | P>|z| | [95% Conf. Interval] |
  |--------|-----------|----|-------|---------------------|
  | age    |          |    |       |                     |
  | 1._at  |          |    |       |                     |
  | 1      | .0056454 | .0001263 | 44.70 | 0.000 | .0053978 | .0058929 |
  | 2      | .0072988 | .0001734 | 42.09 | 0.000 | .0069589 | .0076387 |
  | 3      | .0089942 | .000245  | 36.71 | 0.000 | .0085140 | .0094744 |
  | 4      | .0103355 | .0003148 | 32.83 | 0.000 | .0097184 | .0109526 |
  | 5      | .0108342 | .0003262 | 33.21 | 0.000 | .0101949 | .0114736 |
  | 6      | .0102041 | .0002508 | 40.69 | 0.000 | .0097125 | .0106957 |

- Here we do something similar, setting female=0 and then female=1

  \[
  \text{. margins female, dydx(age) at(age=(20(10)70)) vsquish}
  \]

  Average marginal effects Number of obs = 10,351
  Model VCE : OIM
  Expression : Pr(highbp), predict()
dy/dx w.r.t.: age
1. _at : age = 20
2. _at : age = 30
3. _at : age = 40
4. _at : age = 50
5. _at : age = 60
6. _at : age = 70

<table>
<thead>
<tr>
<th>Delta-method</th>
</tr>
</thead>
<tbody>
<tr>
<td>dy/dx</td>
</tr>
<tr>
<td>Std. Err.</td>
</tr>
<tr>
<td>z</td>
</tr>
<tr>
<td>P&gt;</td>
</tr>
<tr>
<td>[95% Conf. Interval]</td>
</tr>
</tbody>
</table>

| age     | dy/dx Std. Err. | z     | P>|z|   | 95% Conf. Interval |
|---------|----------------|-------|-------|-------------------|
| _at#female |                |       |       |                   |
| 1 0     | .0060242       | .0002192 | 27.48 | 0.000          | .0055945 .0064538 |
| 1 1     | .0050964       | .0001457 | 34.98 | 0.000          | .0048108 .005382  |
| 2 0     | .0067761       | .0003143 | 21.56 | 0.000          | .0061601 .007392  |
| 2 1     | .0076423       | .0001587 | 48.17 | 0.000          | .0073313 .0079532 |
| 3 0     | .0073341       | .0003896 | 18.82 | 0.000          | .0065704 .0080978 |
| 3 1     | .0105163       | .0002922 | 35.99 | 0.000          | .0099436 .011089  |
| 4 0     | .0076144       | .0004244 | 17.94 | 0.000          | .0067825 .0084463 |
| 4 1     | .0129499       | .0004576 | 28.30 | 0.000          | .0120531 .0138467 |
| 5 0     | .0075668       | .000407  | 18.59 | 0.000          | .006769  .0083645 |
| 5 1     | .0139526       | .0005002 | 27.89 | 0.000          | .0129722 .0149331 |
| 6 0     | .0071918       | .00034   | 21.15 | 0.000          | .0065255 .0078581 |
| 6 1     | .0129829       | .0003617 | 35.90 | 0.000          | .012274  .0136917 |

Plots of Marginal Effects

We can, of course, plot these marginal effects, to see how they change with different values of female and age.

```
marginsplot
```

Average Marginal Effects of age with 95% CIs
3.4 Other Models

**Margins with Other Estimation Commands**

- `margins` works after most estimation commands
- The default prediction for `margins` is the same as the default prediction for `predict` after a given command
- See help `command postestimation` for information on postestimation commands and their defaults after a given command
- You can specify different predictions from `margins` using the `predict()` option

---

**Modeling Household Size**

- For the next set of examples we will model the number of individuals in a household (houssiz) using a Poisson model
- Our model will include covariates `age`, `age^2`, `region`, `rural`, and a `region` by `rural` interaction
- We’ve been working with `age` and `region` but we'll take a look at the new variables

```
  . codebook houssiz rural

<table>
<thead>
<tr>
<th></th>
<th># persons in household, 1-14</th>
</tr>
</thead>
<tbody>
<tr>
<td>houssiz</td>
<td>type: numeric (byte)</td>
</tr>
<tr>
<td></td>
<td>range: [1,14]</td>
</tr>
<tr>
<td></td>
<td>units: 1</td>
</tr>
<tr>
<td></td>
<td>unique values: 14</td>
</tr>
<tr>
<td></td>
<td>missing .: 0/10,351</td>
</tr>
<tr>
<td></td>
<td>mean: 2.94377</td>
</tr>
<tr>
<td></td>
<td>std. dev: 1.69516</td>
</tr>
<tr>
<td>percentiles:</td>
<td>10%  25%  50%  75%  90%</td>
</tr>
<tr>
<td></td>
<td>1  2  2  4  5</td>
</tr>
<tr>
<td>rural</td>
<td>type: numeric (byte)</td>
</tr>
<tr>
<td></td>
<td>range: [0,1]</td>
</tr>
<tr>
<td></td>
<td>units: 1</td>
</tr>
<tr>
<td></td>
<td>unique values: 2</td>
</tr>
<tr>
<td></td>
<td>missing .: 0/10,351</td>
</tr>
<tr>
<td>tabulation:</td>
<td>Freq. Value</td>
</tr>
<tr>
<td></td>
<td>6,548 0</td>
</tr>
<tr>
<td></td>
<td>3,803 1</td>
</tr>
</tbody>
</table>
```

- Now we can fit our model

```
  . poisson houssiz i.region##i.rural age c.age#c.age

Iteration 0:  log likelihood = -18385.275
Iteration 1:  log likelihood = -18385.272
Iteration 2:  log likelihood = -18385.272

Poisson regression  Number of obs   =    10,351
```

Interpreting Models for Categorical and Count Outcomes © StataCorp LLC
LR chi2(9) = 1780.26
Prob > chi2 = 0.0000
Log likelihood = -18385.272
Pseudo R2 = 0.0462

------------------------------------------------------------------------------
houssiz | Coef. Std. Err. z P>|z| [95% Conf. Interval]
-------------+----------------------------------------------------------------
region | 
| NE | 0 (base) 
| MW | -0.0586473 .0204129 -2.87 0.004 -.0986558 -.0186387 
| S | .0021845 .021345 0.10 0.918 -.0396509 .04402 
| W | -0.0305816 .0208232 -1.47 0.142 -.0713943 .0102311 
| rural | 
| 0 | 0 (base) 
| 1 | .0441422 .0278741 1.58 0.113 -.0104901 .0987745 
| region#rural | 
| MW#1 | .0474625 .036487 1.30 0.193 -.0240508 .1189758 
| S#1 | -.0013947 .0352449 -0.04 0.968 -.0704734 .0676839 
| W#1 | .0303079 .0366293 0.82 0.412 -.0417541 .10183 
| age | .0561718 .025069 22.41 0.000 .012584 .0610852 
| c.age#c.age | -.0007312 .0000272 -26.87 0.000 -.0007845 -.0006779 
| _cons | .2472973 .0539633 4.58 0.000 .1415311 .3530634 
------------------------------------------------------------------------------
margins after poisson

- predict's default after poisson is the predicted count
- To obtain the average predicted count, using the observed values of all covarites use
  . margins

Predictive margins

Expression : Predicted number of events, predict()

| Delta-method
| Margin Std. Err. z P>|z| [95% Conf. Interval]
| cons | 2.943774 .016864 174.56 0.000 2.910721 2.976826

- As before, we can request predicted counts at specified values of factor variables
  . margins region#rural

Predictive margins

Expression : Predicted number of events, predict()

| Delta-method
| Margin Std. Err. z P>|z| [95% Conf. Interval]
| cons | 2.943774 .016864 174.56 0.000 2.910721 2.976826

Interpreting Models for Categorical and Count Outcomes © StataCorp LLC
| Margin   | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|----------|-----------|------|-------|-----------------------|
| region#rural |           |      |       |                       |
| NE#0      | 2.942144  | .0441807 | 66.59 | 0.000 | 2.855552  | 3.028737 |
| NE#1      | 3.074926  | .0722057 | 42.59 | 0.000 | 2.933405  | 3.216447 |
| MW#0      | 2.774558  | .0383527 | 72.34 | 0.000 | 2.699388  | 2.849728 |
| MW#1      | 3.040725  | .0579537 | 52.47 | 0.000 | 2.927138  | 3.154312 |
| S#0       | 2.948578  | .0447353 | 65.91 | 0.000 | 2.860899  | 3.036258 |
| S#1       | 3.077355  | .0472768 | 65.09 | 0.000 | 2.984695  | 3.170016 |
| W#0       | 2.853531  | .0411629 | 69.32 | 0.000 | 2.772853  | 2.934209 |
| W#1       | 3.073255  | .0580446 | 52.95 | 0.000 | 2.959489  | 3.18702  |

- And continuous variables
  
  . margins, at(age=(20(10)70)) vsquish

Predictive margins
Number of obs = 10,351
Model VCE : OIM
Expression : Predicted number of events, predict()

1._at : age = 20
2._at : age = 30
3._at : age = 40
4._at : age = 50
5._at : age = 60
6._at : age = 70

<table>
<thead>
<tr>
<th>Delta-method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Margin</td>
</tr>
<tr>
<td>--------------</td>
</tr>
<tr>
<td>_at</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
<td>6</td>
</tr>
</tbody>
</table>

Plotting Predicted Counts

. marginsplot
Other Margins

- After poisson, margins can be used to predict the following
  - \( n \) number of events; the default
  - \( \text{ir} \) incidence rate, \( \exp(xb) \), \( n \) when the exposure variable = 1
  - \( \text{pr}(n) \) probability that \( y=n \)
  - \( \text{pr}(a,b) \) probability that \( a \leq y \leq b \)
  - \( xb \) the linear prediction

- Predicted probability that \( \text{houssiz}=1 \)

  ```
  . margins rural, predict(pr(1))
  ```

  Predictive margins
  Number of obs = 10,351
  Model VCE : OIM

  Expression : Pr(houssiz=1), predict(pr(1))

  +--------------------------------------------------+
  | Delta-method | Margin | Std. Err. | z   | P>|z| | [95% Conf. Interval] |
  +--------------------------------------------------+
  rural |        |        |        |    |     |                    |
  0  | .1714666 | .0020282 | 84.54 | 0.000 | .1674915 | .1754417 |
  1  | .1541716 | .0025566 | 60.30 | 0.000 | .1491608 | .1591823 |
  +--------------------------------------------------+

- Predicted probability that \( 3 \leq \text{houssiz} \leq 5 \)

  ```
  . margins region#rural, predict(pr(3,5))
  ```

  Predictive margins
  Number of obs = 10,351
  Model VCE : OIM

  Expression : Pr(3<=houssiz<=5), predict(pr(3,5))
| Delta-method | Margin Std. Err. z P>|z| [95% Conf. Interval] |
|-------------+------------------------------------------------|
| region#rural |------------------------------------------------|
| NE#0 | .4557062 .0047091 96.77 0.000 .4464765 .464936 |
| NE#1 | .4682528 .0063677 73.54 0.000 .4557723 .4807332 |
| MW#0 | .4365671 .0049383 88.41 0.000 .4268883 .4462459 |
| MW#1 | .4652407 .005386 86.38 0.000 .4546843 .4757971 |
| S#0 | .4563673 .0047189 96.71 0.000 .4471185 .4656162 |
| S#1 | .468461 .004296 109.05 0.000 .460041 .4768809 |
| W#0 | .4460472 .004858 91.82 0.000 .4365256 .4555688 |
| W#1 | .4681091 .0051371 91.12 0.000 .4580405 .4781777 |

Multiple Responses

- Starting in Stata 14, margins can compute margins for multiple responses at the same time
  - After, for example, ologit, mlogit, mvreg
- To demonstrate this, we'll model self-rated health in a different version of the NHANES dataset
  
  . webuse nhanes2f
  . codebook health

<table>
<thead>
<tr>
<th>health</th>
<th>1=poor,..., 5=excellent</th>
</tr>
</thead>
<tbody>
<tr>
<td>type:</td>
<td>numeric (byte)</td>
</tr>
<tr>
<td>label:</td>
<td>hlthgrp</td>
</tr>
<tr>
<td>range:</td>
<td>[1,5]</td>
</tr>
<tr>
<td>units:</td>
<td>1</td>
</tr>
<tr>
<td>unique</td>
<td>values: 5</td>
</tr>
<tr>
<td>missing</td>
<td>.: 2/10,337</td>
</tr>
</tbody>
</table>

  tabulation: Freq. Numeric Label
  729 1 poor
  1,670 2 fair
  2,938 3 average
  2,591 4 good
  2,407 5 excellent
  2 .

- Our model is
  
  . ologit health i.female age c.age#c.age

  Iteration 0: log likelihood = -15764.397
  Iteration 1: log likelihood = -15042.53
  Iteration 2: log likelihood = -15036.362
  Iteration 3: log likelihood = -15036.355
  Iteration 4: log likelihood = -15036.355

  Ordered logistic regression
  Number of obs = 10,335
  LR chi2(3) = 1456.09
  Prob > chi2 = 0.0000
  Log likelihood = -15036.355
  Pseudo R2 = 0.0462
## Specifying the Response

- **By default** `margins` will produce the average predicted probability of each value of `health`.

```
margins
```

Predictive margins

|  | Coef. | Std. Err. | z   | P>|z|  | [95% Conf. Interval] |
|---|-------|-----------|-----|-----|----------------------------|
| female | 0 | 0 (base) | | | |
| | 1 | -.1223788 | .0355107 | -3.45 | .001 | -.1919786 | -.052779 |
| age | | -.0251916 | .0076063 | -3.31 | .001 | -.0400997 | -.0102834 |
| c.age#c.age | | -.00016 | .0000812 | -1.97 | .049 | -.0003191 | -9.73e-07 |

```
/cut1 | -4.442363 | .1659171 | -4.767554 | -4.117171 |
/cut2 | -2.975821 | .1632372 | -3.29576 | -2.655882 |
/cut3 | -1.573015 | .1618158 | -1.890168 | -1.255862 |
/cut4 | -.3384551 | .1606298 | -.6532838 | -.0236264 |
```

- To request a single outcome we can use `predict(outcome(#))`.

```
margins, predict(outcome(2))
```

Predictive margins

|  | Delta-method |
|---|-------------|-----------|-----|-----|----------------------------|
| _predict | Coef. | Std. Err. | z   | P>|z|  | [95% Conf. Interval] |
| 1 | .0709472 | .0024959 | 28.43 | 0.000 | .0660554 | .075839 |
| 2 | .1643302 | .0035781 | 45.93 | 0.000 | .1573172 | .1713432 |
| 3 | .2868785 | .0044083 | 65.08 | 0.000 | .2782384 | .2955187 |
| 4 | .2474815 | .004184 | 59.15 | 0.000 | .239281 | .255682 |
| 5 | .2303626 | .0039468 | 58.37 | 0.000 | .222627 | .2380981 |

---

Interpreting Models for Categorical and Count Outcomes © StataCorp LLC
For multiple responses from a single command, repeat the `predict()` option.

```stata
predict(outcome(1)) predict(outcome(2))
```

Predictive margins

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta-method</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Margin</td>
<td>Std. Err.</td>
<td>z</td>
<td>P&gt;</td>
</tr>
<tr>
<td>_predict</td>
<td>1</td>
<td>.0709472</td>
<td>.0024959</td>
<td>28.43</td>
</tr>
<tr>
<td>2</td>
<td>.1643302</td>
<td>.0035781</td>
<td>45.93</td>
<td>0.000</td>
</tr>
</tbody>
</table>

To obtain predictions across values of age

```stata
at(age=(20(10)70)) pr(out(1)) pr(out(2))
```

Predictive margins

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta-method</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Margin</td>
<td>Std. Err.</td>
<td>z</td>
<td>P&gt;</td>
</tr>
<tr>
<td>_predict#_at</td>
<td>1   1</td>
<td>.0217005</td>
<td>.0013107</td>
<td>16.56</td>
</tr>
<tr>
<td>1   2</td>
<td>.0299861</td>
<td>.001366</td>
<td>21.95</td>
<td>0.000</td>
</tr>
<tr>
<td>1   3</td>
<td>.0425874</td>
<td>.0019332</td>
<td>22.03</td>
<td>0.000</td>
</tr>
<tr>
<td>1   4</td>
<td>.0619896</td>
<td>.0019332</td>
<td>23.05</td>
<td>0.000</td>
</tr>
<tr>
<td>1   5</td>
<td>.0920429</td>
<td>.0026898</td>
<td>23.05</td>
<td>0.000</td>
</tr>
<tr>
<td>1   6</td>
<td>.1383404</td>
<td>.0032038</td>
<td>24.86</td>
<td>0.000</td>
</tr>
<tr>
<td>2   1</td>
<td>.0659885</td>
<td>.0030238</td>
<td>20.60</td>
<td>0.000</td>
</tr>
<tr>
<td>2   2</td>
<td>.0881333</td>
<td>.0030238</td>
<td>31.85</td>
<td>0.000</td>
</tr>
<tr>
<td>2   3</td>
<td>.1189848</td>
<td>.0036317</td>
<td>32.76</td>
<td>0.000</td>
</tr>
<tr>
<td>2   4</td>
<td>.1605636</td>
<td>.0045152</td>
<td>35.56</td>
<td>0.000</td>
</tr>
<tr>
<td>2   5</td>
<td>.2130434</td>
<td>.0049117</td>
<td>43.37</td>
<td>0.000</td>
</tr>
<tr>
<td>2   6</td>
<td>.2717448</td>
<td>.0066991</td>
<td>40.56</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Interpreting Models for Categorical and Count Outcomes

Plots with Multiple Responses

```stata
marginsplot, legend(order(3 "Poor" 4 "Fair"))
```
4 Conclusion

4.1 Conclusion

Conclusion

- We’ve seen how to obtain a variety of predictions and marginal effects after regression models
- We now know how to perform contrasts of predictions and marginal effects
- We’ve also seen how to graph these results
Index