Indiana University

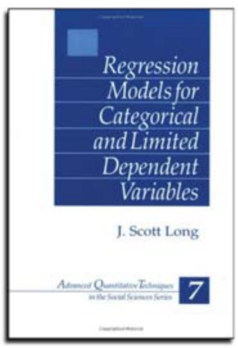
Interpreting regression models using Stata

Scott Long

August 13, 2013

Draft: Long-StataCorp-2013-08-07.docx

Interpreting regression models



1980s Interpreting log-linear and multinomial models to support substantive research

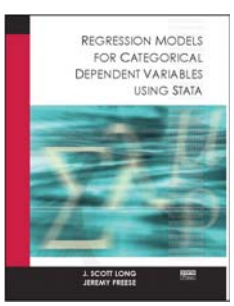
1991 *Markov: A Statistical Environment for GAUSS*

1996 change.ado and genpred.ado in Stata 4

1997 *Regression Models for Categorical and Limited Dependent Variables*

1997 *Markov 2.5*

Working with StataCorp



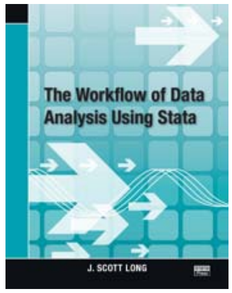
1998 Bill Sribney on post-estimation
Bill Gould on returns

1999 SPost with Jeremy Freese

2000 David Drukker and StataPress

2001 *Regression Models for Categorical Dependent Variables with Stata* with Jeremy Freese.

Continuing work...



2005	*Regression Models with Stata, 2nd*
2005	SPost9 20,000 downloads.
2008	*The Workflow of Data Analysis using Stata*
2009	Stata 11 and **`margins`** and factor variables.
2011	Stata 12 with **`marginsplot`**
2012	SPost13 for 3rd edition
2013	Stata 13

Stata at Indiana

My students appeared in class wearing...

Goals for visiting StataCorp

Demo SPost13 wrappers for margins

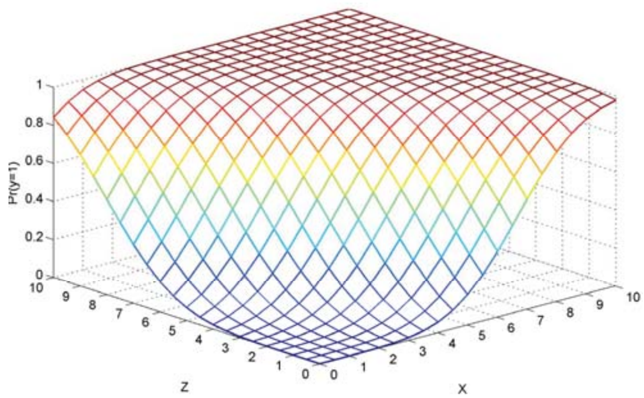
- Did we miss something? Are there better ways to do things?
- Do our new methods of interpretation make sense?

Other SPost13 commands

- Why we wrote them
- Why StataCorp might want to improve them

Things we'd like to see in Stata

Interpretation using predictions



With multiple outcomes and K predictors...

Interpreting nonlinear models

1. Requires functions of parameters.
2. Requires the observed data.

Ways to use predictions

Tables: Predictions at multiple levels of regressors.

Marginal effects: Changes in predictions.

Graphs: Predictions at many levels of regressors.

The tools

Official Stata

`margins`

`marginsplot`

SPost13 wrappers for margins and lincom

`mtable`: tables of predictions

`mchange`: marginal effects

`mgen`: predictions to plot

`mlistat`: compact at() matrix listing

`mlincom`: tables of linear combinations (wrapper for **`lincom`**)

Why not simply use margins and marginsplot?

Tables of predictions

Predictions at substantively informative values of regressors.

Binary outcome

```
sysuse binlfp4, clear
logit lfp k5 k618 i.agecat i.wc i.hc lwg inc
```

Question

How does the number of children and a woman's education affect labor force participation?

margins

```
. margins, atmeans at(wc=(0 1) k5=(0 1 2 3))

Adjusted predictions                              Number of obs   =        753
Model VCE     : OIM

Expression    : Pr(lfp), predict()

1._at         : wc              =           0
                k5              =           0
                k618            =    1.353254 (mean)
                1.agecat        =    .3957503 (mean)
                2.agecat        =    .3851262 (mean)
                3.agecat        =    .2191235 (mean)
                0.hc            =    .6082337 (mean)
                1.hc            =    .3917663 (mean)
                lwg             =    1.097115 (mean)
                inc             =    20.12897 (mean)

2._at         : wc              =           0
:::snip:::
3._at         : wc              =           0
:::snip:::
4._at         : wc              =           0
:::snip:::
5._at         : wc              =           1
:::snip:::
6._at         : wc              =           1
```



```
:::snip:::
7._at         : wc              =           1
:::snip:::
8._at         : wc              =           1
:::snip:::

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         _at |
          1  |   .6035431   .0256741    23.51   0.000     .5532229    .6538633
          2  |   .2746181   .0359919     7.63   0.000     .2040752    .3451609
          3  |   .0860471   .0280757     3.06   0.002     .0310198    .1410744
          4  |   .0228776   .0121605     1.88   0.060    -.0009566    .0467119
          5  |    .771705   .0349691    22.07   0.000     .7031668    .8402432
          6  |   .4567078   .0566536     8.06   0.000     .3456687    .5677469
          7  |   .1729059   .0532296     3.25   0.001     .0685779     .277234
          8  |    .049419    .025671     1.93   0.054    -.0008953    .0997333
------------------------------------------------------------------------------
```

mtable: simple

```
. mtable, atmeans at(wc=(0 1) k5=(0 1 2 3))
```

<= pass through to margins

```
Expression: Pr(lfp)

          |        1.
          |        wc         k5         pr
----------+----------------------------------
        1 |         0          0      0.604
        2 |         0          1      0.275
        3 |         0          2      0.086
        4 |         0          3      0.023
        5 |         1          0      0.772
        6 |         1          1      0.457
        7 |         1          2      0.173
        8 |         1          3      0.049

Constant values of at() variables

                     2.          3.          1.
     k618      agecat      agecat          hc         lwg         inc
-----------------------------------------------------------------
    1.353       0.385       0.219       0.392       1.097      20.129
```


mtable: building a table

```
. qui mtable, atmeans at(wc=0 k5=(0 1 2 3)) estname(NoCol)

. qui mtable, atmeans at(wc=1 k5=(0 1 2 3)) estname(College) ///
>     atvars(_none) right

. mtable, atmeans dydx(wc) at(k5=(0 1 2 3)) estname(Diff) stats(est p) ///
>     atvars(_none) names(columns) right

      k5     NoCol   College      Diff         p
------------------------------------------------
       0     0.604     0.772     0.168     0.000
       1     0.275     0.457     0.182     0.001
       2     0.086     0.173     0.087     0.013
       3     0.023     0.049     0.027     0.085
```


Categorical outcomes

```
. sysuse ordwarm4, clear
. tab warm

Working mom |
   can have |
       warm |
relations w |
     child? |      Freq.     Percent        Cum.
------------+-----------------------------------
       1_SD |        297       12.95       12.95
        2_D |        723       31.53       44.48
        3_A |        856       37.33       81.81
       4_SA |        417       18.19      100.00
------------+-----------------------------------
      Total |      2,293      100.00

. ologit warm i.yr89 i.male i.white age i.edcat prst
```

Question

How do age and gender affect support for working women as mothers?

margins

```
. foreach iout in 1 2 3 4 {
  2.     margins, at(yr89=(0 1) male=(0 1)) atmeans predict(outcome(`iout'))
  3. }

Adjusted predictions                              Number of obs   =       2293
Model VCE    : OIM

Expression   : Pr(warm==1), predict(outcome(1))

1._at        : yr89            =           0
:::snip:::
------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         _at |
          1  |   .0981207   .0074061    13.25   0.000      .083605    .1126365
          2  |   .1868221   .0117184    15.94   0.000     .1638545    .2097897
          3  |   .0604381   .0053787    11.24   0.000      .049896    .0709802
          4  |   .1195914   .0095217    12.56   0.000     .1009293    .1382536
------------------------------------------------------------------------------
```



```
Adjusted predictions                              Number of obs   =       2293
Model VCE    : OIM

Expression   : Pr(warm==2), predict(outcome(2))
:::snip:::

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         _at |
          1  |   .3069102   .0125571    24.44   0.000     .2822987    .3315216
          2  |   .4029306   .0127015    31.72   0.000      .378036    .4278251
          3  |   .2265499   .0119914    18.89   0.000     .2030473    .2500525
          4  |   .3398556   .0137531    24.71   0.000     .3129002    .3668111
------------------------------------------------------------------------------

:::snip:::

:::snip:::
```


mtable: quick

```
. mtable, at(yr89=(0 1) male=(0 1)) atmeans

Expression: Pr(warm)

          |       1.        1.
          |     yr89      male      1 SD       2 D       3 A      4 SA
----------+------------------------------------------------------------
        1 |        0         0     0.098     0.307     0.415     0.180
        2 |        0         1     0.187     0.403     0.316     0.094
        3 |        1         0     0.060     0.227     0.442     0.271
        4 |        1         1     0.120     0.340     0.391     0.150

Constant values of at() variables

        1.                    2.         3.         4.
    white         age      edcat      edcat      edcat       prst
-----------------------------------------------------------------
    0.877      44.935      0.341      0.196      0.171     39.585
```

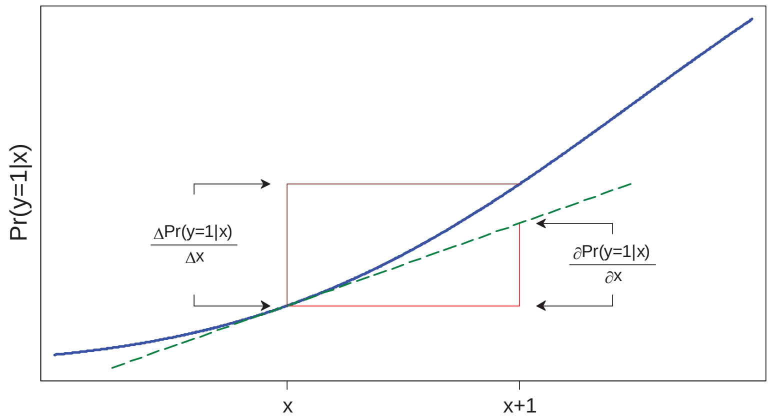
mtable: building

```
. qui mtable, at(yr89=0 male=1) atmeans rowname(Men) clear roweq(1977)
. qui mtable, at(yr89=0 male=0) atmeans rowname(Women) below roweq(1977)
. qui mtable, dydx(male) at(yr89=0) atmeans rowname(M-W) below roweq(1977)

. qui mtable, at(yr89=1 male=1) atmeans rowname(Men) below roweq(1989)
. qui mtable, at(yr89=1 male=0) atmeans rowname(Women) below roweq(1989)
. qui mtable, dydx(male) at(yr89=1) atmeans rowname(M-W) below roweq(1989)

. qui mtable, dydx(yr89) at(male=1) atmeans rowname(77to89) below roweq(Men)
. mtable, dydx(yr89) at(male=0) atmeans rowname(77to89) below roweq(Women)

          |     1 SD       2 D       3 A      4 SA
----------+----------------------------------------
1977      |
      Men |    0.187     0.403     0.316     0.094
    Women |    0.098     0.307     0.415     0.180
      M-W |    0.089     0.096    -0.099    -0.086
1989      |
      Men |    0.120     0.340     0.391     0.150
    Women |    0.060     0.227     0.442     0.271
      M-W |    0.059     0.113    -0.051    -0.121
Men       |
   77to89 |   -0.067    -0.063     0.075     0.055
Women     |
   77to89 |   -0.038    -0.080     0.027     0.091
```


SUGGESTION

1. **`margins`** for multiple outcomes
   - o Joint estimation, not simply accumulation over outcomes
2. Compact summary of **`at()`** values.

Marginal effects



Mathematically, ...

Marginal change

$$\frac{\partial \Pr(y=1|\mathbf{x})}{\partial x_k} = f(\mathbf{x}\beta)\beta_k$$

Discrete change

$$\frac{\Delta \Pr(y=1|\mathbf{x})}{\Delta x_k} = \Pr(y=1|\mathbf{x}^*, \text{End } x_k) - \Pr(y=1|\mathbf{x}^*, \text{Start } x_k)$$

Binary outcome

```
sysuse binlfp4, clear
logit lfp k5 k618 i.agecat i.wc i.hc lwg inc
```

Question

How to assess the magnitudes of the effects?

mchange

```
. mchange

logit: Changes in Pr(lfp) | N = 753

                |    Change      P>|z|
----------------+---------------------
1.wc            |
         0 to 1 |    0.1624     0.0002
k5              |
        +1 cntr |   -0.2818     0.0000
       +SD cntr |   -0.1503     0.0000
       Marginal |   -0.2888     0.0000
k618            |
        +1 cntr |   -0.0136     0.3354
       +SD cntr |   -0.0180     0.3353
       Marginal |   -0.0136     0.3354
```



```
1.hc            |
         0 to 1 |    0.0282     0.5076
lwg             |
        +1 cntr |    0.1260     0.0000
       +SD cntr |    0.0742     0.0000
       Marginal |    0.1266     0.0000
inc             |
        +1 cntr |   -0.0073     0.0000
       +SD cntr |   -0.0845     0.0000
       Marginal |   -0.0073     0.0000
agecat          |
 40-49 vs 30-39 |   -0.1242     0.0017
   50+ vs 30-39 |   -0.2624     0.0000
   50+ vs 40-49 |   -0.1382     0.0024

Average predictions

            not in LF      in LF
Pr(y|base)     0.4316     0.5684

1: Predictions averaged over the sample.
```

mchange with options (edited)

```
. mchange, stats(from to change pvalue)

logit: Changes in Pr(lfp) | N = 753

                |      From         To     Change       P>|z|
----------------+--------------------------------------------
1.wc            |
         0 to 1 |    0.5251     0.6875     0.1624     0.0002
k5              |
        +1 cntr |    0.7040     0.4222    -0.2818     0.0000
       +SD cntr |    0.6420     0.4917    -0.1503     0.0000
       Marginal |         .          .    -0.2888     0.0000
inc             |
        +1 cntr |    0.5720     0.5648    -0.0073     0.0000
       +SD cntr |    0.6101     0.5257    -0.0845     0.0000
       Marginal |         .          .    -0.0073     0.0000
agecat          |
 40-49 vs 30-39 |    0.5521     0.6764    -0.1242     0.0017
   50+ vs 30-39 |    0.4139     0.6764    -0.2624     0.0000
   50+ vs 40-49 |    0.4139     0.5521    -0.1382     0.0024

Average predictions

            not in LF      in LF
Pr(y|base)     0.4316     0.5684

1: Predictions averaged over the sample.
```


margins

```
margins, at(k5=gen(k5-.5)) at(k5=gen(k5+.5)) post
    lincom _b[2._at]-_b[1._at]
    est restore blm
margins, at(k5=gen(k5-.2619795189419575)) ///
         at(k5=gen(k5+.2619795189419575)) post
    lincom _b[2._at]-_b[1._at]
    est restore blm
margins, dydx(k5)
margins, at(k618=gen(k618-.5)) at(k618=gen(k618+.5)) post
    lincom _b[2._at]-_b[1._at]
    est restore blm
margins, at(k618=gen(k618-.6599369652141052)) ///
         at(k618=gen(k618+.6599369652141052)) post
    lincom _b[2._at]-_b[1._at]
    est restore blm
margins, dydx(k618)
margins, at(wc=(0 1)) post
    lincom _b[2._at]-_b[1._at]
    est restore blm
margins, at(hc=(0 1)) post
    lincom _b[2._at]-_b[1._at]
    est restore blm
margins, at(lwg=gen(lwg-.5)) at(lwg=gen(lwg+.5)) post
    lincom _b[2._at]-_b[1._at]
    est restore blm
margins, at(lwg=gen(lwg-.2937782125573122)) ///
         at(lwg=gen(lwg+.2937782125573122)) post
```



```
    lincom _b[2._at]-_b[1._at]
    est restore blm
margins, dydx(lwg)
margins, at(inc=gen(inc-.5)) at(inc=gen(inc+.5)) post
    lincom _b[2._at]-_b[1._at]
    est restore blm
margins, at(inc=gen(inc-5.817399266696214)) ///
         at(inc=gen(inc+5.817399266696214)) post
    lincom _b[2._at]-_b[1._at]
    est restore blm
margins, dydx(inc)
margins agecat, pwcompare
```

Ordinal outcomes

```
. sysuse ordwarm4, clear
. ologit warm i.yr89 i.male i.white age ed prst
```

mchange

```
. mchange

ologit: Changes in Pr(warm) | N = 2293

              |      1 SD        2 D        3 A       4 SA
--------------+--------------------------------------------
1.yr89        |
       0 to 1 |   -0.0532    -0.0642     0.0423     0.0751
       pvalue |    0.0000     0.0000     0.0000     0.0000
1.male        |
       0 to 1 |    0.0787     0.0873    -0.0657    -0.1003
       pvalue |    0.0000     0.0000     0.0000     0.0000
1.white       |
       0 to 1 |    0.0375     0.0480    -0.0264    -0.0591
       pvalue |    0.0003     0.0015     0.0000     0.0021
age           |
      +1 cntr |    0.0023     0.0025    -0.0018    -0.0030
       pvalue |    0.0000     0.0000     0.0000     0.0000
     +SD cntr |    0.0387     0.0420    -0.0300    -0.0507
       pvalue |    0.0000     0.0000     0.0000     0.0000
     Marginal |    0.0023     0.0025    -0.0018    -0.0030
       pvalue |    0.0000     0.0000     0.0000     0.0000
```

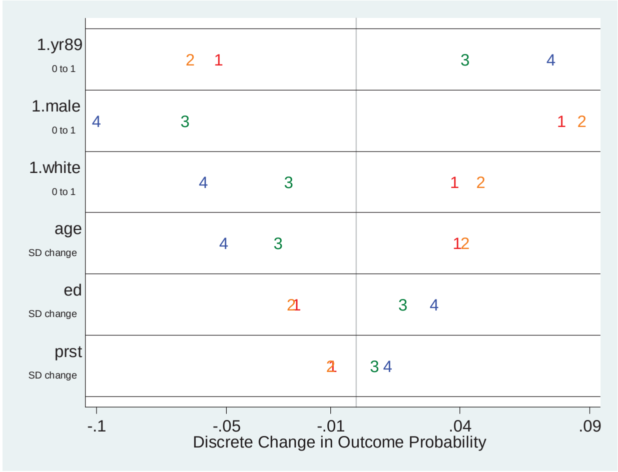


```
ed            |
      +1 cntr |   -0.0071    -0.0078     0.0056     0.0094
       pvalue |    0.0000     0.0000     0.0000     0.0000
     +SD cntr |   -0.0226    -0.0246     0.0176     0.0296
       pvalue |    0.0000     0.0000     0.0000     0.0000
     Marginal |   -0.0071    -0.0078     0.0056     0.0094
       pvalue |    0.0000     0.0000     0.0000     0.0000
prst          |
      +1 cntr |   -0.0006    -0.0007     0.0005     0.0008
       pvalue |    0.0661     0.0648     0.0668     0.0649
     +SD cntr |   -0.0094    -0.0102     0.0073     0.0123
       pvalue |    0.0662     0.0647     0.0666     0.0649
     Marginal |   -0.0006    -0.0007     0.0005     0.0008
       pvalue |    0.0661     0.0648     0.0668     0.0649

1: Predictions averaged over the sample.
```

A lot of numbers to absorb, so plot them...

dcplot: marginal effect plotter (meplot would be a better name)

```
dcplot, mcolor(rainbow)
```



margins

```
foreach iout in 1 2 3 4 {
    margins, at(yr89=(0 1) ) post predict(outcome(`iout'))
        lincom _b[2._at] - _b[1._at]
        estimate restore olm
    margins, at(male=(0 1) ) post predict(outcome(`iout'))
        lincom _b[2._at] - _b[1._at]
        estimate restore olm
    margins, at(white=(0 1) ) post predict(outcome(`iout'))
        lincom _b[2._at] - _b[1._at]
        estimate restore olm
    margins, at(age=gen(age - .5) ) at(age=gen(age + .5) ) ///
        post predict(outcome(`iout'))
        lincom _b[2._at] - _b[1._at]
        estimate restore olm
    margins, at(age=gen(age - 8.389516848965164) ) ///
        at(age=gen(age + 8.389516848965164) ) post predict(outcome(`iout'))
        lincom _b[2._at] - _b[1._at]
        estimate restore olm
    margins, dydx(age) predict(outcome(`iout'))
    margins, at(ed=gen(ed - .5) ) at(ed=gen(ed + .5) ) ///
        post predict(outcome(`iout'))
        lincom _b[2._at] - _b[1._at]
        estimate restore olm
    margins, at(ed=gen(ed - 1.58041337227172) ) ///
        at(ed=gen(ed + 1.58041337227172) ) post predict(outcome(`iout'))
        lincom _b[2._at] - _b[1._at]
        estimate restore olm
```



```
    margins, dydx(ed) predict(outcome(`iout'))
    margins, at(prst=gen(prst - .5) ) at(prst=gen(prst + .5) ) ///
        post predict(outcome(`iout'))
        lincom _b[2._at] - _b[1._at]
        estimate restore olm
    margins, at(prst=gen(prst - 7.24612929840372) ) ///
        at(prst=gen(prst + 7.24612929840372) ) post predict(outcome(`iout'))
        lincom _b[2._at] - _b[1._at]
        estimate restore olm
    margins, dydx(prst) predict(outcome(`iout'))
}
```


What logit output might look like

	Coef	OR	P>|z|	AME	P>|z|
lfp					
k5	-1.392	0.249	0.000	-0.150	0.000
k618	-0.066	0.936	0.336	-0.018	0.335
wc	0.798	2.220	0.001	0.162	0.000
hc	0.136	1.146	0.508	0.028	0.508
lwg	0.610	1.840	0.000	0.074	0.000
inc	-0.035	0.966	0.000	-0.084	0.000
40-49vs30-39	1.481	4.396	0.000	-0.124	0.002
50+vs30-39	0.854	2.349	0.005	-0.262	0.000
50+vs40-49	0.202	1.224	0.500	-0.138	0.002
Constant	1.014	2.757	0.000		

AME and MEM

A sometimes less than fruitful debate...

MEM

$$MCM: \frac{\partial \Pr\left(y=1|\bar{\mathbf{x}}\right)}{\partial x_k} = f(\bar{\mathbf{x}}\beta)\beta_k \qquad DCM: \frac{\Delta \Pr\left(y=1|\bar{\mathbf{x}}\right)}{\Delta x_k}$$

AME

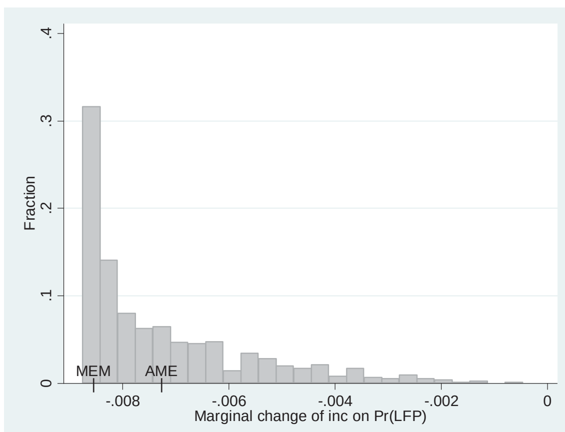
$$AMC = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial \Pr\left(y=1|\mathbf{x}_i\right)}{\partial x_{ik}} \qquad ADC = \frac{1}{N}\sum_{i=1}^{N}\frac{\Delta \Pr\left(y=1|\mathbf{x}_i\right)}{\Delta x_{ik}}$$

Should you replace one mean with another?

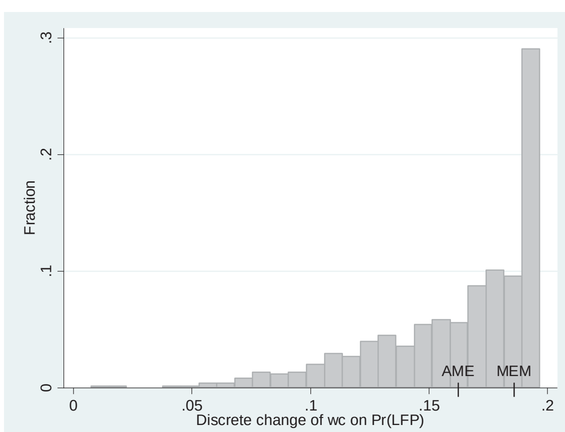
- o What is the question you are trying to answer?
- o Maddala's 1980 advice was pretty good.

Distribution of ME's

Marginal change for income



Discrete change for woman attending college



Compute marginal effects (not recommended)

```
predict double prhat if e(sample)
gen double mcinc = prhat * (1-prhat) * _b[inc]
label var mcinc "Marginal change of inc on Pr(LFP)"
```

Compute effects: with mgen (not recommended)

```
mgen, dydx(wc) over(caseid) stub(wc) nose
label var wcdydx "Discrete change of wc on Pr(LFP)"
```

Compute effects with predict (not recommended)

```
gen wc_orig = wc
replace wc = 0
predict double prhat0
replace wc = 1
predict double prhat1
replace wc = wc_orig
drop wc_orig
gen double dcwc = prhat1 - prhat0
label var dcwc "Discrete change of wc on Pr(LFP)"
```

SUGGESTION

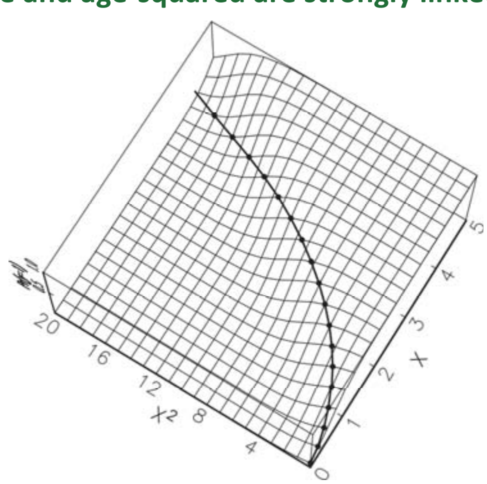
1. Let **`predict`** predict anything **`margins`** can compute.
2. Add **`gen()`** option to **`margins`** to save any variables with its predictions.

Linked marginal effects

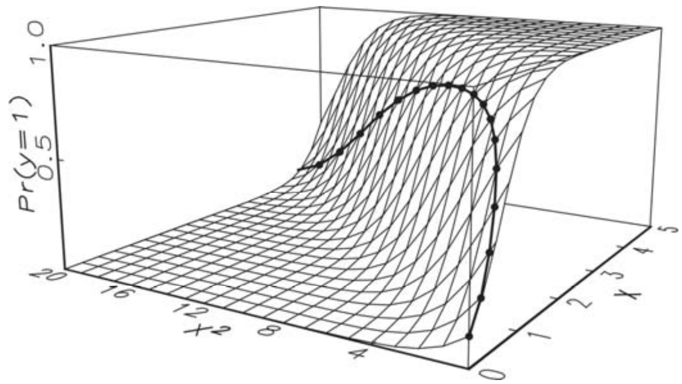
1. As observed and at means are part of a continuum.
2. It is too limiting to think of these as either/or.
3. Consider "strongly linked" variables which are handled by factor variables.
4. Weakly linked variables can be handed with **`at(x=gen())`**

Start with strongly linked variables...

Age and age-squared are strongly linked



Leading to



Which **`margins`** with factor variables handles with ease.

Modeling the effect of height and weight on arthritis

`logit arthritis c.age i.female i.ed3cat height weight`

The question

Does height "by itself" increase the probability of arthritis?

The problem

1. Height and weight are linked.
2. Increasing height, holding weight constant is not the question.
3. Allow height to increase and let weight increase a corresponding amount.
   - o The type of problem has many applications.

Estimate the model

```
. sysuse svyhrs3, clear
. svyset secu [pweight=kwgtr], strata(stratum) ///
>     vce(linearized) singleunit(missing)
. svy: logit arthritis c.age i.female i.ed3cat height weight
. estimates store lgt
```

Predict weight from height

```
. svy: reg weight height
. local a = _b[_con]
. local b = _b[height]
```

Compute std. dev. of height

```
. svy: mean height
. estat sd
. local sd = el(r(sd),1,1)
. estimates restore lgt
```

Compute predicted probabilities

```
. mtable, ///

> /// predict at observed
> ///
>     at( height=gen(height)  ///
>         weight=gen(weight)) ///
>
> /// change height only
> ///
>     at( height=gen(height+`sd') ///
>         weight=gen(weight))     ///
>
> /// change height and weight
> ///
>     at( height=gen(height+`sd') ///
>         weight=gen(`a'+`b'*(height +`sd')) ) post

Expression: Pr(arthritis)

          |       pr
----------+---------
        1 |    0.570
        2 |    0.538
        3 |    0.589
```


Discrete changes: mlincom

Instead of **`lincom _b[2._at] - _b[1._at]`**

```
. mlincom 2 - 1, rowname(height_only)

              |   lincom    pvalue        ll        ul
--------------+----------------------------------------
  height_only |   -0.031     0.000    -0.046    -0.017

. qui mlincom 3 - 1, rowname(and_weight) add

. mlincom 3 - 2, rowname(2nd_difference) add

              |   lincom    pvalue        ll        ul
--------------+----------------------------------------
  height_only |   -0.031     0.000    -0.046    -0.017
   and_weight |    0.020     0.008     0.005     0.034
2nd_differnce |    0.051     0.000     0.046     0.056
```


Table with global and local means

Global means

```
. sysuse binlfp4, clear
. logit lfp i.wc k5 k618 i.agecat i.hc lwg inc

. qui mtable, atmeans at(wc=0 k5=(0 1 2 3)) estname(NoCol)
. qui mtable, atmeans at(wc=1 k5=(0 1 2 3)) estname(College) ///
>     atvars(_none) right
. mtable, atmeans dydx(wc) at(k5=(0 1 2 3)) estname(Diff) stats(est p) ///
>     atvars(_none) names(columns) right

      k5     NoCol   College      Diff         p
------------------------------------------------
       0     0.604     0.772     0.168     0.000
       1     0.275     0.457     0.182     0.001
       2     0.086     0.173     0.087     0.013
       3     0.023     0.049     0.027     0.085

. matrix k5wc_global = _mtab_displayed
```

Local means

```
. mtable, over(k5) at(wc=0) estname(NoCol)   atmeans atvars(k5)

Expression: Pr(lfp)

           |       1.                                 2.         3.         1.
           |       wc         k5       k618     agecat     agecat         hc
 ----------+-----------------------------------------------------------------
         1 |        0          0       1.28       .436       .269       .358
         2 |        0          1       1.75       .212      .0169       .517
         3 |        0          2       1.31      .0385          0       .538
         4 |        0          3       1.33          0          0          1
         5 |        1          0       1.28       .436       .269       .358
         6 |        1          1       1.75       .212      .0169       .517
         7 |        1          2       1.31      .0385          0       .538
         8 |        1          3       1.33          0          0          1

           |
           |      lwg        inc         pr
 ----------+-----------------------------
         1 |     1.11         20      0.583
         2 |     1.03       20.8      0.337
         3 |     1.18       17.6      0.154
         4 |     1.08       46.1      0.017
         5 |     1.11         20      0.757
         6 |     1.03       20.8      0.530
         7 |     1.18       17.6      0.288
         8 |     1.08       46.1      0.037
```



```
. qui mtable, over(k5) at(wc=1) estname(College) atmeans atvars(_none) right
. mtable, over(k5) dydx(wc) estname(Diff) atmeans stats(est p) ///
>     atvars(_none) names(columns) right

      k5     NoCol   College       Diff          p
------------------------------------------------
       0     0.583     0.757      0.173      0.000
       1     0.337     0.530      0.193      0.000
       2     0.154     0.288      0.134      0.003
       3     0.017     0.037      0.020      0.070

. matrix k5wc_localk5 = _mtab_displayed
```


Comparing global and local means

```
      | Global                | Local                 | Global - Local
   k5 | NoCol     Col    Diff | NoCol     Col    Diff | NoCol     Col    Diff
------+-----------------------+-----------------------+---------------------
 0.00 |  0.60    0.77    0.17 |  0.58    0.76    0.17 | -0.02   -0.02    0.01
 1.00 |  0.27    0.46    0.18 |  0.34    0.53    0.19 |  0.06    0.07    0.01
 2.00 |  0.09    0.17    0.09 |  0.15    0.29    0.13 |  0.07    0.11    0.05
 3.00 |  0.02    0.05    0.03 |  0.02    0.04    0.02 | -0.01   -0.01   -0.01
```

Plots with global and local means

If time permits...

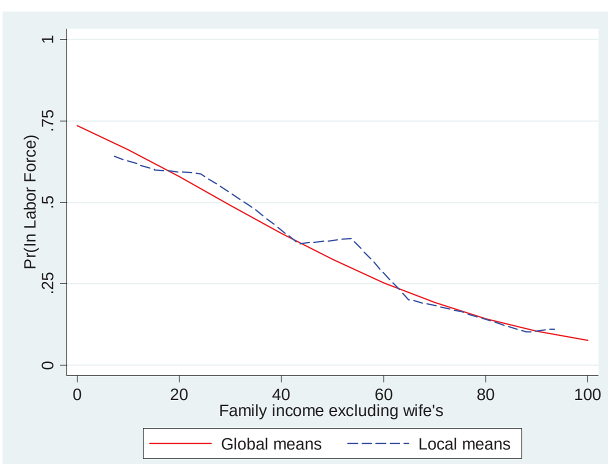
Predictions with global means

```
. sysuse binlfp4, clear
. logit lfp k5 k618 i.agecat i.wc i.hc lwg inc, nolog

. mgen, at(inc=(0(10)100)) atmeans stub(global_) predlabel(Global means)

Variables computed by the command:

. margins , at(inc=(0(10)100)) atmeans

Variable     Obs Unique      Mean        Min       Max  Label
------------------------------------------------------------------------------
global_pr     11     11  .3608011   .0768617  .7349035  Global means
global_ll     11     11  .2708139  -.0156624  .6641427  95% lower limit
global_ul     11     11  .4507883   .1693859  .8056643  95% upper limit
global_inc    11     11        50          0       100  Family income exclud...
------------------------------------------------------------------------------
```


Predictions with local means

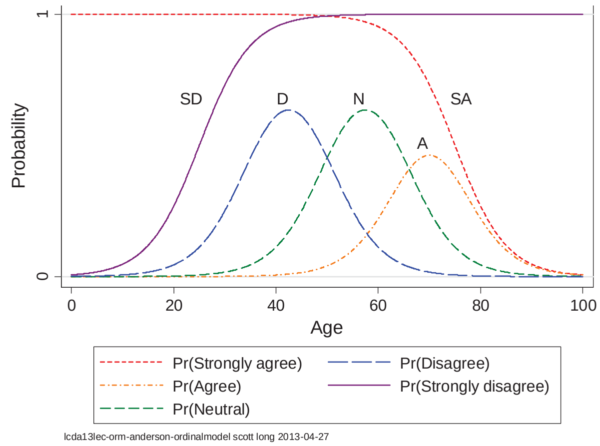
```
. gen inc10k = trunc(inc/10) // income in 10K categories
. mtable, over(inc10k) atmeans stat(est ll ul)

Expression: Pr(lfp)

           |                      2.         3.         1.         1.
           |       k5      k618   agecat     agecat        wc         hc
 ----------+--------------------------------------------------------------
         1 |     .202      1.43     .303       .222      .121      .0808
         2 |     .261      1.29     .363       .215      .212       .312
:::snip:::

           |
           |      lwg       inc       pr         ll        ul
 ----------+---------------------------------------------------
         1 |     .922      7.25    0.641      0.584     0.698
         2 |     1.08      15.1    0.600      0.559     0.642
:::snip:::

. matrix tab = r(table)
. matrix tab = tab[1...,8..11]
. matrix colnames tab = local_inc local_pr local_ll local_ul
. svmat tab, names(col)
. label var local_pr  "Local means"
. label var local_ll  "95% lower limit"
. label var local_ul  "95% upper limit"
. label var local_inc "Family income excluding wife's"
```


Comparing global and local predictions



Beyond the parameters

Ordinal models are very restrictive



Party identification

```
. use partyid01, clear
. tab party5, miss

     Party: |
1StDem 2Dem |
3Indep 4Rep |
     5StRep |      Freq.     Percent        Cum.
------------+-----------------------------------
       1_SD |        266       19.25       19.25
        2_D |        427       30.90       50.14
        3_I |        151       10.93       61.07
        4_R |        369       26.70       87.77
       5_SR |        169       12.23      100.00
------------+-----------------------------------
      Total |      1,382      100.00

. nmlab party5 age income black female highschool college

party5      Party: 1StDem 2Dem 3Indep 4Rep 5StRep
age         Age
income      Income (Thousands of dollars)
black       Respondent is black
female      Respondent is female
highschool  High school is highest degree
college     College is highest degree
```


ologit of partyid

```
. ologit party5 age10 income10 i.black i.female i.highschool i.college
. listcoef, help

ologit (N=1382): Factor Change in Odds

  Odds of: >m vs <=m (More Republican vs Less Republican)

----------------------------------------------------------------------
      party5 |      b         z     P>|z|     e^b    e^bStdX      SDofX
-------------+--------------------------------------------------------
       age10 | -0.06359    -2.037   0.042   0.9384    0.8988     1.6783
    income10 |  0.09611     4.792   0.000   1.1009    1.3060     2.7781
     1.black | -1.47593    -9.824   0.000   0.2286    0.6014     0.3445
    1.female | -0.15711    -1.584   0.113   0.8546    0.9244     0.5001
1.highschool |  0.29417     1.943   0.052   1.3420    1.1563     0.4937
   1.college |  0.64204     3.543   0.000   1.9004    1.3250     0.4383
----------------------------------------------------------------------
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
     e^b = exp(b) = factor change in odds for unit increase in X
 e^bStdX = exp(b*SD of X) = change in odds for SD increase in X
   SDofX = standard deviation of X
```

Parallel regression assumption

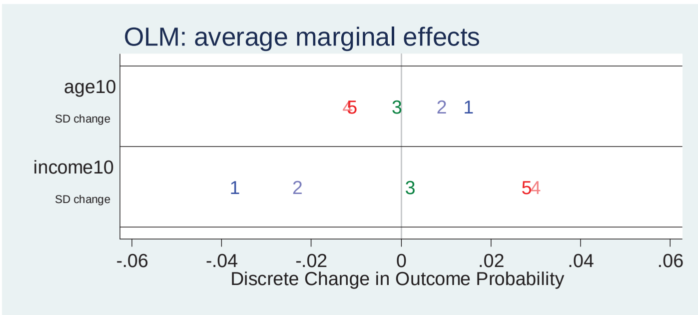
```
. brant

Brant Test of Parallel Regression Assumption

    Variable |      chi2   p>chi2    df
-------------+--------------------------
         All |     89.84    0.000    18
-------------+--------------------------
       age10 |     42.87    0.000     3
    income10 |      2.11    0.550     3
     1.black |     12.82    0.005     3
    1.female |      6.54    0.088     3
1.highschool |      2.92    0.404     3
   1.college |     12.24    0.007     3
----------------------------------------

A significant test statistic provides evidence that the parallel
regression assumption has been violated.
```

SUGGESTION

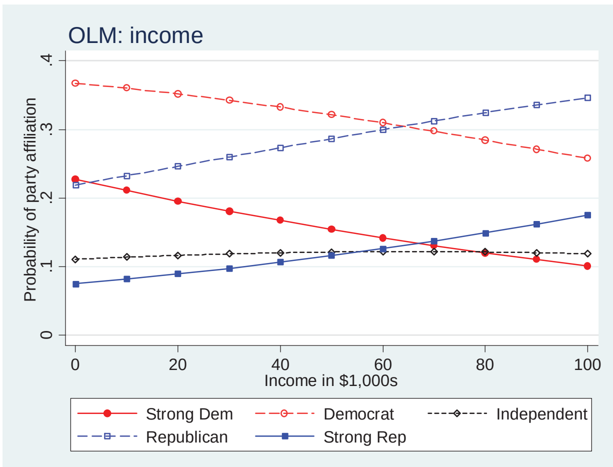
1. Results of tests should be clearly explained (like chibar2).

AME

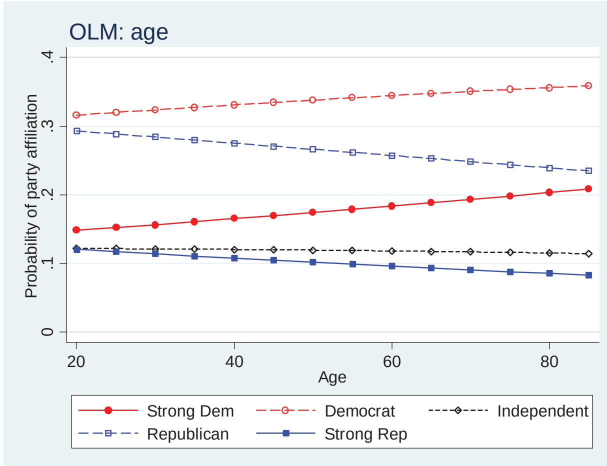
```
mchange
dcplot age10 income10, ...
```



ologit by income



ologit by age



mlogit of partyid

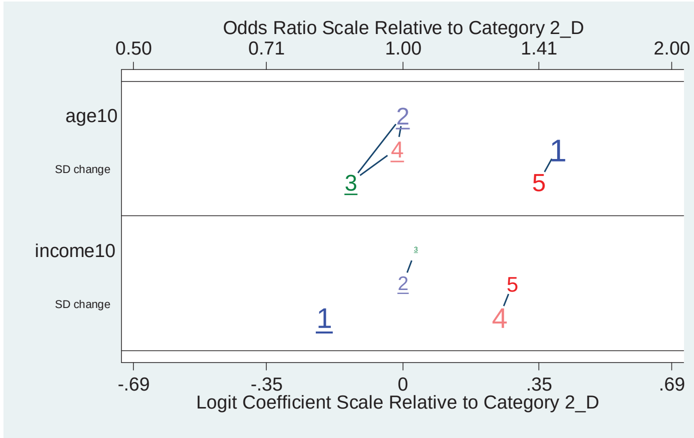
```
. mlogit party5 age10 income10 i.black i.female i.highschool i.college
::: snip :::

. mlogtest age10 income10, wald

Wald tests for independent variables (N=1382)

  Ho: All coefficients associated with given variable(s) are 0

             |       chi2    df    P>chi2
-------------+-------------------------
       age10 |     43.815     4     0.000
    income10 |     22.985     4     0.000
---------------------------------------
```



```
. listcoef age10 income10

mlogit (N=1382): Factor Change in the Odds of party5

Variable: age10 (sd=1.6783108)

Category 1  : Category 2  |       b         z     P>|z|     e^b    e^bStdX
--------------------------+--------------------------------------------
1_SD        : 2_D         |   0.23617     4.761   0.000   1.2664    1.4864
1_SD        : 3_I         |   0.31618     4.781   0.000   1.3719    1.7000
1_SD        : 4_R         |   0.24533     4.576   0.000   1.2780    1.5094
1_SD        : 5_SR        |   0.02819     0.438   0.662   1.0286    1.0484
2_D         : 1_SD        |  -0.23617    -4.761   0.000   0.7896    0.6728
2_D         : 3_I         |   0.08001     1.287   0.198   1.0833    1.1437
:::snip:::
5_SR        : 4_R         |   0.21714     3.594   0.000   1.2425    1.4397
------------------------------------------------------------------------

Variable: income10 (sd=2.7781476)
:::

. mchange
. local min = log(.1)
. local max = log(3)
. local graphnm "`pgm'-partyid-mnlm-orplot"
. orplot, dc mcolors(`partycolor') min(`min') max(`max').
```

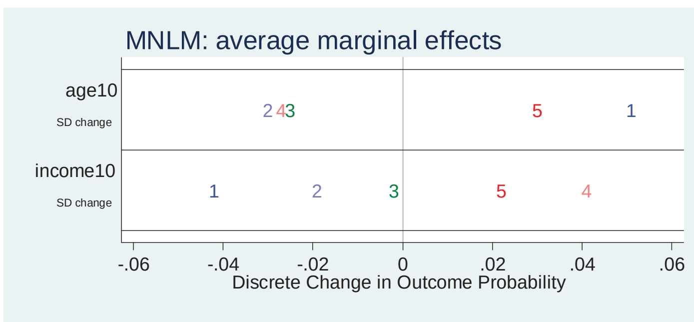
mlogit odds ratio plot with ame's

```
orplot age10 income10, dc
```



mlogit AME

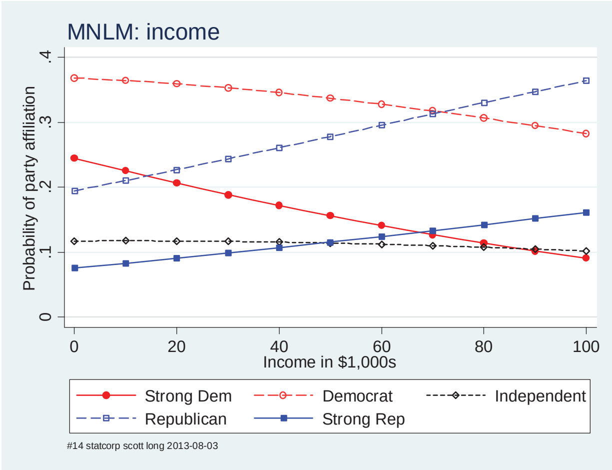
```
mchange
dcplot age10 income10, std(ss) min(-.06) max(.06) gap(.02) ...
```



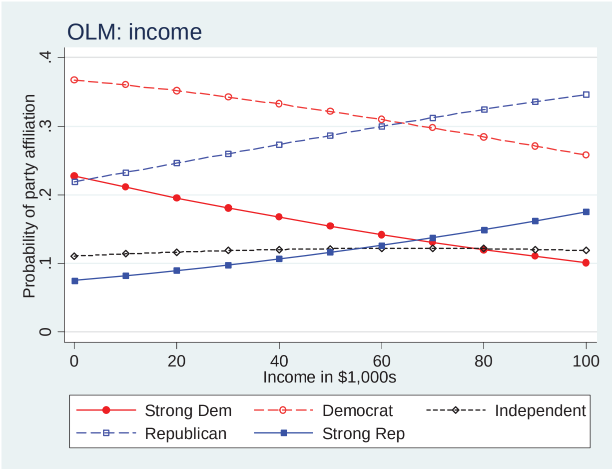
mlogit Probabilities to plot

```
. mgen, atmeans at(`at_age') stub(mnlmage)
:::snip:::

. mgen, atmeans at(`at_inc') stub(mnlminc)
:::snip:::
```

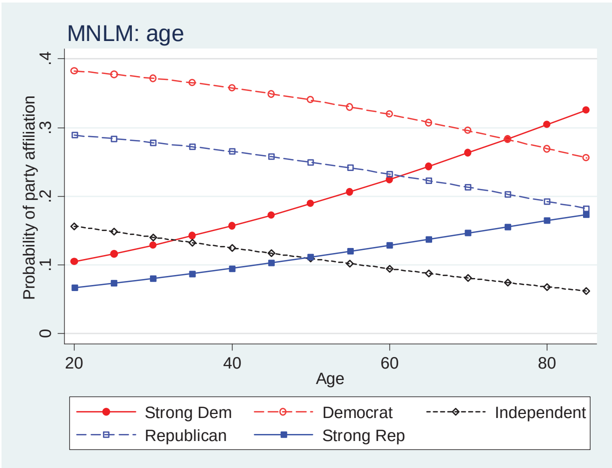
mlogit by income



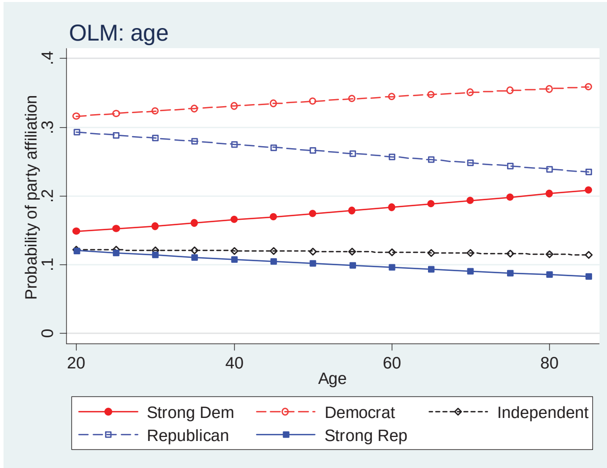
ologit by income



mlogit by age



ologit by age



Post-estimation test & fit

brant: parallel regression test

mlogtest, wald or lr

```
. mlogtest, lr

Likelihood-ratio tests for independent variables (N=337)

  Ho: All coefficients associated with given variable(s) are 0

             |       chi2    df    P>chi2
-------------+-------------------------
       white |      8.095     4     0.088
          ed |    156.937     4     0.000
       exper |      8.561     4     0.073
--------------------------------------
```

Why I'd like this included in the **mlogit** output...

Base BlueCol: 0 significant coefficients

```
                      e^b      P>|z|
WhiteCol: BlueCol   1.3978    0.720
Prof    : BlueCol   1.7122    0.501
Craft   : BlueCol   0.4657    0.227
Menial  : BlueCol   0.2904    0.088
```

Base Craft: 1 significant coefficient

```
                      e^b      P>|z|
BlueCol : Craft     2.1472    0.227
WhiteCol: Craft     3.0013    0.179
Prof    : Craft     3.6765    0.044
Menial  : Craft     0.6235    0.434
```

Base Menial: 1 significant coefficient

```
                      e^b      P>|z|
Craft   : Menial    1.6037    0.434
BlueCol : Menial    3.4436    0.088
WhiteCol: Menial    4.8133    0.082
Prof    : Menial    5.8962    0.019
```

Base Prof: 2 significant coefficients

```
                     e^b     P>|z|
WhiteCol: Prof     0.8163    0.815
BlueCol : Prof     0.5840    0.501
Craft   : Prof     0.2720    0.044
Menial  : Prof     0.1696    0.019
```

Base WhiteCol: 0 significant coefficients

```
                     e^b     P>|z|
-----------------+-----------------
Prof    : WhiteCol 1.2250    0.815
BlueCol : WhiteCol 0.7154    0.720
Craft   : WhiteCol 0.3332    0.179
Menial  : WhiteCol 0.2078    0.082
```

mlogtest, combine

Testing if outcome categories are significantly differentiated.

mlogtest, iia

Various not very useful but highly requested IIA tests.

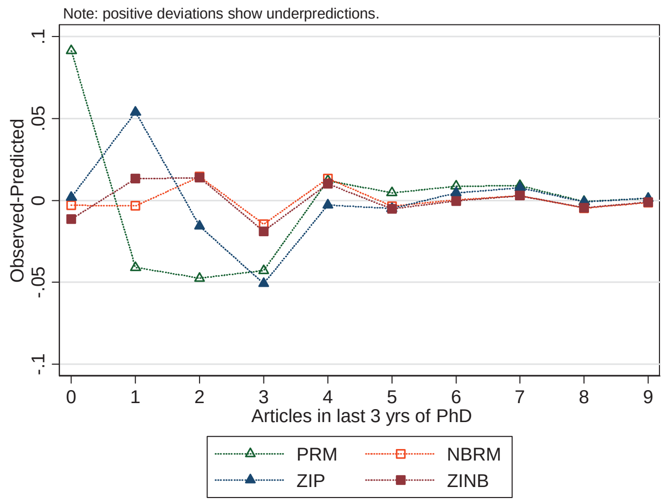
countfit: borrowed by SAS's countreg

```
. countfit art fem mar kid5 phd ment, gen(cfeg) replace ///
>         inflate(fem mar kid5 phd ment) maxcount(6) ///

----------------------------------------------------------------------
                        Variable | Base_PRM    Base_NBRM   Base_ZIP
---------------------------------+------------------------------------
art                              |
         Gender: 1=female 0=male |     0.799       0.805       0.811
                                 |     -4.11       -2.98       -3.30
             Married: 1=yes 0=no |     1.168       1.162       1.109
                                 |      2.53        1.83        1.46
          Number of children < 6 |     0.831       0.838       0.866
                                 |     -4.61       -3.32       -3.02
                    PhD prestige |     1.013       1.015       0.994
                                 |      0.49        0.42       -0.20
 Article by mentor in last 3 yrs |     1.026       1.030       1.018
                                 |     12.73        8.38        7.89
                        Constant |     1.356       1.292       1.898
                                 |      2.96        1.85        5.28
---------------------------------+------------------------------------
lnalpha                          |
                        Constant |                 0.442
                                 |                 -6.81
```

And so on for all models...


```
Comparison of Mean Observed and Predicted Count

            Maximum       At       Mean
Model      Difference    Value    |Diff|
---------------------------------------------
PRM          0.091         0      0.026
NBRM        -0.015         3      0.006
ZIP          0.054         1      0.015
ZINB        -0.019         3      0.008

PRM: Predicted and actual probabilities

Count   Actual    Predicted    |Diff|   Pearson
------------------------------------------------
0        0.301       0.209      0.091    36.489
1        0.269       0.310      0.041     4.962
2        0.195       0.242      0.048     8.549
3        0.092       0.135      0.043    12.483
4        0.073       0.061      0.012     2.174
5        0.030       0.025      0.005     0.760
6        0.019       0.010      0.009     6.883
7        0.013       0.004      0.009    17.815
8        0.001       0.002      0.001     0.300
9        0.002       0.001      0.001     1.550
------------------------------------------------
Sum      0.993       0.999      0.259    91.964
```

And so on for all models summarized as a graph...




```
Tests and Fit Statistics

PRM              BIC=  3343.026  AIC=  3314.113  Prefer  Over  Evidence
-------------------------------------------------------------------------
  vs NBRM        BIC=  3169.649  dif=   173.377  NBRM    PRM   Very strong
                 AIC=  3135.917  dif=   178.196  NBRM    PRM
                 LRX2=  180.196  prob=    0.000  NBRM    PRM   p=0.000
-------------------------------------------------------------------------
  vs ZIP         BIC=  3291.373  dif=    51.653  ZIP     PRM   Very strong
                 AIC=  3233.546  dif=    80.567  ZIP     PRM
                 Vuong=   4.180  prob=    0.000  ZIP     PRM   p=0.000
-------------------------------------------------------------------------
  vs ZINB        BIC=  3188.628  dif=   154.398  ZINB    PRM   Very strong
                 AIC=  3125.982  dif=   188.131  ZINB    PRM
-------------------------------------------------------------------------
NBRM             BIC=  3169.649  AIC=  3135.917  Prefer  Over  Evidence
-------------------------------------------------------------------------
  vs ZIP         BIC=  3291.373  dif=  -121.724  NBRM    ZIP   Very strong
                 AIC=  3233.546  dif=   -97.629  NBRM    ZIP
-------------------------------------------------------------------------
  vs ZINB        BIC=  3188.628  dif=   -18.979  NBRM    ZINB  Very strong
                 AIC=  3125.982  dif=     9.935  ZINB    NBRM
                 Vuong=   2.242  prob=    0.012  ZINB    NBRM  p=0.012
-------------------------------------------------------------------------
ZIP              BIC=  3291.373  AIC=  3233.546  Prefer  Over  Evidence
-------------------------------------------------------------------------
  vs ZINB        BIC=  3188.628  dif=   102.745  ZINB    ZIP   Very strong
                 AIC=  3125.982  dif=   107.564  ZINB    ZIP
                 LRX2=  109.564  prob=    0.000  ZINB    ZIP   p=0.000
```


fitstat

These are generally not very useful, so don't waste time computing them...

```
. fitstat

Measures of Fit for logit of lfp

Log-Lik Intercept Only:      -514.873   Log-Lik Full Model:           -452.724
D(744):                       905.447   LR(8):                         124.299
                                        Prob > LR:                       0.000
McFadden's R2:                  0.121   McFadden's Adj R2:               0.103
ML (Cox-Snell) R2:              0.152   Cragg-Uhler(Nagelkerke) R2:      0.204
McKelvey & Zavoina's R2:        0.215   Efron's R2:                      0.153
Tjur's Discrimination Coef:     0.153
Variance of y*:                 4.192   Variance of error:               3.290
Count R2:                       0.676   Adj Count R2:                    0.249
AIC:                          923.447   AIC/N:                           1.226
BIC:                          965.064   k:                               9.000
```

ic compare

```
. logit lfp i.wc k5 k618 age i.hc lwg inc
. fitstat, ic saving(nofv)
. logit lfp i.wc k5 k618 i.agecat i.hc lwg inc
. fitstat, ic using(nofv) dif

                              Current            nofv       Difference
Model:                          logit           logit
N:                                753             753                0
AIC                           923.447         921.266            2.181
AIC/N                           1.226           1.223            0.003
BIC                           965.064         958.258            6.805
k                               9.000           8.000            1.000
BIC (deviance)              -4022.857       -4029.663            6.805
BIC'                          -71.307         -78.112            6.805

Difference of    6.805 in BIC provides strong support for saved model.
```

SUGGESTION

1. A "`lrtest`" like command for use with IC measures.

Listing coefficients

```
. listcoef, help

zip (N=915): Factor Change in Expected Count

 Observed SD: 1.926069

Count Equation: Factor Change in Expected Count for Those Not Always 0

----------------------------------------------------------------------
         art |      b         z     P>|z|     e^b    e^bStdX      SDofX
-------------+--------------------------------------------------------
         fem |  -0.20914   -3.299   0.001   0.8113   0.9010     0.4987
         mar |   0.10375    1.459   0.145   1.1093   1.0503     0.4732
        kid5 |  -0.14332   -3.022   0.003   0.8665   0.8962     0.7649
         phd |  -0.00617   -0.199   0.842   0.9939   0.9939     0.9842
        ment |   0.01810    7.886   0.000   1.0183   1.1872     9.4839
----------------------------------------------------------------------
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
     e^b = exp(b) = factor change in expected count for unit increase in X
 e^bStdX = exp(b*SD of X) = change in expected count for SD increase in X
   SDofX = standard deviation of X
```



```
Binary Equation: Factor Change in Odds of Always 0

----------------------------------------------------------------------
     Always0 |      b         z     P>|z|     e^b    e^bStdX      SDofX
-------------+--------------------------------------------------------
         fem |   0.10975    0.392   0.695   1.1160   1.0563     0.4987
         mar |  -0.35401   -1.115   0.265   0.7019   0.8458     0.4732
        kid5 |   0.21710    1.105   0.269   1.2425   1.1806     0.7649
         phd |   0.00127    0.009   0.993   1.0013   1.0013     0.9842
        ment |  -0.13411   -2.964   0.003   0.8745   0.2803     9.4839
----------------------------------------------------------------------
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
     e^b = exp(b) = factor change in odds for unit increase in X
 e^bStdX = exp(b*SD of X) = change in odds for SD increase in X
   SDofX = standard deviation of X
```

Suggestion

margins related

1. More compact output.
2. Multiple outcomes in same estimation.
3. Save individual observations: **`margins, gen()`**
4. Let **`predict`** predict everything that **`margins`** can estimate
5. **`margins, at(x=gen(x+sd(x))`**: **`egen()`** for **`at()`**
6. **`marginsplot`**: save graphing variables and allow multiple outcomes
7. **`margins, autopost`**: automatically save current estimation command if it is in memory; if not in memory, load the one that was autoposted.
8. Better ways to incorporate local predictions: **`over(x=gen())`**?

Data analysis

1. A unified method for collecting results.
2. lrtest type command for ic
3. vuong function to compare models.
4. **`datasignature`** to detect all changes (controlled by save and use)
5. sem: LCA

Really useful that seem easy

1. **`tab`** with variable name and variable label; values with value labels.
2. **`svy: means`** for fv's
3. **`reallyclearall`**
4. fastcd by Nick Winter

Programming

1. Better tools for factor variables (or let Jeff make house calls)
   - factor variables have greatly increased the barrier to user written commands.
2. r(table) for all commands with all key results (e.g., lincom)
3. Stronger controls for value labels

Graphics

1. 3d wireframe graphics

For workflow

1. help mix not help me!

Move the best functions of SPost into Stata

Thank you

Contents